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Modeling energy efficiency to improve air quality and health effects of China's cement industry

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HIGHLIGHTS

- An integrated model was used to model the co-benefits for China's cement industry.
- $PM_{2.5}$ would decrease by 2–4% by 2030 through improved energy efficiency.
- 10,000 premature deaths would be avoided per year relative to the baseline scenario.
- Total benefits are about two times higher than the energy efficiency costs.

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ABSTRACT

Actions to reduce the combustion of fossil fuels often decrease GHG emissions as well as air pollutants and bring multiple benefits for improvement of energy efficiency, climate change, and air quality associated with human health benefits. The China's cement industry is the second largest energy consumer and key emitter of CO_2 and air pollutants, which accounts for 7% of China's total energy consumption, 15% of CO_2, and 14% of $PM_{2.5}$, respectively. In this study, a state-of-the art modeling framework is developed that comprises a number of different methods and tools within the same platform (i.e. provincial energy conservation supply curves, the Greenhouse Gases and Air Pollution Interactions and Synergies, ArcGIS, the global chemistry Transport Model, version 5, and Health Impact Assessment) to assess the potential for energy savings and emission mitigation of CO_2 and $PM_{2.5}$, as well as the health impacts of pollution arising from China's cement industry. The results show significant heterogeneity across provinces in terms of the potential for $PM_{2.5}$ emission reduction and $PM_{2.5}$ concentration, as well as health impacts caused by $PM_{2.5}$. Implementation of selected energy efficiency measures would decrease total $PM_{2.5}$ emissions by 2% (range: 1–4%) in 2020 and 4% (range: 2–8%) by 2030, compared to the baseline scenario. The reduction potential of provincial annual $PM_{2.5}$ concentrations range from 0.03% to 2.21% by 2030 respectively, when compared to the baseline scenario. 10,000 premature deaths are avoided by 2020 and 2030 respectively relative to baseline scenario. The provinces of Henan and Hubei account for 43% of total avoided premature deaths, followed by Chongqing (9%) and Shanxi (10%), respectively. If only considering the energy saving benefits, 37% of energy efficiency measures are not cost effective. However, the co-benefits (including energy saving, CO_2 reduction, and health benefits) are about two times higher than the costs of energy efficiency measures. Hence, this study clearly demonstrates that simultaneous planning of energy and air quality policies creates a possibility of increasing economic efficiency in both policy areas.

1. Introduction

Air pollution due to massive use of fossil fuels has received considerable attention in recent years [1–3]. The World Health Organization (WHO) estimates that about one million premature deaths are caused by outdoor air pollution in the world each year, with

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Nomenclature

WHO	World Health Organization
$PM_{2.5}$	fine particulate matter with a diameter smaller than 2.5 μm
GHGs	greenhouse gases
BC	Black Carbon
OC	Organic Carbon
VOC	volatile organic compounds
CEV	cerebrovascular disease
IHD	ischemic heart disease
MESSAGE	The Model for Energy Supply Strategy Alternatives and their General Environmental Impact
GAINS	The Greenhouse Gases and Air Pollution Interactions and Synergies
UKIAM	the UK integrated assessment model
SIRMOD	Surface Irrigation Model
GIS	geographical information system
LCA	life cycle assessment
SFA	substance flow analysis
ADM	air dispersion modeling
HIA	health impact assessment
MCDA	Multi-Criteria Decision Analysis
CMAQ	Community Multiscale Air Quality
BenMAP	the environmental Benefits Mapping and analysis Program
ECSC	Energy Conservation Supply Curves
IIASA	International Institute for Applied Systems Analysis
USEPA	the United States Environmental Protection Agency
EPPA-HE	emission prediction and policy analysis model with health effects
AirQUIS	the air quality management tool
TM5	the global chemistry Transport Model, version 5
TM	Tracer Model
TM5-FASST	TM5 with fast scenario screening tool
ECMWF	the European Centre for Medium Range Weather Forecast
IPCC	Intergovernmental Panel on Climate Change
AR5	Fifth Assessment Report
HIA	health impact assessments
YOLL	Years Of Life Lost
DALY	Disability Adjusted Life Years
PAF	the population-attributable fraction
C-R	concentration-response
COPD	chronic obstructive pulmonary disease
IHD	ischemic heart disease
VOSL	the value of a statistical life
WTP	willingness to pay
COI	cost of illness
BTA	the benefit transfer approach
WEO	World Energy Outlook
IEA	International Energy Agency
SCC	social cost of carbon
MIIT of China	Ministry of Industry and Information Technology of China
LBNL	Lawrence Berkeley National Laboratory
ERI of China	Energy Research Institute of China
WBCSD	World Business Council for Sustainable Development
MEP of China	Ministry of Environmental Protection of China
CVD	cardiovascular disease
LC	lung cancer disease
RD	disease of the respiratory system
BL	baseline scenario
EEPTP	Energy Efficiency Policy with technical energy saving potential scenario
AEEI	annual autonomous energy efficiency improvement
NSP	new suspension preheater

Symbols

CCE	cost of conserved energy
I	investment
AF	annuity factor
M	annual change in operation and maintenance costs
E	annual energy saving potential
P	energy price
d	discount rate
n	lifetime of the energy efficiency measures
$E_{i,p}$	emissions of pollutant p (for BC, OC, VOC, CO, and dust) in county i
$A_{i,k}$	activity level of type k (e.g., fuel consumption, production of cement/clinker in cement plants) in county i
$ef_{i,k,p}$	emission factors of pollutant p for activity k in county i.
ΔY	the change of mortality/morbidity rate
$\alpha_{2010,>30ages}$	the mortality/morbidity rate of over 30 years of age cohort at the base year (2010)
HR	the Hazard ratio for an increase in $PM_{2.5}$ concentration of 10 μg/m^3
ΔC	the changes of $PM_{2.5}$ concentration under different scenarios
P	the affected population
$VOSL_i$	the VOSL of the year i (2020 and 2030)
$VOSL_{2010}$	the VOSL of the year 2010
I_{2010}	the personal income of the year 2010
I_i	the personal income of the year i
e	the personal income elasticity.

Subscript

i, k, p	county, activity type, pollutant, respectively.

fine particulate matter with a diameter smaller than 2.5 μm ($PM_{2.5}$) as one of the prominent contributors [4,5]. Based on the database of global burden of disease, Lelieveld et al. [6] found that $PM_{2.5}$ related mortality in 2010 was 3.15 million people per year worldwide (1.61–4.81 million death per year at 95% confidence interval), with cerebrovascular disease (CEV) accounting for 42% (1.31 million) of total premature deaths and 34% (1.08 million) due to ischemic heart disease (IHD) [6]. The study also found that the contribution of outdoor air pollution to premature death would double (6.6 million) by 2050 in a business-as-usual scenario [6]. In 2013, an estimated 0.26 million premature deaths in 31 Chinese capital cities could be linked to $PM_{2.5}$ air pollution. The study also found that if the annual $PM_{2.5}$ concentration meets the Air Quality Guidelines set by Chinese government standards, the mortality rate could be decreased by 0.41‰, compared to 2013 [7]. During the period of April 5, 2014 and August 5, 2014, China's population-weighted exposure to $PM_{2.5}$ was 52 μg/m^3, which led to about 1.6 million deaths per year (0.7–2.2 million deaths per year at 95% confidence interval). The diseases of Ischemic heart, lung cancer and strokes accounted for 17% of total number of deaths in China, together [8]. Therefore, the Chinese government released the national action plan on air pollution control. In this strategy, $290 billion (1.75 trillion yuan) has been invested between 2013 and 2017, of which the industry will absorb 36.7%

of total investment to deliver clean air, caused by the use of cleaner energy sources (28.2%) [9]. The national five year plan (2013–2017) aims to decrease the concentrations of $PM_{2.5}$ by 10% by 2017 in populated regions and metropolises, compared to 2012 [10].

There is growing recognition that actions to reduce the combustion of fossil fuels often decrease GHG emissions as well as air pollutants, and thus bring multiple benefits for energy efficiency, climate change, air quality, and human health benefits related to air quality [11–15]. Several studies have shown that it is more cost effective for governments to consider health impacts when planning energy policy than to pay for the resulting damage later [16]. If health externalities of ambient PM pollution are used as input to existing energy models, the total health related externality costs and total energy system costs relative to technology and relocation of plants in the heat and power sector can be decreased by 18% and 4% respectively [17]. The understanding on many aspects of energy efficiency, climate change, air quality and associated health effects has drastically increased in recent years on global [18,19], national [20–22] and sub-regional scales [23–27].

In recent decades, several models have seen a rapid development in the possibility to decrease costs, improve efficiency, and simulate the interaction between energy, water, climate, and air quality associated with health effects in agriculture and manufacturing industries [28–31]. Valipour using Surface Irrigation Model (SIRMOD) software studied the performance of full hydrodynamic, zero inertia, and kinematic wave models in surface irrigation processes. The findings showed that full hydrodynamic and zero inertia models are very powerful in simulation process and all these models can simulate the surface irrigation processes [32]. The Model for Energy Supply Strategy Alternatives and their General Environmental Impact (MESSAGE) combined with the off-line global TM5 chemistry-transport model and WHO Comparative Risk Assessment approach was used to estimate the policy synergies of energy access, climate change, and air pollution and related health impacts [1,18]. The results show that 80% of the population is exposed to air quality levels higher than the WHO air quality guidelines which results in 4.8 million deaths caused by air pollution worldwide. The study also indicates that if stringent policy (e.g. air pollution, climate change, and clean cooking fuels) is implemented in the future, $PM_{2.5}$ emissions would decrease effectively. This would result in a significant decline in the global burden of disease [1,18]. Shih et al., developed and adopted a novel Air Resource Co-benefits model combined with system dynamics model to conduct a co-benefit between energy saving potential, greenhouse gas mitigation and abatement of air pollution, as well as health benefits in the energy sector through accelerating the application of a sustainable energy policy [33]. The Greenhouse Gases and Air Pollution Interactions and Synergies (GAINS) model, parallel to MESSAGE, has been developed and used to assess the co-benefits between GHG emission and air pollution mitigation, as well as $PM_{2.5}$ related health effects (i.e. life shortening due to $PM_{2.5}$) through adopting comprehensive strategies (i.e. together implementation of energy policy, climate change and air quality policies). The synergies between different pollutants are highlight in the model [34,35]. For example, Dholakia et al., employed the GAINS model to assess the impacts of current policies on future air quality and related health effects in Delhi India. The study found that adopting stringent policy portfolios that include adopting advanced control measures and switch to cleaner fuels, and transboundary sources can meet the national air quality standards [36]. The UK Integrated Assessment model (UKIAM) was developed to optimize abatement strategies for improving UK's air quality by bringing together information on projected air pollution, atmospheric dispersion, urban air quality, and health outcomes of ambient air pollution, and alternative strategies on potential abatement measures to reduce emissions [37]. An integrated approach that includes a number of different methods and tools within the same platform (i.e. geographical information system (GIS), Life Cycle Assessment (LCA), Substance Flow Analysis (SFA), Air Dispersion Modeling (ADM), Health Impact Assessment (HIA), and Multi-Criteria Decision Analysis (MCDA)) was employed to assess the environmental and health impacts of pollution arising from different source in Sheffield. The study found that the absence of the current industrial sources would decrease SO_2 atmospheric emissions by 80–90%, NO_2 by 65–70%, and PM_{10} by up to 20%. This would result in a reduction of premature deaths and respiratory-related hospital admissions of 0.53% and 0.49% respectively [38]. The co-benefits of energy efficiency, climate change, air quality, and associated health effects in China have only been given limited attention. It means that mounting studies only adopted the air quality model (i.e. CMAQ) combined with health impact assessment approach (i.e. BenMAP) in China to evaluate the impacts of air pollution on health under alternative energy policies on a national and regional level [12,13,39,40]. However, limited attention has been paid to industrial contributions of ambient air pollution levels and their health effects through implementing energy efficiency measures. Furthermore, the interactions and synergies between energy consumption, GHGs and air pollution, as well as the health effects of pollution (e.g. energy and air quality policy) are usually neglected by industrial policy makers [20,41–43]. The main reason is that there is limited data and few mature methodologies to measure their scope and scale. This knowledge gap is starting point for this study that aims to model the relationship between energy efficiency and air quality in China's cement industry at various scales. The main innovation of this study is the modeling framework that is developed and which can close the gap between energy, air quality, and health models, at various scales. To meet this objective, we quantify co-benefits of energy savings and emission mitigation of air pollutants, as well as the environmental and health impacts of pollution arising from China's cement industry at a provincial level during the period 2011–2030. Furthermore, how co-benefits would affect the selected energy efficiency measures is also estimated by simulating the economic energy saving potential. To meet this objective, the provincial Energy Conservation Supply Curves (ECSC) combined with GAINS are first adopted to model $PM_{2.5}$ emissions on county level. Then, the TM5 model is used to simulate the relationships between explicit emissions and atmospheric concentrations with a 1 degree longitude $\times$ 1 degree latitude resolution. Next, the HIA and economic assessment of avoided health impacts module are used to examine the health benefits of $PM_{2.5}$. Finally, a co-benefits module is employed to quantify the social co-benefits of energy efficiency for improving air quality and health effects. The modeling framework in the study not only closes the gaps between energy, air quality, and health models, but also is performs a similar analysis for other industries/regions.

2. The regional air pollution and related health effects in China

In 2010, total $PM_{2.5}$ emissions amounted to 12 Mt with varying spatial distribution among provinces [44] (see Fig. 1). Specifically, the provinces of Hebei and Shandong are the top two $PM_{2.5}$ emitters, with about 1 Mt emissions and together accounting for 16% of total $PM_{2.5}$ emissions. The next four largest contributors were Jiangsu, Anhui, Sichuan, and Henan, accounting for 6%, respectively. Two developed cities (Beijing and Tianjin) and seven developing provinces (Fujian, Hainan, Ningxia, Qinghai, Tibet, and Xinjiang) had the lowest emissions, accounting for less than 1% of total emissions. As depicted in Fig. 1, the share of $PM_{2.5}$ emissions from China's cement industry amounted to 14% (range: 1–54%) of the China's total emissions in 2010. The cement industry

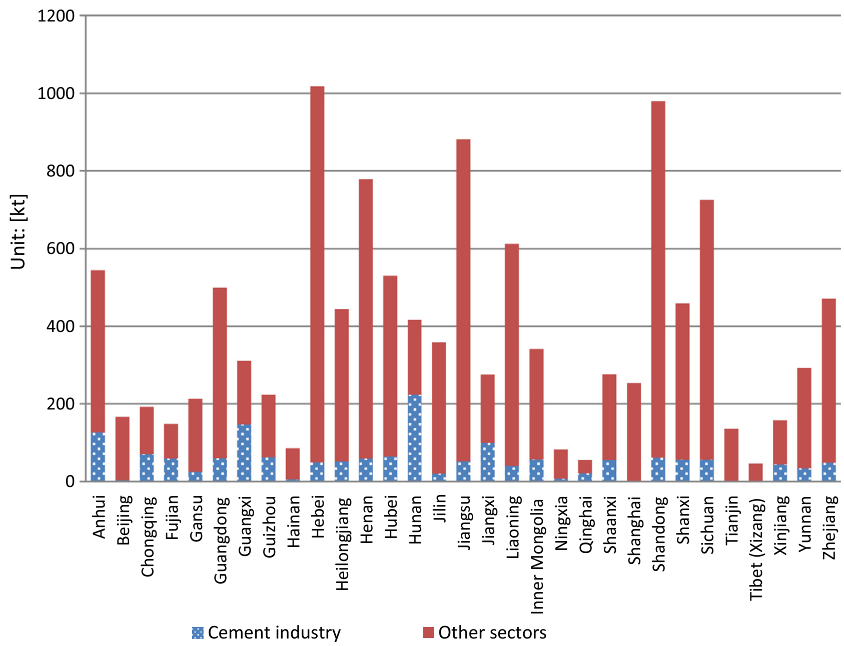

Fig. 1. The $PM_{2.5}$ emissions in cement industry and total sectors in 2010. Note: The $PM_{2.5}$ emission in cement industry are from Zhang et al. [45]; the $PM_{2.5}$ emission in other sectors are from GAINS-WEO-2011-450 scenarios.

contributed to above 40% of total $PM_{2.5}$ emissions in three provinces (Hunan, Guangxi, and Fujian), followed by Qinghai (39%), Chongqing (37%), and Jiangxi (36%), respectively. Cities of Beijing, Tianjin, and Shanghai, had the lowest contribution of total emissions, accounting for 2.25%, 0.62% and 0.03% respectively. The contribution of the cement industry to $PM_{2.5}$ emissions in different provinces shows large variations, predominantly in the middle of China (see Fig. 1). Three developing provinces (i.e. Hunan, Guangxi, and Anhui) with the most prolific cement raw material reserves together account for one-third of total emissions in the cement industry. Another one-third of total emissions in the cement industry were emitted from seven developing regions, named Chongqing, Fujian, Guangdong, Guizhou, Henan, Hubei, and Shandong, respectively.

Similar to the differences in provincial $PM_{2.5}$ emissions, the distribution of annual $PM_{2.5}$ concentrations in regions shows a similar pattern - the regions with higher emissions often yield a higher concentration. Fig. 2 shows the comparison between $PM_{2.5}$ concentrations and related loss of life expectancy in the various regions in 2010. The annual average $PM_{2.5}$ concentration amounted to 77.75 $\mu g/m^3$, which was 33% higher than the period in 2014 (from April to August) [8]. Because both models (GAINS and Kriging interpolation) employ different calibrations and modeling approaches and the latter doesn't consider the winter period (i.e.

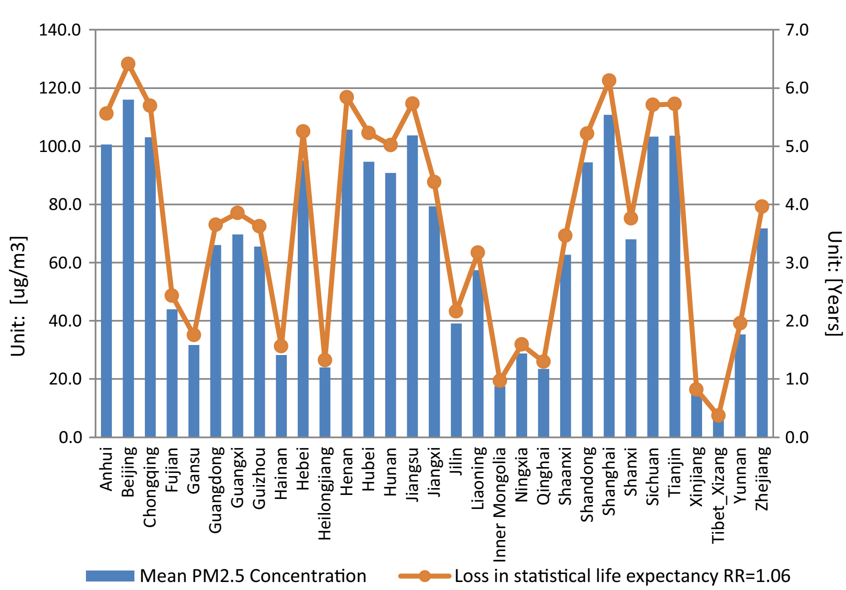

Fig. 2. The Mean $PM_{2.5}$ concentrations and $PM_{2.5}$ related life shortening per capita in 2010. Note: 1. The Mean $PM_{2.5}$ concentration and loss of life expectancy are from GAINS-WEO-2011-450 scenarios and calculated by authors. 2. The loss of life expectancy was calculated by GAINS, based on the value using a 1.06 relative risk, the methodology for computing the loss in life expectancy can be found in [46].

to meet the heating demands in building industry, the coal consumption often increased drastically in winter, compared to other seasons of the year). Furthermore, although the emissions in Beijing were lower than in developing regions, the annual $PM_{2.5}$ concentration in Beijing was highest (116 $\mu g/m^3$), due to transportation of air pollutants from surrounding areas. For example, the emissions from the Hebei province (a dominant emitter nearby Beijing) are easily transported to Beijing. The similar phenomena can be found in other developed regions, such as Tianjin and Shanghai.

Also the distributions of population numbers have large impacts for the average life shortening in the provinces. Fig. 2 presents the distribution of the loss of statistical life expectancy attributable to $PM_{2.5}$ concentrations for the year 2010 in China. As depicted in Fig. 2, the national average shortening was approximately 4.3 years with a varying distribution among provinces. The life shortening in Beijing was 49% higher than the national average, followed by Shanghai and Henan respectively. In Hebei, the largest emitter of $PM_{2.5}$, the individual life shortening was only 22% higher than national average, but 21% lower than that of Beijing. Regions of Chongqing, Jiangsu, Sichuan, and Tianjin have a similar shortening (5.73 year lost per capita) which is 33% higher than the national average. The others developing areas (e.g. Tibet and Xinjiang) show the lowest shortening of individual life expectancy by approximately 4–8 months, which is caused by the lower density of industrial activity and related urbanization processes.

3. Method and material

3.1. Modeling framework

Several studies have been conducted to estimate co-benefits of energy saving, emission mitigation of GHGs and air pollution as well as health effects from implementing advanced technologies, with varying methods under different scopes [3,43,47–49]. However, most of these studies only focused on the national level and neglected the regional heterogeneity. The industrial co-benefits of energy efficiency for air quality and health effects in China have not yet been systematically assessed, at the provincial level. According to our knowledge, this paper would be the first study to simulate the co-benefits of energy efficiency for air quality and health effects for China's cement industry at the provincial level. In this paper, the following sections introduce a state-of-the art modeling framework to estimate the co-benefits of energy savings, emission mitigation of CO_2 and air pollutants as well as health effects from air pollution through implementation of current commercially available energy efficiency measures in China's cement industry up to 2030. The innovative element of this study is the modeling framework that is developed and which can close the gap between energy, air quality, and health models, at the provincial level. Note that this study focuses only on assessing the actions of selected energy efficiency measures in China's cement industry, therefore many avoided air pollution effects and related health impacts (i.e. the advanced end-of-pipe measures might be more efficient than energy efficiency measures to avoid $PM_{2.5}$ emissions) will not be accounted for, possibly underestimating the abatement of air pollution and health impacts.

Five modules, in this study, were integrated to assess the co-benefits of energy savings and emission mitigation of air pollutants, as well as the environmental and health impacts and to quantify how co-benefits would affect the benefits of selected energy efficiency measures (see Fig. 3). The energy and emission modules that comprises provincial Energy Conservation Supply Curves (ECSC) and GAINS, was used.

1. Forecast the future energy saving potential in China's cement industry. First, the ESCS model was used to project the future energy saving potential in China's cement industry in technical and economic terms, respectively [42].
2. Calculate the emission inventory. The historical and future ambient air pollutant emissions inventory of China's cement industry at the county level are estimated using GAINS and a downscaling method, based on our recent study [45] and China's cement map [50]. Next, ArcGIS was used to convert the emission data from county level to $1° \times 1°$ grid cell. Specifically, the function of polygon to raster was used to convert the shapefiles to raster layer, and then the fishnet was adapted to convert it to grid format. Finally, the function raster to netCDF was used to produce the netCDF file. A detailed description on how to convert and output the format from shapfiles to netCDF file is given in ArcGIS Resource center [51].
3. Estimate the changes in annual average concentration of $PM_{2.5}$ with varying emissions. The annual average concentrations of $PM_{2.5}$ with changes in emissions under different scenarios were simulated by using the TM5 model.
4. Convert $PM_{2.5}$ concentrations from $1° \times 1°$ grid cell format to provincial level using ArcGIS.
5. Assess the health impacts from air pollution. The health impact assessment module was used to examine the relationship between air pollution and adverse health effects.
6. Monetize the avoided health benefits using economic assessment in the health impacts module.
7. Finally, the co-benefits module was employed to quantify co-benefits of selected energy efficiency measures in China.

Note that the advantage feature in the study is that the activity inputs to the next sub module are developed outside of the model. For example, the sub module of GAINS, TM5, and HIA model does not model the activity level of energy consumption, which has a large effect on the emissions from cement industry [52]. In addition, the current modeling framework doesn't quantify feedback effects between the modules, however, the consistency among inputs for different modules are considered. (e.g. population assumptions underlying the energy and HIA modules). These will be described in the next sections (Section 3.2), followed by data sources (Section 3.3) and scenario design (Section 3.4).

3.2. Introduction of sub modules

3.2.1. Energy module

ECSC, a bottom-up energy analysis technique, has been widely used for the assessment of cost related to energy saving and emission reduction measures in different economic sectors and industries in China, such as the iron and steel industry [53,54], ammonia industry [55], pulp and paper industry [56], and cement industry [41,57,58]. Provincial ECSC was developed to calculate the cost effectiveness and technical potential for energy saving in China's cement industry. In addition, different discount rates have widely adopted to calculate the costs and benefits of energy efficiency. High discount rates (30%) are often being used for the individual investment decisions, while energy modelers and policy makers prefer to use low social discount rates (4%) for forecasting long-term issues [30,59]. Hence, in the study a technology specific discount rate of 10% was used to reflect the barriers (e.g. lack of information) for energy efficiency investment. The methodology used for the calculation of energy saving potentials on economic and technical perspectives by Equation (1) (see [54,60,61] for more details):

$$\mathrm{CCE} = \frac{\mathrm{I} \times \mathrm{AF} + \mathrm{M} - \mathrm{ESP} \times \mathrm{P}}{\mathrm{ESP}} \tag{1}$$

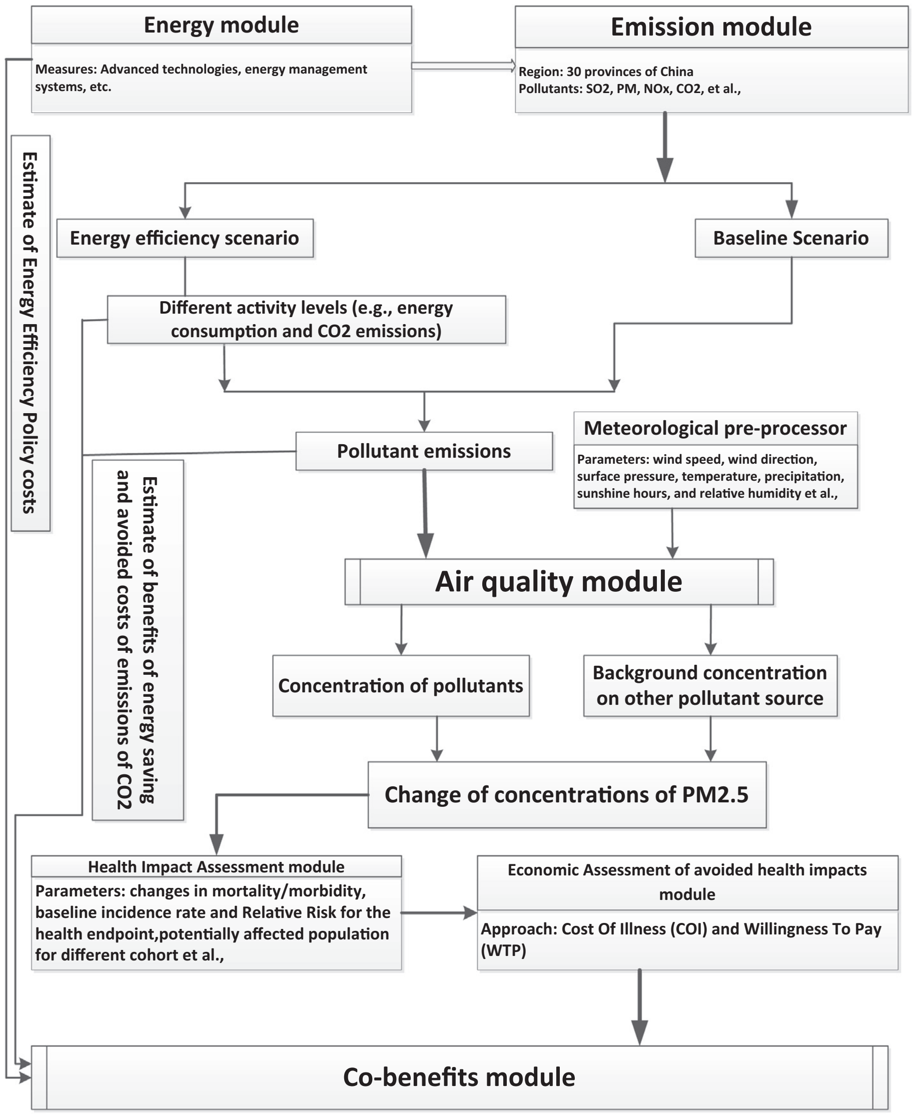

Fig. 3. Modeling framework.

where

CCE = Cost of conserved energy for energy efficiency measures, in $/GJ.
I = Investment.
AF = Annuity factor.
M = Annual change in operation and maintenance costs.
ESP = Annual energy saving potential.
P = Energy price ($/GJ).

The annuity factor is calculated by Eq. (2).

$$AF = \frac{d}{(1-(1+d)^{-n})} \tag{2}$$

where

d = Discount rate.
n = Lifetime of the energy efficiency measures.

Finally, the results of the energy module were introduced exogenously into the GAINS model.

3.2.2. Emission module

The GAINS model, developed by the International Institute for Applied Systems Analysis (IIASA), has been used to assess synergy effects of air pollutant and greenhouse gases (GHGs) emissions and explores cost-effective strategies to achieve environmental targets, as well as human health impacts related to $PM_{2.5}$ [62,63]. The pollutants and impacts are considered in GAINS by a multi-pollutant multi-effect approach [64]. GAINS also can used to estimate the economic and technical interactions in the mitigation measures for GHGs and selected air pollutants (i.e. SO_2, NOx, VOC, and PM). GAINS calculates the emissions of GHGs and air pollutants based on activity data, uncontrolled emission factors and the removal efficiency of end-of-pipe measures, as well as the application rates of selected emission control technologies [65]. A detailed description of the GAINS approach is provided in GAINS Development Team [66] and Amann et al. [34,67]. In this study, the emissions of CO_2, SO_2, NOx on county level are calculated through downscaling the provincial emissions as simulated by the GAINS model, described in Zhang et al. [42,45]. In the study, Emission factors of fuels for CO_2, PM, SO_2 and NOx are mainly from the GAINS database and calibrated based on the EMEP/EEA air pollutant emission inventory guidebook 2013 [68], production of industrial pollution discharge coefficient [69] and related studies [70]. The other emissions of BC, OC, VOC, CO, and dust are calculated through Eq. (3), using the emission factors of process and fuel, and the activity level of fuel consumption and production of cement and clinker.

$$E_{i,p} = \sum A_{i,k} ef_{i,k,p} \tag{3}$$

where

i, k, p = County, activity type, pollutant, respectively.
$E_{i,p}$ = Emissions of pollutant p (for BC, OC, VOC, CO, and dust) in county i.
$A_{i,k}$ = Activity level of type k (e.g., fuel consumption, production of cement/clinker in cement plants) in county i.
$ef_{i,k,p}$ = Emission factors of pollutant p for activity k in county i. The detailed data can be found in Table 1.

This approach allows not only to capture the critical distribution across counties but also reflects the contribution from different emission sources (including fuel consumption emission and process emission) that could justify differentiated emission reduction targets in a cost-effective strategy.

3.2.3. Air quality module

Several simple tools/approaches have been developed to simulate the spatial response of pollution concentration to changes in precursor emissions in a given region. The annual mean concentration of $PM_{2.5}$ are calculated based on a rollback model, which represents the relationship between air pollutants emissions and annual $PM_{2.5}$ concentration that can be extrapolated into the future [33,39,71]. The air quality management tool (AirQUIS) with pre-calculated exposure-response functions was adopted to estimate the relationship between energy consumption, air pollution, and health impacts in Taiyuan for 2000–2015 under different scenarios, and found that about 2.4–4.9% of GDP was lost due to particulate matter pollution [2]. To shorten simulation time, linear-source receptor relationships, a simple linear air quality model, are widely used to link the Integrated Assessment Models to track how emission scenarios influence the concentration of primary as well as secondary pollutants in the atmosphere [34,72]. The TM5 with Fast Scenario Screening Tool (TM5-FASST), a linearized source–receptor model, was employed to simulate relations between precursor's emissions and pollutant's concentrations on a $1° \times 1°$ grid cell level and to assess the impact of air quality improvements on human health [73]. The weakness of these simple tools/approaches is that they do not account for non-linear processes, such as the non-linear response of atmospheric chemistry to emission changes.

In this study, the global chemistry Transport Model, version 5 (TM5) was used to simulate the impacts of spatial explicit emissions from China's cement industry with a 1 degree longitude × 1 degree latitude resolution, and on 60 terrain following vertical layers. The TM5 model is a three-dimensional off-line model, based on earlier versions of the Tracer Model (TM), with chemical and physical parameters and meteorological data that are obtained from the model of the European Centre for Medium Range Weather Forecast (ECMWF). TM5 is used to study the chemical composition of the atmosphere at various resolutions and to estimate the relationships between explicit emissions and atmospheric concentrations [1,18,74]. The detailed information of photochemical mechanism (e.g., the gas-phase reaction scheme, the photolysis parameterization, the heterogeneous reactions the chemical solver, the description of aerosol processes, the treatment of the stratosphere, and the dry and wet deposition parameterizations) are described by Huijnen et al. [75]. The use of the model aerosol scheme M7 is described in Brugh et al. [76] and Noije et al. [77].

In this paper we mainly focus on the health effects of $PM_{2.5}$. The TM5 model calculates contributions from (1) primary $PM_{2.5}$ released from China's cement plants on county level, (2) secondary aerosols formed from cement plants emissions of Black Carbon (BC), Organic Carbon (OC), Volatile organic compounds (VOCs), SO_2 and NOx (NO/NO_2), (3) particulate matter from natural sources (soil dust, sea salt, and biogenic sources). The original emissions data were augmented with emissions from the cement industry, which were previously not included in the inventories because of data limitation. The data were pre-processed onto a China $1° \times 1°$ grid using ArcGIS tool. No seasonal variation in emissions is assumed for this study in order to avoid introducing bias because of extreme meteorological situations, which has been disaggregated as described by Houweling et al. [78] and Bergamaschi et al. [79]. Note that the particulate matter from natural sources as well as the other sectors are based on Intergovernmental Panel on Climate Change (IPCCC) Fifth Assessment Report (AR5) scenarios. For each emission source in this study, the TM5 model requires the annual emissions of $PM_{2.5}$ to be specified as dust, BC, primary organic matter, and the precursors (SO_2, VOC, CO, and NOx) in order to simulate the corresponding $PM_{2.5}$ concentrations in the receptor cells, for the year 2010, 2020, and 2030 under different scenarios. Considering the national average production capacity rates in China's cement industry was 72% in 2010 (equal to 300 days of annual production time [41]), with varying differences in the province (minimum = 57% in Liaoning and maximum = 99% in Hainan) [80]. Therefore, we assumed that all cement plants would run every month. Since the TM5 simulations require a substantial amount of computational time, we decided to shorten the simulation period. We have simulated two 2-month periods (Jan-Feb 2010, and Jul-Aug 2010, i.e. a winter and summer period). Based on the mid-January-February period and the mid-July-August periods we then estimated annual averages. In addition, the assessment of air pollutant emissions and dispersion in the TM5 model is global scale, the advantage of this scale allows accounting for the transboundary character of air pollution and capturing the influence from global boundary conditions. The multidimension tool "Make NetCDF Raster Layer" in ArcGIS was used to convert the netCDF file (output format from TM5 model) to ArcGIS raster. Next, the raster layer as ArcGIS grid format was converted to polygon shapefile. A detailed description on how to import, open, and convert the format between shapefile and netCDF file can be found in Hong et al. and ArcGIS Resource Center [51,81]. Finally, the changes of $PM_{2.5}$ concentrations at the provincial level were introduced into the Health Impact Assessment module.

3.2.4. Health Impact Assessment module

Health impact assessments (HIA) methods associated with Years Of Life Lost (YOLL) and Disability Adjusted Life Years (DALY) has been widely used to estimate health effects related to air pollution [37]. The population-attributable fraction (PAF) approach has been adopted to estimate health impacts from ambient air pollution, based on the gradient of the risk between the theoretical minimum level of air pollution exposure and the estimated observed exposure [36,82,83]. The refined method and sensitive indicators (changes in lung function and inflammation markers) were employed to examine the effects of air pollution on health outcomes [84]. The Exposure-response functions, a typical HIA, have been widely used in epidemiological studies to examine the relationship between $PM_{2.5}$ and adverse health effects [27,85–88]. The tool of concentration-response (C-R) shapes also has been used to describe the relative risks attributable to $PM_{2.5}$ exposure, based on cohort studies [23,40]. Similarly, the environmental

Benefits Mapping and analysis Program (BenMAP), a health impact assessment tool developed by the United States Environmental Protection Agency (USEPA), was employed to quantify the number of cases of deaths and illnesses related to $PM_{2.5}$. Considering this PM is the largest contributor to health impacts, it has been widely accepted as a surrogate indictor when estimating health effects [2]. Most studies prefer selected $PM_{2.5}$ due to the established robust causal relationships between long/short-term exposure to $PM_{2.5}$ and premature mortality from health endpoints [1,19]. However, PM_{10} as an indicator of air pollution has been used to model the health effects in China due to the limitation of data availability [12]. In the present study, the output of TM5 is exogenously passed to the HIA model as an input, to project health benefits of pollution. We calculated the impacts in health endpoints that could be achieved with the reductions in $PM_{2.5}$ concentration at the provincial level for the year 2020 and 2030. The year 2010 was selected as the base year in the health impact assessment module. In this module, both acute and chronic exposures to $PM_{2.5}$ are considered. Specifically, the acute effects represent the changes in response to day-to-day variations in ambient exposure, while chronic effects reflect longer-term exposure [89]. We consider premature mortality attributable to $PM_{2.5}$ for seven major health endpoints that have been often used in current studies. The impacts of each health endpoint from reduced exposure to $PM_{2.5}$ (the effects of mortality/morbidity) under different scenarios are estimated using Eq. (4) [22]:

$$\Delta Y = \alpha_{2010,>30\ ages} * \left(1 - \frac{1}{HR^{\Delta C}}\right) P \tag{4}$$

where

ΔY = The change of mortality/morbidity rate;
$\alpha_{2010,>30\ ages}$ = The mortality/morbidity rate of over 30 years of age cohort at the base year (2010);
HR = The Hazard ratio for an increase in $PM_{2.5}$ concentration of 10 $\mu g/m^3$ (see Table 3);
ΔC = The changes of $PM_{2.5}$ concentration under different scenarios;

The population with above 30 ages in 2020 and 2030 were calculated by Eqs. (5) and (6):

$$P_{2020} = P_{2010,>30\ ages} * \alpha_{2010,>30\ ages} + P_{2010,20-30\ ages} * \alpha_{2010,20-30\ ages} \tag{5}$$

$$P_{2030} = P_{2020,>30\ ages} * \alpha_{2010,>30\ ages} + P_{2010,10-20\ ages} * \alpha_{2010,10-20\ ages} \tag{6}$$

where P is Population; α is the mortality rate for different cohorts.

All mortality/morbidity rates in base year are obtained from peer reviewed literature (see Table 3). In addition the mortality rates of Lung cancer, Chronic obstructive pulmonary disease (COPD), Cerebrovascular, and Ischemic heart disease (IHD) are obtained from Pan et al. [7].

3.2.5. Economic assessment of avoided health impacts module

The value of a statistical life (VOSL) was adopted to assess the economic cost of health effects related to air pollution, which represents an individual's willingness to pay (WTP) for a marginal reduction in the risk of mortality [13,90]. Another similar approach is cost of illness (COI). The approach of WTP was mainly used to estimate the economic cost of health effects due to air pollution, while the COI was also adopted as an alternative method for quantify the costs of health endpoints that could not be monetized based on current WTP studies [12]. However, the COI approach does not include the value of avoiding the pain and suffering resulting from the illness, which lead to underestimating total economic value of avoiding the illness [91]. Because of data limitation, the benefit transfer approach (BTA) was used to estimate the cost of health effects in the base year (2010) and future years, calculated as follows [90]:

$$VOSL_i = VOSL_{2010} * \left(\frac{I_i}{I_{2010}}\right)^e \tag{7}$$

where

$VOSL_i$ and $VOSL_{2010}$ = The VOSL of the year i (2020 and 2030) and 2010, respectively.
I_i and I_{2010} = The personal income of the year i and 2010 respectively.
e is the personal income elasticity.

A personal income elasticity of 0.5 is assumed, based on West et al. [14]. The personal income of the year 2020 and 2030 is taken from GAINS based on the World Energy Outlook (WEO) 2012 baseline scenario of the International Energy Agency (IEA) (see Appendix A - Table A.2).

We do not only quantify the mortality outcomes related to long-term exposure to $PM_{2.5}$, but also estimate the morbidity outcomes due to short-term exposure to $PM_{2.5}$ which provides a part of the total burden of air pollution [4]. Both VOSL and COI are employed to quantify the benefits of avoided cases of premature death and delayed illnesses, respectively. However, in order to avoid double counting, the benefits from short-term exposure to $PM_{2.5}$ should not be considered when assessing co-benefits.

3.2.6. Co-benefits module

The co-benefits module was used to estimate the co-benefits of energy saving and emission mitigation of CO_2 and air pollutants, as well as the environmental and health impacts of pollution arising from China's cement industry at the provincial level. How the co-benefits would affect the economics of selected energy efficiency measures was assessed. In this module, three types of benefits are estimated: (1) energy saving benefits that are obtained from previous studies; (2) CO_2 emissions reduction benefits. We monetize benefits of CO_2 emissions reduction using CO_2 emissions reduction from Zhang el al. [45] and social cost of carbon (SCC). The SCC represents monetized climate damages due to an incremental increase in CO_2 emissions in a given year [92,93]; (3) avoided health benefits that are taken from economic assessment of avoided health impacts module.

3.3. Data sources

The historical and future ambient air pollutant emissions inventory of China's cement industry at the provincial level are obtained from our recent study [45]. The data (including production capacity of each clinker/grinding production line of each cement plant are taken from China's cement map that was released by China Cement Association [50]. Data on the potential and costs of energy efficiency measures (including international technologies and Chinese domestic technologies) in cement industry are obtained from our previous studies [42,45], as well as other sources such as Lawrence Berkeley National Laboratory (LBNL) [57,58], Energy Research Institute of China (ERI of China) [94,95], Ministry of Industry and Information Technology of China (MIIT of China) [96], and other institutes [63,64].

The original population data are from National Scientific Data Sharing Platform For Population and Health [97], Tabulation on the 2010 population census of the people's republic of China by County [98], and the Almanac of China's population [99].

Table 1
Emission factors of air pollutants in the cement industry.

Item	Unit	Emission factor	Note	Reference
BC	%	3.0%	Mass ratio of BC to $PM_{2,5}$	[100]
OC	%	1.0%	Mass ratio of OC to $PM_{2,5}$	[104]
SOx	kt/Mt_clinker	0.27	Process emission factor	[102]
NOx	kt/Mt_clinker	0.81	Process emission factor	[101]
CO	kt/Mt_clinker	1.40	Process emission factor	[100]
CO	kg/GJ	1.00	Fuel emission factor	[105]
VOC	kt/Mt_clinker	0.109	Process emission factor	[103,106]
VOC	kg/GJ	0.132	Fuel emission factor	[103]

Note: The fuel emission factors of SOx and NOx are calculated based on the Process emission factor and previous study [45].

Table 2
The value of social cost of carbon.

Year	$2007	$2010
2020	43	41.28
2030	52	49.92

Note: The currency conversion rates derived from International Monetary Fund [108].

The emission factors of BC, OC, SOx, NOx, CO, and VOC are obtained from IPCC [100], the World Business Council for Sustainable Development (WBCSD) [101], USEPA [102], Ministry of Environmental Protection of China (MEP of China) [103], and existing studies [104] (see Table 1).

3.22 of US$/GJ is assumed to estimate energy saving benefits which are taken from GAINS and widely used in other studies [42,54]. Two values of Social Cost of Carbon (SCC) are obtained from integrated assessment model (i.e. $43 per ton in 2020, and $52 per ton in 2030) are used, based on the value using a 3% interest rate, and converted to 2010 USD (see Table 2) [107].

The baseline (2010) mortality rates are based on National Scientific Data Sharing Platform For Population and Health [97]. The baseline rates of various morbidity endpoints, hazard rates of premature mortality and morbidity are from recent epidemiological studies and China Public Health Statistical Yearbook [109] (see Table 3).

The unit values of premature death and various health endpoints are taken from recent studies (see Table 4). The value of a statistical life (VOSL) in 2010 was obtained from Pan et al. [113]. The values of VOSL in China often lower than the developed countries/regions (e.g., US and western Europe), which heavily depend on economic development progress and personal income [14,90].

3.4. Scenario design

In this study, we mainly focus on 37 selected energy efficiency measures to estimate the impacts on changes of $PM_{2.5}$ concentrations and related health effects in China's cement industry at the provincial level. In addition, how co-benefits (including the benefits of energy saving, CO_2 reduction, and health impacts of pollution reduction) would affect the selected energy efficiency measures is also quantified when simulating the economic energy saving potential. Hence, we developed two scenarios for China's cement industry, described in detail in [42,45], as a basis to estimate the potential co-benefits of energy saving, emission mitigation of CO_2 and air pollutants, as well as health effects rising from $PM_{2.5}$. The scenarios are named Baseline scenario (BL) and Energy Efficiency Policy with technical energy saving potential (EEPTP) scenario. The baseline scenario assumed annual autonomous energy efficiency improvement (AEEI) was 0.2%, which is consistent with the GAINS model. This assumption represents the future trajectory for the China's cement industry in the absence of advanced technologies. Alternatively, all selected energy efficiency measures and their related implementation rates are projected in energy efficiency policies with technical energy saving potential (EEPTP) scenario by 2030 with a five year step. Note that the affected population, social cost of carbon, rates of mortality and morbidity and related hazard rates are assumed to be the same in all scenarios. A more in-depth description of energy efficiency measures is provided in our previous studies [42,45]. These scenarios combine assumptions about future output of cement and clinker, application of advanced energy efficiency measures with projected implementation rates, leading to long-term energy saving of 4.2 EJ. The co-effects of energy efficiency measures would result in decreasing 8% of CO_2, 5% of particulate matter, 25% of SO_2, 20% of NOx by 2030, compared to baseline scenario. Furthermore, the average marginal costs of energy efficiency would be decrease by 20%, when take into account the co-benefits of energy efficiency for clean air [42]. This paper goes a step further to simulate the co-benefits of energy efficiency for air quality and health effects in China's cement industry.

4. Results and discussion

4.1. Spatial distribution of $PM_{2.5}$ emissions

Fig. 4 shows the spatial distribution of $PM_{2.5}$ emissions in China's cement industry at the county level for the year 2020,

Table 3
Relative risk factor used for the calculations for a change 10 μg/m^3 of $PM_{2.5}$.

Health endpoints	Hazard rates (95% CI)		Baseline mortality rate (‰)	Reference
All-cause mortality caused by $PM_{2.5}$	1.07	1.05–1.09	–	[7,110,111]
Cardiovascular disease (CVD)	1.06	1.11–1.12	0.052	[88,112,113]
Stroke disease	1.10	1.03–1.17	0.102	[7,114–116]
Ischemic heart disease (IHD)	1.06	0.99–1.14	0.244	[7,114,116]
Lung cancer disease (LC)	1.10	0.99–1.22	–	[7,114]
Cardiopulmonary Disease	1.09	1,03–1,16	0.114	[86,109,117]
Hypertensive disease	1.20	1.06–1.35	0.002	[109,110]
Disease of the respiratory system (RD)	1.05	0.95–1.15	0.036	[88,109]

Note: – represent that the baseline mortality/morbidity rate of each health endpoint are obtained from [113].

Table 4
Value of health endpoints due to $PM_{2.5}$ Unit: [Million $].

Cause of health endpoints	Costs in base year	Reference
All-cause mortality	0.116	[113]
Cardiovascular disease (CVD)	0.0037	[2]
Disease of the respiratory system	0.0025	[2]

and 2030. The $PM_{2.5}$ emissions vary dramatically across counties depending on geography and production scales. Nationally, $PM_{2.5}$ emissions from cement plants in the baseline scenario would grow by 11% (range: 9–48%) for the year 2020 and by 37% (range: 16–39%) lower by 2030, compared to 2010 (see Fig. 4, Appendix B - Fig. A.1, and Appendix C). Overall, $PM_{2.5}$ emissions vary dramatically across regions, depending on geography, urbanization, and resource endowments. Using the Heihe-Tengchong line as dividing line between western and eastern China. Most of the total $PM_{2.5}$ emissions (including primary and secondary $PM_{2.5}$ emissions (particulate matter with aerodynamic diameter equal or smaller than 2.5 μm)) occur in the eastern part of China, and less of total $PM_{2.5}$ emissions occur in western China with small-scale cement plants (see Fig. 4). The spatial distribution of total $PM_{2.5}$ emissions has a similar trend to the pattern of primary emissions during the study period. Note that the discussion for chemical composition of the $PM_{2.5}$ emissions is beyond the scope of our study. The future trends of total PM2.5 emissions expected to shift from eastern to middle and western regions due to the consideration of the location of new cement plants [80]. For example, between 2007 and 2013, the middle and western regions built 829 new suspension preheater dry process (NSP) cement production lines, representing 75% of new capacity [80,118]. We assume that the geographic distribution of cement plants will remain unchanged in the future. On average, about 2% (range: 1–4%) and 4% (range: 2–8%) of total cement plant $PM_{2.5}$ emissions in EEPTP scenario will decrease by 2020 and 2030, compared to the BL scenario. Furthermore, nearly one-third of the counties have cement plants in China, i.e. 936 counties have cement plants with varying production capacity among the counties. Counties with larger-scale cement plants are usually located in developing provinces (e.g., shuangyashan of Heilongjiang, Fanchang of Anhui) with middle income and higher population density. Most $PM_{2.5}$ emissions from cement plants occur in developing counties. For example, the largest top-10 emitters on the county scale like shuangyashan of Heilongjiang, Fanchang and Tongling of Anhui, Beiliu, Gui and Pingnan of Guangxi, Zhangping of Fujian, Changsha of Hunan, Ruichang of Jiangxi, and Tongchuan of Shaanxi accounted for 1.2% (equal to 144 kt) of total $PM_{2.5}$ emission in 2010, while the share of $PM_{2.5}$ emissions from these ten counties will increased to 1.3% in 2020 and decreased to 1.2% in 2030 of the national total, respectively.

4.2. Changes in $PM_{2.5}$ concentrations

Table 5 shows the changes of $PM_{2.5}$ concentration due to the changes of emissions in China's cement industry at the provincial level, the year 2020 and 2030 for the Baseline and EEPTP scenarios, compared to 2010. On average, the changes of national annual $PM_{2.5}$ concentrations in the baseline scenario will increase by 0.11 μg/m^3 by 2020 and then decrease by 0.35 μg/m^3 by 2030. Under EEPTP scenario, in which all selected energy efficiency measures with projected implementation rates are implemented, the national annual average $PM_{2.5}$ concentrations will further decrease by 0.15 μg/m^3 compared to 2010. As shown in Table 5, the reduction potential of provincial $PM_{2.5}$ concentrations is diverse in different provinces. In the baseline scenario, the changes of provincial annual $PM_{2.5}$ concentrations across the counties varied (range: −2.62 of Anhui and 1.97 μg/m^3 of Hubei by 2020 and −3.92 of Shanxi and 0.25 μg/m^3 of Zhejiang by 2030, respectively). Furthermore, the provincial annual $PM_{2.5}$ concentrations in six provinces (e.g. Anhui, Guangdong, Henan, Hunan, Shanxi, and Sichuan) will decrease to some extent by 2020, with an average of 0.8 μg/m^3

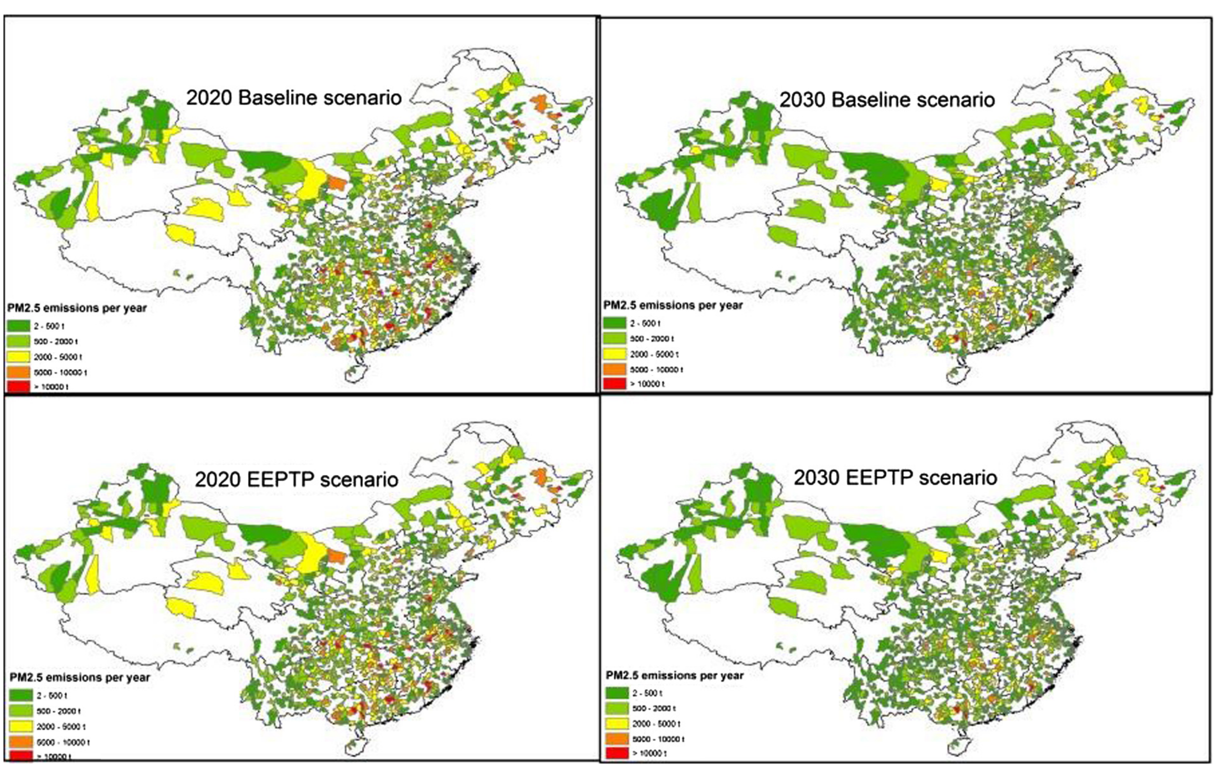

Fig. 4. $PM_{2.5}$ emissions for the year 2020 and 2030 under different scenarios at the county level.

Table 5
Changes of $PM_{2.5}$ concentrations for the year 2020 and 2030, compared to 2010 Unit:[$\mu g/m^3$].

Region	2010	2020		2030	
	Baseyear	BL	EEPTP	BL	EEPTP
Anhui	100.60	−2.62	−2.67	−3.17	−3.32
Beijing	116.00	0.00	−0.17	0.17	0.08
Chongqing	103.10	0.75	0.10	−0.14	−0.19
Fujian	44.00	0.74	0.63	−0.36	−0.40
Gansu	31.70	0.05	0.02	0.00	−0.01
Guangdong	66.10	−0.02	−0.08	−0.33	−0.37
Guangxi	69.70	0.29	0.18	−0.04	−0.09
Guizhou	65.50	1.02	0.58	−0.07	−0.10
Hainan	28.30	0.04	0.00	0.00	−0.06
Hebei	95.00	0.08	−0.02	0.00	−0.05
Heilongjiang	24.00	0.20	0.11	−0.02	−0.05
Henan	105.70	−0.92	−1.38	−0.88	−0.99
Hubei	94.60	1.97	1.12	−0.13	−0.24
Hunan	90.80	−1.13	−1.19	−0.76	−0.82
Jilin	103.80	0.10	−0.04	−0.15	−0.31
Jiangsu	79.40	1.15	1.12	−0.07	−0.19
Jiangxi	39.10	0.00	−0.02	−0.66	−0.72
Liaoning	57.40	0.03	0.01	−0.20	−0.35
Inner Mongolia	17.50	0.00	−0.01	−0.01	−0.02
Ningxia	28.80	0.00	−0.04	0.00	−0.11
Qinghai	23.50	0.00	−0.01	0.00	−0.02
Shaanxi	62.70	0.13	0.10	−0.08	−1.40
Shanghai	94.40	0.19	0.05	0.00	−0.09
Shandong	110.80	0.00	−0.02	0.00	−0.04
Shanxi	68.00	−0.06	−0.66	−3.92	−4.21
Sichuan	103.30	−0.02	−0.08	−0.06	−0.16
Tianjin	103.70	0.17	0.13	0.00	−0.08
Tibet (Xizang)	14.80	0.05	0.00	0.11	0.07
Xinjiang	6.70	0.00	−0.01	0.00	−0.03
Yunnan	35.40	0.59	0.42	0.00	−0.23
Zhejiang	71.70	0.63	0.61	0.25	−0.14
National average level	68.54	0.11	−0.04	−0.35	−0.49

(range: 0.02 of Sichuan–2.62 $\mu g/m^3$ of Anhui), compared to 2010. If all energy efficiency measures are implemented as modeled (EEPTP scenario) by 2020, there will be a decrease of approximately 0.42 $\mu g/m^3$ (range: 0.01 of Xinjiang and 2.67 of Anhui) of provincial annual $PM_{2.5}$ concentrations in fifteen provinces (i.e. Anhui, Beijing, Guangdong, Hebei, Henan, Hunan, Jilin, Jiangxi, Inner Mongolia, Ningxia, Qinghai, Shanxi, Shandong, Sichuan, and Xinjiang), compared to 2010. The main reason is that these provinces play a key role in China's cement production and have large potential to improve energy efficiency and reduce air pollution. For example, province of Anhui contributes to 4% of total cement production and account for 4.3% of total air pollution abatement by 2020. In the Baseline scenario, the average provincial annual $PM_{2.5}$ concentrations in provinces/cities of Beijing, Tibet, and Zhejiang would be 0.18 $\mu g/m^3$ (min = 0.11 in Tibet province and Tianjin, max = 0.25 in Zhejiang province) higher by 2030 relative to 2010. Under EEPTP scenario, the $PM_{2.5}$ concentrations in Beijing and Tibet are still higher with 0.07 $\mu g/m^3$, compared to the base year (2010). The main reason is that the transportation of air pollution between different provinces contributes to the provincial annual $PM_{2.5}$ concentration. Overall, the national annual $PM_{2.5}$ concentrations in the EEPTP scenario would be 0.2% lower than in the baseline during the same period. Similarly, the reduction potential of provincial annual $PM_{2.5}$ concentrations in EEPTP scenario varies among different provinces, ranging from 0.03% in Zhejiang to 0.9% in Hubei by 2020 and from 0.03% in Guangdong to 2.2% in Shaanxi by 2030 respectively. Note that, the regional transport of air pollutants plays a key role for the regional annual $PM_{2.5}$ concentrations [119]. For example, the total $PM_{2.5}$ concentrations in 2030 at Beijing are 0.17 $\mu g/m^3$ higher than 2010 level, the main reason is that the emissions from surrounding regions (e.g., Hebei, Shandong, Henan) would transport to Beijing. The similar phenomena can be found in other regions, such as Shanghai, Tianjin, and Zhejiang.

4.3. Health effects from $PM_{2.5}$

We estimated the avoided premature deaths caused by $PM_{2.5}$ for the year 2020 and 2030 under different scenarios (in comparison to 2010) (see Appendix A - Table A.3). On the whole, in the baseline scenario 2 thousand cases of premature deaths related to $PM_{2.5}$ would increase each year by 2020, inversely, 36 thousand cases of premature deaths would be reduced each year in 2030 when compared to 2010. Assuming full implementation of all energy efficiency measures as in the EEPTP scenario, 10 thousand premature deaths would be avoided per year in 2020 and 2030 respectively when comparing with the baseline scenario (see Fig. 5). As shown in Fig. 5, there is a large potential to reduce the case of premature deaths from $PM_{2.5}$ in all provinces in the future. The potential reduction of premature deaths varies substantially by province. Especially, the provinces of Henan and Hubei rank among the highest contributors to avoided premature deaths, accounting for 43% of the total, followed by Chongqing (9%) and Shanxi (10%), respectively. The main reason is that these areas have large size and density of the exposed population and high share of cement in total PM emissions, while the changes of $PM_{2.5}$ concentrations caused by using energy efficiency measure also have a large contribution. By 2030, Shaanxi province ranks a top contributor to the total number of avoided premature deaths, due to the high change of $PM_{2.5}$ concentration caused by the implementation of energy efficiency measures. Although the megacities (i.e. Beijing, Tianjin and Shanghai) have a large size and dense population exposure, these three megacities together only prevent about 325 deaths each year by 2020 and 262 deaths each year by 2030, respectively. The potential of avoided premature deaths at the eight developing regions (i.e. Anhui, Jiangsu, Jiangxi, Liaoning, Shaanxi, Shandong, Yunnan, and Zhejiang) in the long term period (2020–2030) is higher than in the short term (2015–2020), while

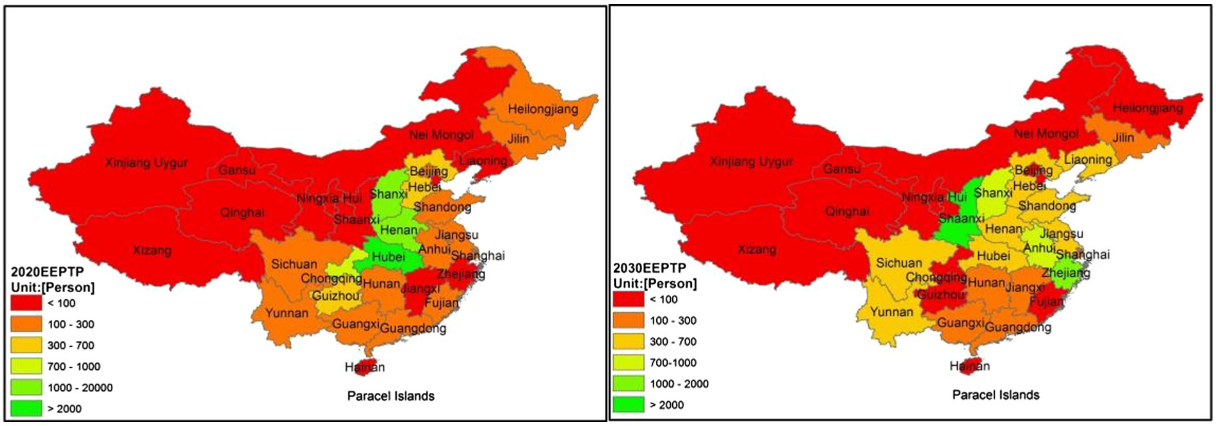

Fig. 5. Comparison of computed (avoid) premature death caused by $PM_{2.5}$ for the year 2020 and 2030, compared to BL scenario.

other provinces (i.e. Henan, Hubei, Shanxi, and Heilongjiang) have opposite trends.

We also estimated the morbidity effects attributed to $PM_{2.5}$ as seen in Fig. 6. There are large potential reductions in seven health endpoints of death that would be achieved from air pollution reduction. This means that implementing energy efficiency measures in China's cement industry significantly reduced the health issues related to $PM_{2.5}$ in all regions, compared to the baseline. Nationwide, by 2020 the number of morbidity cases decreased by 474 of cardiovascular disease, 1540 of stroke disease, 255 of Disease of the respiratory system (RD), 81 of hypertensive diseases, 1500 of cardiopulmonary disease, 6700 of lung cancer disease, and 7000 of Ischemic heart disease under EEPTP scenario, compared to baseline. These avoided morbidity cases would further increase by 4%, 7%, 2%, 17%, 6%, 4%, and 3% in 2030, respectively. Similar to the trend for the avoided premature deaths, the morbidity effects varied in the provinces. By 2020, about ~40% of the avoided cases of lung cancer will occur in the provinces of Henan and Hubei, followed by Shanxi (10%), Chongqing (9%), and Guizhou (6%). The other 25 developed/developing regions have a small contribution to the number of avoided cases of health endpoints attributable to $PM_{2.5}$, with 1–3% of each, respectively. Similar trends can be observed in the other six health endpoints. In contrast, under the same scenario the share of total avoided case of morbidity effects in these five provinces together has decreased from 65% by 2020 to 20% by 2030. Provinces of Shaanxi and Zhejiang rank top 2 contributors to total avoided morbidity cases up to 2030, which account for 28% and 11%, respectively. The next five largest contributors are Shanxi, Anhui, Henan, Jiangsu, Yunnan, account for ~6%, respectively. Summarizing, the largest potential reductions in seven illnesses can be found in central China in 2020 and shift to western regions up to 2030.

4.4. Economic assessment of health impacts

Figs. 7 and 8 display the geographic distribution of the monetized mortality/morbidity benefits in the EEPTP scenario for 2020 and 2030, compared to the baseline scenario. We employed the

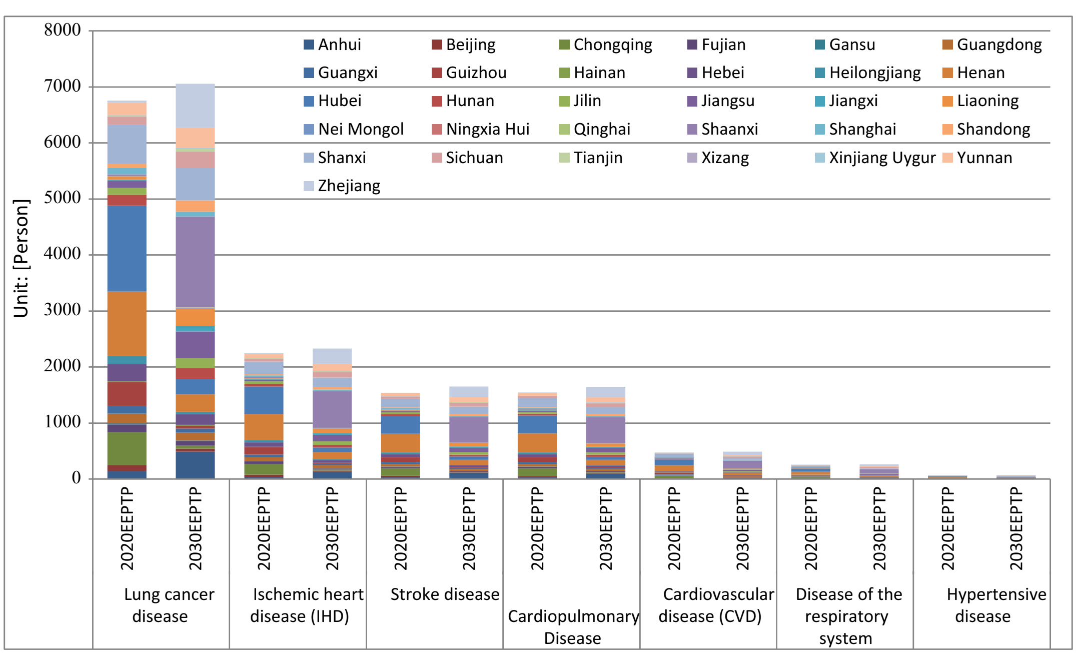

Fig. 6. Comparison of computed health endpoints caused by $PM_{2.5}$ for the year 2020 and 2030, compared to BL. Note: the number of IHD include stroke, sum of number health endpoints may be greater than the total number of premature deaths, since some subject (i.e. IHD and CVD) had the other health endpoint (i.e. Stroke disease and Hypertensive disease).

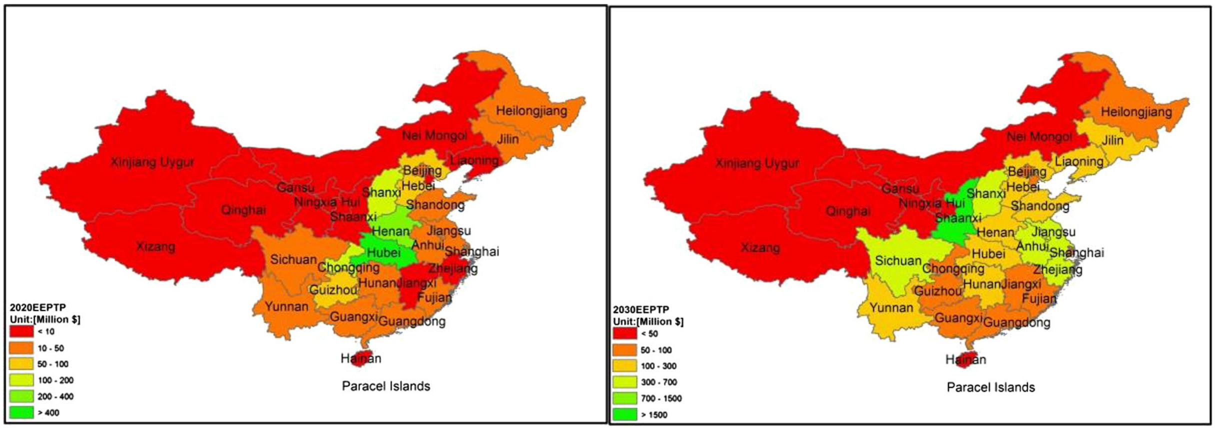

Fig. 7. Health benefits from avoid cases of premature death in EEPTP scenario, compared to BL.

estimated value of a statistical life (VOSL) and cost of illness (COI) from Table 4 to quantify the benefits of averted mortality and morbidity (including Cardiovascular disease (CVD) and Disease of the respiratory system (RD)). As depicted in Fig. 7, totally, ~10 thousand premature deaths are valued at $1670 Million by 2020 and $2085 Million by 2030, respectively. Comparing to the spatial distribution of benefits in Figs. 7 and 8, we found that both benefits of mortality and morbidity are largest in regions with large population effected by the $PM_{2.5}$ decrease. Specifically, the highest mortality benefits are observed in Henan and Hubei by 2020 and Shaanxi by 2030, owing to large changes in $PM_{2.5}$ concentrations and large population effected. The smallest health benefits in relative terms would be felt in megacities (Beijing, Shanghai, and Tianjin) and western regions (i.e. Xinjiang, Qinghai, Tibet, and Inner Mongolia) with large population effected, due to the small potential reductions of $PM_{2.5}$ during the whole period.

4.5. Co-benefits analysis

Fig. 9 depicts the costs and co-benefits under the EEPTP scenario for 2020 and 2030. The Annualized costs of the EEPTP scenario, in this study, includes the investment (capital) costs of energy efficiency technologies and costs associated with operation and maintenance of these technologies. Note that a discount rate of 10% was used to calculate the annualized costs of the energy efficiency measures. More detailed information can be found in Zhang

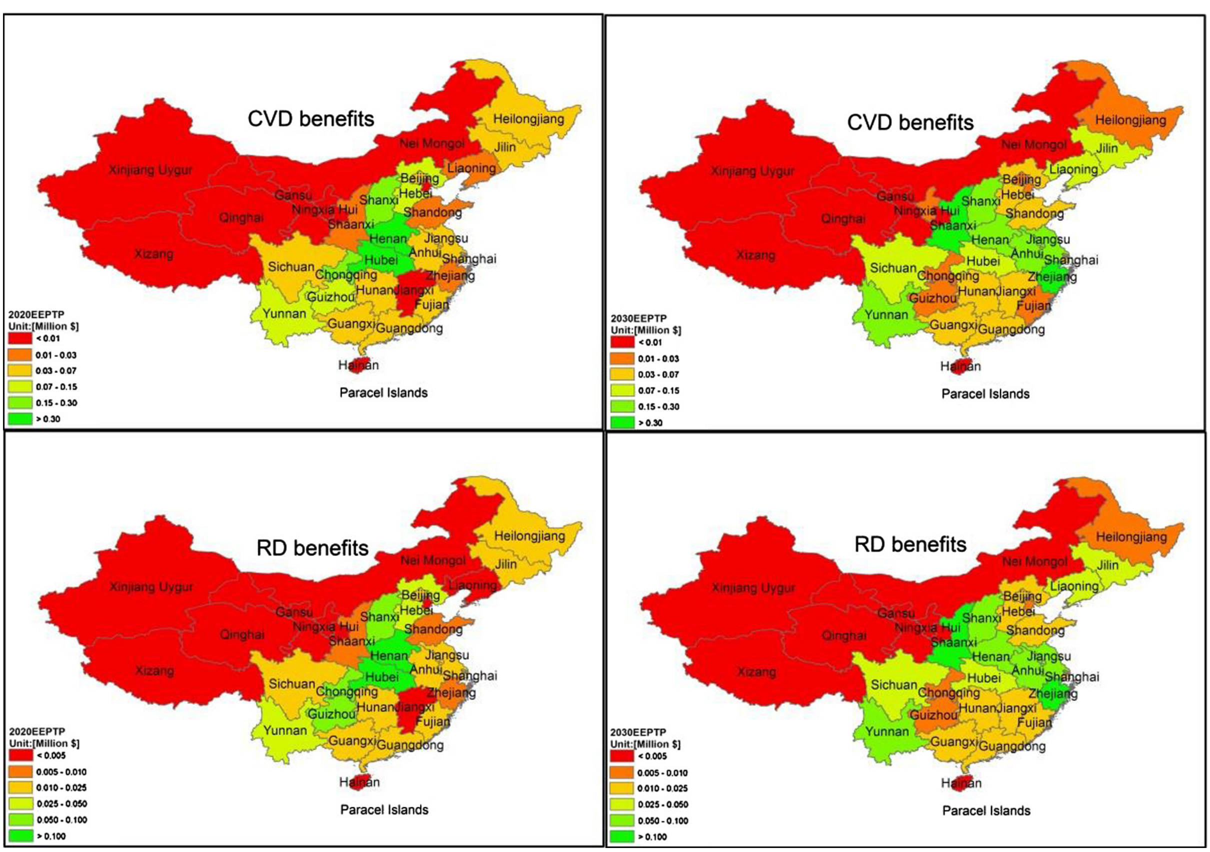

Fig. 8. Health benefits from avoid cases of morbidity effects in EEPTP scenario, compared to BL.

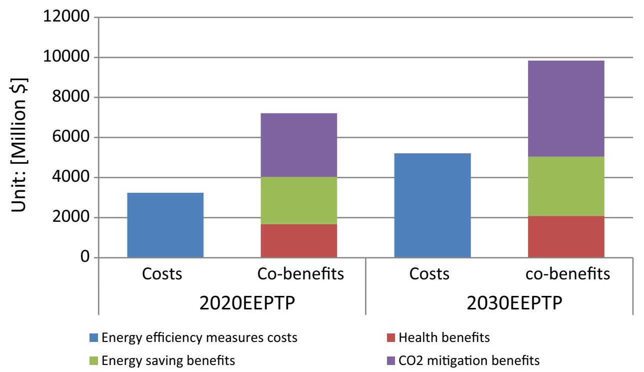

Fig. 9. The investment costs and benefits of energy efficiency measures in EEPTP scenario between 2020 and 2030.

et al. [42]. As shown in Fig. 9, applying selected energy efficiency measures result in total annual investments of $3200 Million by 2020 and $5200 Million by 2030, respectively. In this assessment, the energy efficiency measures packages are not cost-effective, if only the benefits from saved energy are considered. If we further consider the others benefits (including CO_2 reduction and avoided premature deaths), energy efficiency measures would become economical. Specifically, by 2020 the benefits of energy saving, CO_2 reduction, and avoided premature death under the EEPTP scenario are projected to be $2370 Million, $3170 Million, and $1670 Million, respectively. These benefits would further increase by 25%, 51%, 25% by 2030, respectively. Overall, co-benefits for the EEPTP scenario of energy saving, CO_2 reduction, and averted mortality account for 33%, 44%, and 23% by 2020 and 30%, 49%, and 21% by 2030, respectively. The total economic benefits are about two times higher than the costs of energy efficiency measures during the whole period. Note that the co-benefits of energy efficiency measures in clinker-exporting provinces would be higher than those of clinker-importing provinces.

5. Sensitivity and uncertainty analysis

A detailed sensitivity and uncertainty analysis is conducted for energy price, discount rates, SCC, air quality module, and health impact assessment module (include population affected, value of a statistical life (VOSL) and cost of illness (COI)).

5.1. Energy price and discount rates

Energy prices and the discount rate play a key role in the cost and benefit analysis. In general, Higher energy prices and a lower discount rate would lead to a higher cost-effective energy savings potential. The historical trends of energy prices in China indicate that future energy prices would be higher than the current [120]. In this study, three discount rate levels of 4%, 10%, and 30% were employed to assess the sensitivity of the total costs of energy efficiency measures per year. At the same time, three energy price levels of 2.42 $/GJ, 3.22 $/GJ, and 4.03 $/GJ were used to estimate the sensitivity of the economic potentials. Unsurprisingly, the energy efficiency measures with high energy saving and low investments are cost effectiveness. However, the high costs with low energy saving energy efficiency measure will become non cost effectiveness under the high discount rate (30%). In addition, the contribution of energy saving benefits to total benefits would increase from 29% to 43% up to 2030, due to changing energy price from 2.42 $/GJ to 4.03 $/GJ.

5.2. Social cost of carbon

The social cost of carbon (SCC), the damage avoided or the cost to social of an additional unit of CO_2 emissions, is a vital factor in cost benefit analysis of climate policy [92,121]. In this study we use the SCC to quantify the CO_2 reduction benefits rather than CO_2 price because the former are more efficient to describe fully the benefits by reducing CO_2 emissions by one ton. In addition, the SCC was calculated based on integrated climate-economy model that can capture the trajectories of temperature change, economy change, and additional CO_2 emissions. However, the CO_2 price was set based on taxes or cap-and-trade systems [122]. Note that both SCC and CO_2 prices vary significantly, from less than $1 to above $200 per ton of CO_2. We will use ±25% of SCC to assess the changes of CO_2 reduction benefits achieved through implementing energy efficiency measures. As shown in Fig. 10, on the whole the SCC has a large influence on the total benefits, keeping all other parameters constant. In 2020 the total benefits will increase by 25%, from $6420 Million ($30.9 per ton) to $8000 Million ($51.6 per ton), at the same time the contribution of CO_2 reduction benefits will increase from 37% to 50% to the total. Compared to 2020, the total benefits will increase by 28% from $8650 Million ($37.4 per ton) to $11,050 Million ($62.4 per ton), while the share of CO_2 reduction benefits of total benefits will increase from 41% to 49%.

5.3. Air quality module

Several studies have been carried out to investigate the sensitivities and uncertainties of the TM5 model in recent years [78]. The impacts of transport model errors, a typical example, have been carried out by Houweling et al. to simulate the sources and sinks of CO_2 and found that the transport model errors have large impacts on the accuracy of model simulation [123]. Similarly, the factors of the maximum absolute uncertainty and relative uncertainty were adopted to simulate the sensitivity of TM5 model [124]. Both studies point that flux optimization would make the simulation more realistic. As mentioned in Section 3.2.3, the TM5 model needs a substantial amount of computational time and costs. The uncertainties from the transport model and parameters are not included in this study. In addition, because we only use the changes of concentrations under different scenarios rather than the absolute concentrations to simulate the health benefits related to $PM_{2.5}$, the influence of model errors will be more limited.

5.4. Health impact assessment module

In this study several factors have a significant impact on the HIA, such as population affected, location, time, VOSL [40]. Due

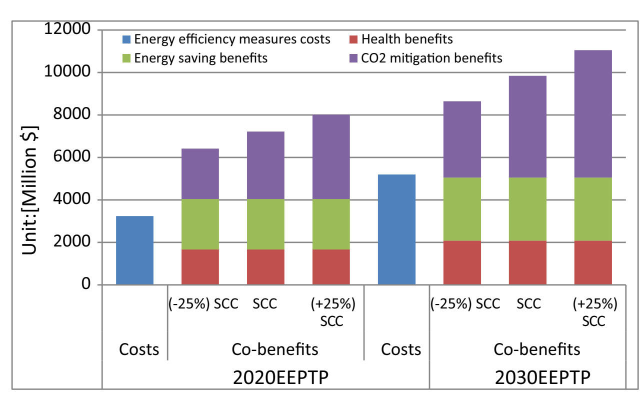

Fig. 10. The costs and benefits of energy efficiency measures in EEPTP scenario with different SCC.

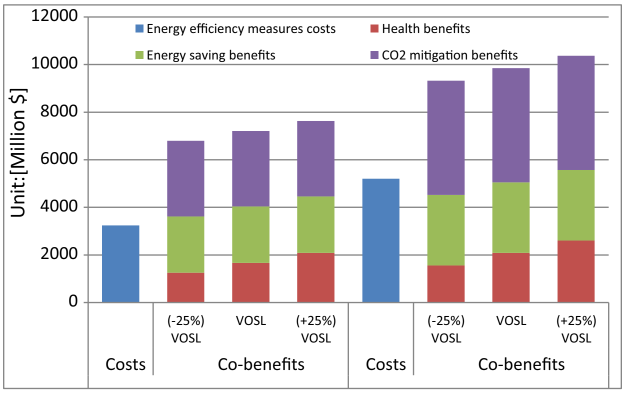

Fig. 11. the costs and benefits of energy efficiency measures in EEPTP scenario with different VSLs.

to limited data availability, the health benefits might be underestimated due to: (1) the uncertainty of future population exposure of each provincial caused by future migration; (2) the same mortality/morbidity data of each health endpoint are assumed and adopted in the provinces, which have a substantial impact on HIA to a particular province/city; (3) we only consider the health impacts to adults over 30 years of age although there is mounting evidence of health impacts for the youth below the ages of 18 years and children below the age of 5 [1,20]; (4) the age- and illness-specific co-risk factors, illness-specific incubation periods, and the other co-benefits (e.g., ecosystem benefits, water saving benefits) from energy efficiency improvement are also excluded in the present study. Hence, future works should quantify these additional energy efficiency co-benefits to improve model accuracy [14]; (5) the future VOSL represent the monetary costs of mortality and morbidity endpoints, depending on differences in location and personal income. Current literature indicates that the VOSL varies worldwide. For example, VOSL of premature deaths in Europe is \$1.8 Million and \$7.4 Million for USA, but \$0.116 Million for China [14,113]. In this study, ±25% of VOSL are used to estimate the changes of health benefits and quantify the contribution of health benefits to total. As seen in Fig. 11, small changes of health/total benefits are observed under different VOSL in 2020 and 2030 for EEPTP scenario. The health benefits will increase by 67% in the whole period, while the increasing benefits would be 50% lower than the changes of health benefits. These results provide further evidence that energy efficiency improvement could subsequently provide health benefits related to $PM_{2.5}$. As we mentioned earlier, the values of VOSL in China often lower than the developed countries/regions. With the development of Chinese industrialization in the future, people are prefer choose pay more cost to avoid premature death relative to air pollution, than to pay for the resulting damage later. Hence, the local policy makers in the provinces/regions with higher personal income have more ability to encourage implementation of advanced energy efficiency measures.

6. Conclusion

Actions to reduce the combustion of fossil fuels often decrease GHG emissions as well as air pollutants and thereby bring multiple benefits. Therefore, air quality and health co-benefits can provide strong additional motivation to improve energy efficiency.

We found that in 2010 China's total $PM_{2.5}$ emission amounted to 12 Mt with varying spatial distribution over the provinces, while the share of $PM_{2.5}$ emissions from China's cement industry amounted to 14% (range: 1–54%) of the total. At the same time, the annual average $PM_{2.5}$ concentration amounted to 78 $\mu g/m^3$ and the national average $PM_{2.5}$-related shortening of individual life expectancy with approximately 4.3 years.

The results show significant heterogeneity across provinces in terms of the potential of $PM_{2.5}$ emission reduction and $PM_{2.5}$ concentration, as well as health impacts caused by $PM_{2.5}$ in the next two decades. In the baseline scenario the average increase in Chinese $PM_{2.5}$ emissions from cement plants are projected to be 11% (range: 9–48%) higher for the year 2020 while it will 37% (range: 16–39%) lower by 2030 relative to 2010. Implementation of selected energy efficiency measures would decrease $PM_{2.5}$ by 2% (range: 1–4%) by 2020 and 4% (range: 2–8%) by 2030, compared to the baseline scenario. The emissions from top-10 counties account for 1.3% of the national total up to 2030. Compared to the base year, the changes of national annual $PM_{2.5}$ concentrations from China's cement industry in the baseline scenario will increase by 0.11 $\mu g/m^3$ (range: -2.62–1.97 $\mu g/m^3$) by 2020 and then decrease by 0.35 $\mu g/m^3$ (range: -3.92–0.25 $\mu g/m^3$) by 2030, respectively. The reduction potential of provincial annual $PM_{2.5}$ concentrations in the Energy Efficiency Policy with technical energy saving potential (EEPTP) scenario is diverse among different provinces, ranging from 0.03% in Zhejiang to 0.90% in Hubei by 2020 and from 0.03% in Guangdong to 2.21% in Shaanxi by 2030 respectively, when compared to the baseline.

The health impact assessment module indicates that nationally in the baseline scenario 2000 $PM_{2.5}$-related premature deaths will increase by 2020 and 36,000 will reduced by 2030, relative to 2010. In EEPTP scenario, 10,000 premature deaths would be avoided per year in 2020 and 2030, respectively, compared to the baseline scenario. The provinces of Henan and Hubei rank among the highest contributors to the avoided premature deaths, accounting for 43% of the total, followed by Chongqing (9%) and Shanxi (10%), respectively. the megacities (i.e. Beijing, Tianjin and Shanghai) together only prevent about 325 deaths by 2020 and 262 deaths by 2030, respectively. The potential of avoided premature deaths at the eight developing regions (i.e. Anhui, Jiangsu, Jiangxi, Liaoning, Shaanxi, Shandong, Yunnan, and Zhejiang) in the long term period (2020–2030) is higher than in the short term period (2015–2020). Similar to the trend for avoided premature deaths, by 2020 about ~40% of total avoided cases of lung cancer will occur in 5 provinces situated in central China. The other 25 regions have a small contribution to the number of avoided cases of illnesses attributable to $PM_{2.5}$. Furthermore, the highest mortality benefits are observed in Henan and Hubei by 2020 and Shaanxi by 2030, while the smallest health benefits are found in the megacities and western China.

The energy efficiency measures are not cost-effective, if only the benefits from saved energy are considered. The total benefits (including energy saving benefit, CO_2 reduction benefit, and averted health benefit), however, are about two times higher than the costs of energy efficiency measures. In addition, the co-benefits of energy efficiency measures in clinker-exporting provinces would be higher than those of clinker-importing provinces.

The overall findings in the study indicate that the co-benefits of energy efficiency can provide a strong additional motivation for energy efficiency improvement. Policy makers hence can assume that energy efficiency is more cost effective to avoid health damage, than to pay for the resulting damage later. At the regional level, provinces with the following features would have higher co-benefits potentials than others provinces if they have a large share in cement production; are clinker-exporting regions, or are developing provinces located surrounding developed cities. The policy makers in the province with above features should make higher targets to improve energy efficiency and air quality than others. Overall, Policy makers should not only focus on the direct benefits of energy efficiency and air quality policies, but also on the associated co-benefits, like air pollution abatement, avoided climate change damage, and public health impacts arising of pollution. These benefits influence both policy design and investment decisions in energy efficiency and air pollution control options. Thus, policies integrating energy efficiency and air quality policies would be more efficient than when these policies are designed and implemented individually.

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Appendix A

See Tables A.1–A.3.

Appendix B

See Fig. B.1.

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.10.030.

Table A.1
Population and mortality rates for each province.

Region	2010 >30 years	2020 >30 years	2030 >30 years	Mortality rate >30 years (%)
Anhui	35,647,560	43,836,945	51719363.98	0.949
Beijing	11,841,811	16,777,138	18240687.72	0.641
Chongqing	17,982,429	21,516,257	25342673.76	0.995
Fujian	21,153,266	28,191,373	32492465.89	0.836
Gansu	14,490,961	18,363,808	22443260.28	0.888
Guangdong	53,830,113	76,294,926	92490922.27	0.788
Guangxi	25,092,727	32,360,486	38632368.75	0.949
Guizhou	18,656,273	22,948,107	29133288.91	1.009
Hainan	4,593,504	6,140,657	7454691.465	0.700
Hebei	40,945,808	54,019,392	62017494.95	1.060
Heilongjiang	25,340,080	31,289,961	35010928.04	0.746
Henan	51,127,110	66,362,377	79297016.53	0.966
Hubei	34,863,052	44,165,552	51116476.36	0.852
Hunan	39,051,951	49,570,523	56755123.3	0.932
Jilin	18,019,057	22,342,827	24980761.53	0.733
Jiangsu	49,369,335	62,300,719	70554857.42	0.971
Jiangxi	24,321,805	31,154,596	37362157.53	0.910
Liaoning	29,529,760	35,958,268	39957327.26	0.932
Inner Mongolia	15,421,352	19,451,268	22239747.99	0.722
Ningxia	3,348,641	4,371,440	5376363.643	0.855
Qinghai	3,046,513	3,933,677	4811274.143	0.827
Shaanxi	21,738,207	28,309,941	33401615.6	0.887
Shanghai	14,723,614	19,801,941	21328516.84	0.763
Shandong	58,833,882	74,663,977	84151614.3	0.994
Shanxi	20,331,041	26,047,028	31595586.73	0.911
Sichuan	49,683,068	60,038,170	70721576.6	1.028
Tianjin	7,848,209	10,816,309	11954386.41	0.668
Tibet (Xizang)	1,361,962	1,985,755	2484159.917	0.967
Xinjiang	11,660,429	15,518,531	18669970.61	0.681
Yunnan	25,090,509	32,475,111	39298620.05	1.047
Zhejiang	34,228,735	43,354,632	48957187.59	0.841
National	783,172,764	1004361692	1169972234	0.908

Table A.2
Personal income in future years.

Item	Unit	2010	2015	2020	2025	2030
Population [POP]	[Million people]	1352	1394	1429	1451	1461
Gross domestic product [GDP_PPP]	[10^9 Euro PPP]	6884	10,901	13,833	17,082	20,943
Personal income	[Euro per capita]	5092	7821	9680	11,772	14,339

Table A.3
Comparison of computed (avoided) premature death caused by $PM_{2.5}$ for the year 2020 and 2030, compared to 2010 level.

Region	2020 BL	2020 EEPTP	2030 BL	2030 EEPTP
Anhui	−9336	−9552	−13,615	−14,326
Beijing	0	−150	162	81
Chongqing	1061	138	−246	−329
Fujian	879	754	−509	−577
Gansu	61	27	0	−19
Guangdong	−70	−258	−1313	−1468
Guangxi	555	348	−91	−195
Guizhou	1432	828	−128	−192
Hainan	8	0	0	−14
Hebei	396	−99	0	−304
Heilongjiang	425	231	−60	−120
Henan	−3529	−5409	−4060	−4568
Hubei	6279	3675	−495	−938
Hunan	−4861	−5142	−3719	−4019
Jilin	151	−57	−255	−534
Jiangsu	5431	5264	−396	−1045
Jiangxi	0	−46	−1900	−2059
Liaoning	81	20	−551	−951
Nei Mongol	0	−16	−11	−23
Ningxia Hui	0	−6	0	−23
Qinghai	0	−2	0	−3
Shaanxi	232	174	−166	−3145
Shanghai	202	59	0	−110
Shandong	0	−108	0	−304
Shanxi	−99	−1153	−9305	−10,089
Sichuan	−94	−369	−348	−872
Tianjin	129	97	0	−72
Xizang	3	0	7	4
Xinjiang Uygur	0	−6	0	−16
Yunnan	905	645	0	−428
Zhejiang	1409	1362	636	−376
National	1649	−8753	−36,363	−47,032

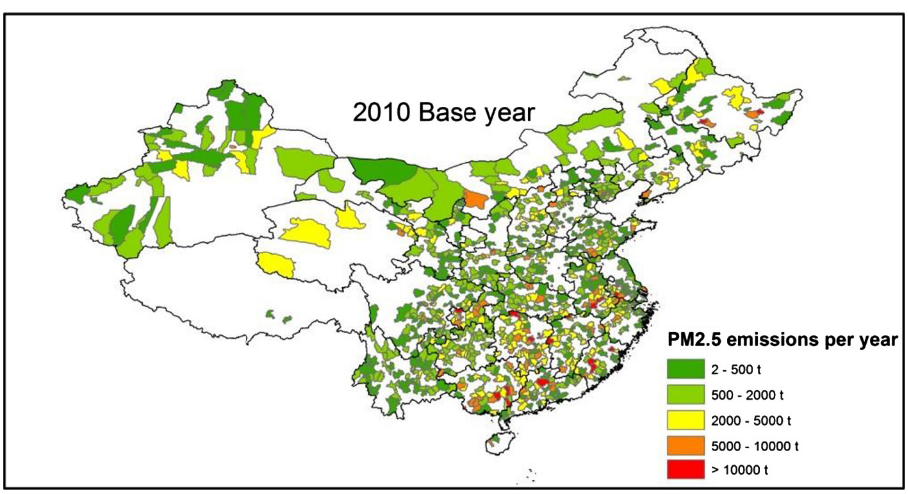

Fig. B.1. $PM_{2.5}$ emissions on county level in 2010.

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