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An economic assessment of the health effects and crop yield losses caused by air pollution in mainland China

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ABSTRACT

Air pollution is severe in China, and pollutants such as $PM_{2.5}$ and surface O_3 may cause major damage to human health and crops, respectively. Few studies have considered the health effects of $PM_{2.5}$ or the loss of crop yields due to surface O_3 using model-simulated air pollution data in China. We used gridded outputs from the WRF-Chem model, high resolution population data, and crop yield data to evaluate the effects on human health and crop yield in mainland China. Our results showed that outdoor $PM_{2.5}$ pollution was responsible for 1.70–1.99 million cases of all-cause mortality in 2006. The economic costs of these health effects were estimated to be 151.1–176.9 billion USD, of which 90% were attributed to mortality. The estimated crop yield losses for wheat, rice, maize, and soybean were approximately 9, 4.6, 0.44, and 0.34 million tons, respectively, resulting in economic losses of 3.4 billion USD. The total economic losses due to ambient air pollution were estimated to be 154.5–180.3 billion USD, accounting for approximately 5.7%–6.6% of the total GDP of China in 2006. Our results show that both population health and staple crop yields in China have been significantly affected by exposure to air pollution. Measures should be taken to reduce emissions, improve air quality, and mitigate the economic loss.

Introduction

Epidemiologic studies and field experiments have consistently demonstrated that air pollution has adverse impacts on human health and crop yield and quality. Among the various atmospheric pollutants, fine particulate matter ($PM_{2.5}$, particulate matter with an aerodynamic diameter less than or equal to 2.5 μm) has received the most attention in recent years because it is more toxic than coarser PM_{10} (particulate matter with an aerodynamic diameter less than or equal to 10 μm) (Pope, 2000; Pope and Dockery, 2006; Pope et al., 2009; Samet et al., 2000). Surface O_3 is now regarded as the most harmful air pollutant to crops due to its photosynthetic toxicity and extensive distribution in the world's main agricultural areas (North America, Europe, and East Asia) (Fuhrer, 2003; Fuhrer and Booker, 2003; Heck et al., 1982, 1984a, 1984b).

Numerous studies have been conducted to quantify the health impact (Chen et al., 2013; Kan et al., 2004; Lim et al., 2012; Zhang et al., 2007) and crop yield loss (Avnery et al., 2011; Tang et al., 2013; Van Dingenen et al., 2009; Wang and Mauzerall, 2004) caused by air pollution. These assessments have linked the science to policy making, rendering it possible to quantify the effect that public policies have on the health of the population and agriculture, and assisting with the allocation of resources to deal with the problem.

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With the rapid growth of the economy and urbanization, fossil fuel consumption has continued to increase, along with the concentrations of tropospheric aerosols and O_3 and will likely rise further in east Asia, particularly China, in the near future (Akimoto, 2003; Chan and Yao, 2008; Horowitz, 2006; Xu et al., 2008).

Previous health impact assessment (HIA) studies have relied mainly on surface monitoring data. Kan and Chen (2004) and Zhang et al. (2007) used monitoring data and epidemiological concentration–response (C–R) functions to evaluate the health effects of PM_{10} in Shanghai and Beijing, with reported losses of 1.03% and 6.55% of local gross domestic product (GDP), respectively. The World Bank (2007) estimated that 352,000 premature deaths were related to PM_{10} exposure among an urban population of 520 million based on air pollution monitoring data. These monitoring data-based studies have indicated that air pollution in China consistently causes health damage to the urban population. However, there are demands for new technologies to better identify the temporal and spatial distribution of air pollution, as monitoring stations are often distributed unevenly.

Model-simulated air pollution results could reproduce the evolution and distribution of pollutants with a high resolution. Several recent studies of $PM_{2.5}$ (Apte et al., 2015; Lim et al., 2012; Rohde and Muller, 2015) have used an integrated exposure-response model together with surface observed data, or a combination of surface observed data, satellite data, and chemical model results, to conclude that 1.2–1.6 million premature deaths from five major diseases per year were related to $PM_{2.5}$ in China. These results suggest that major damage to population health is caused by air pollution, with damage levels higher than previously experienced in China. However, C–R functions, population data, and thresholds still need further verification.

Surface O_3 pollution in China is considered to be high enough to affect crop yields (Chameides et al., 1999). Previous studies (Avnery et al., 2011; Tang et al., 2013; Van Dingenen et al., 2009; Wang and Mauzerall, 2004) have demonstrated that staple crop yields in China (wheat, rice, maize, and soybean) have been suffering losses due to surface O_3 in China, with relative yield losses of 5%–11% for wheat, 10%–15% for rice, 22% for maize, and 16% for soybean. However, global scale studies usually require coarse resolution crop yield data, which may overestimate or underestimate crop yield losses in China. Other studies have only focused on yield loss in one or two staple crops, which may weaken the implications of the results.

To develop new air quality standards for protecting human health and crops and to take measures to mitigate air pollution, more studies are needed to improve policy decision making. There have been no synthesized studies that have focused on both the adverse health effects of $PM_{2.5}$ and the adverse effects on crops countrywide due to surface O_3. In this study, we applied the WRF-Chem (Weather Research and Forecasting model coupled to Chemistry) model, high-resolution population data, and crop yield data, combined with a C–R function derived from a meta-analysis of epidemiological studies and field experiments to perform an integrated assessment of the economic losses resulting from the health effects and crop yield losses due to air pollution in China. The objectives of this study can be summarized as follows: (1) to estimate the health effects due to exposure to $PM_{2.5}$ in China, (2) to estimate the crop yield loss due to surface O_3, and (3) to quantify the economic losses from health effects and crop yield losses.

1. Methods and data

1.1. Air quality model

In this study, the WRF-Chem model (Grell et al., 2005) with updated surface parameters (land cover, green vegetation fraction, and leaf area index) and improved reactions (Huang et al., 2015) were used to simulate $PM_{2.5}$ and surface O_3, with a 50 km × 50 km horizontal resolution and 15 vertical levels. The simulated domain covered the whole of China and its surrounding area with 95 × 110 grid cells (Fig. S1, inner black rectangle). The model setting, meteorological parameters, and emission inputs are described in Huang et al. (2015). Simulated meteorological results and PM_{10} have been evaluated using observed data (Huang et al., 2015). The mean biases (MB) of simulated temperature at 2 m above ground level (T2) and of relative humidity at 2 m above ground level (RH2) were −0.5°C–0.7°C and less than ±4%. The root-mean-square error (RMSE) for T2 and RH2 were 1.55°C–1.8°C and 9%–11%, respectively. The normalized mean biases (NMB) for the simulation of PM_{10} were within ±30%. Generally, the model effectively reproduced the temporal and spatial variations of meteorological conditions and PM_{10} and captured the spatial pattern and seasonal cycle. A detailed comparison of the model results for $PM_{2.5}$ and surface O_3 with those of other studies is provided in Section 2.1. In this study, the annual average concentration of $PM_{2.5}$ was used to evaluate the health effects, and the hourly concentration of surface O_3 was used to calculate the exposure index for crop yield loss assessment.

The assessments of the health impacts and crop yield losses were only conducted in mainland China (Fig. S1, blue line), as population and crop yield data were not available for Hong Kong, Macao, and Taiwan.

1.2. Health endpoints and epidemiological C–R function

1.2.1. Health endpoints

Long-term exposure to $PM_{2.5}$ has been linked to many health effects, including cardiovascular and respiratory mortality and morbidity (Pope and Dockery, 2006). As recommended by the World Bank (2007), all-cause mortality was used for evaluating mortality losses. Hospital admissions for respiratory disease (RD) and cardiovascular diseases (CVD), and chronic bronchitis were selected for evaluating morbidity losses in this study.

1.2.2. Function

The shape of C–R function is critical for assessing health loss. Several forms of C–R function, such as linear, log-linear, power law, have been used in previous researches (Apte et al., 2015; Krewski et al., 2009). Linear or log-linear forms have been regarded as unreasonable in high concentration (Apte et al., 2015; Pope et al., 2011). As emphasized by Pope et al. (2015), recent evidence has suggested that the C–R function between $PM_{2.5}$ exposure and mortality risk may be supralinear across a wide range of exposures. Thus, the power law form was selected to assess the exposure impact in this study. The general form is as follows:

$$E = \exp[\beta \times (C - C_0)] \times E_0 \tag{1}$$

where, β is the concentration-response coefficient, C ($\mu g/m^3$) and C_0 ($\mu g/m^3$) represent the ambient and threshold pollutant concentrations, respectively, and E (case) and E_0 (case) are the health effects at C and C_0, respectively. The health damage caused by air pollution (ΔE, the difference between E and E_0) can be calculated from β, C, C_0, and E.

$$\Delta E = E \times \left[1 - \frac{1}{\exp[\beta \times (C - C_0)]}\right] \tag{2}$$

1.2.3. C–R coefficient β

The C–R coefficient β from long-term cohort studies was derived for assessing the long-term health effects of $PM_{2.5}$. Because the number of long-term cohort studies in China focusing on total suspended particulate (TSP) (Cao et al., 2011) and PM_{10} (Zhang et al., 2014; Zhou et al., 2014) is limited, we selected the C–R coefficient from a recent meta-analysis result for mortality (Hoek et al., 2013). This meta-analysis was based on the 13 most recent cohort studies, conducted over a wide geographic range, and it considered the cohort heterogeneity by using random effects methods. This meta-analysis approach was recommended by the World Health Organization (WHO) for the Euro Health Risks of Air Pollution in Europe (HRAPIE) project (Heroux et al., 2015). C–R coefficients for morbidity were calculated from PM_{10}, as we found no direct $PM_{2.5}$ exposure estimates for hospital admissions and chronic bronchitis. Health endpoint incidence rate data were obtained from the China Health Statistics Yearbook 2007 (CHSY2007) and 2009 (CHSY2009). Health endpoints, C–R coefficients, and incidence rates and the sources are listed in Table 1.

1.2.4. Threshold concentration C_0

The threshold concentration C_0 is a reference concentration, below which an air pollutant has no effect on human health. There is no consensus on whether a threshold concentrations exits (Brunekreef and Holgate, 2002). Most studies have reported that no evidence exists for a threshold for PM_{10} or daily all-cause and cardiorespiratory mortalities, and WHO (2005) recommended a C_0 value of zero in particulate matter (PM) health impact assessments. However, Stylianou and Nicolich (2009) reported a 25–45 $\mu g/m^3$ threshold for PM_{10}, and in the Global Burden of Disease Study 2010 (GBD, 2010), Lim et al. (2012) used a counterfactual threshold of 5.8–8.8 $\mu g/m^3$ for evaluating $PM_{2.5}$ exposure when considering the theoretical-minimum-risk exposure distribution. The atmospheric $PM_{2.5}$ concentration never reaches zero because there is always natural background. It is reasonable to assume that the C_0 can be set as the background concentration for assessing the effects of anthropogenic emissions (Anenberg et al., 2010) and developing new air quality standards. Because it is difficult to define a $PM_{2.5}$ background concentration for the whole of China, we chose 10 $\mu g/m^3$, which is the WHO $PM_{2.5}$ annual air quality guideline value (WHO, 2005). In this context, zero and 10 $\mu g/m^3$ $PM_{2.5}$ were selected as the C_0 values in this study.

1.3. *Crop phenology and C–R function*

1.3.1. Crop phenology

As a large country with a heterogeneous climate, the crop growing seasons in China vary based on the species and climate zone. We followed the same methodology used by Wang and Mauzerall (2004) and Van Dingenen et al. (2009) to define the growing season as the months leading up to the date of ripening. The dates of ripening were obtained from Cui and Liu (1984) for wheat, rice, and maize and from Pan et al. (1984) for soybean.

1.3.2. Crop C–R function

Linear, quadratic, logistic and plateau-linear models have been used to assess crop yield loss (Heck et al., 1983). The Weibull function (Lesser et al., 1990) was considered more suitable to develop the C–R function to link surface O_3 and crop responses due to its flexibility in covering a range of observed biological responses, its easily interpreted parameters, and its homogeneity (Heck et al., 1983). So the Weibull function was selected in this study for assessment crop yield loss. The general form of the Weibull function is

$$Y = A \exp\left[-(X/B)^C\right] \tag{3}$$

where Y (ton) is the crop yield, X is the O_3 exposure index, A (ton) is the hypothetical maximum yield at an O_3 concentration of zero, B (ppm or ppb) is the O_3 concentration when the yield is 0.37 A, and C is a dimensionless shape parameter.

1.3.3. O_3 exposure index

A biologically based index, W126 (ppm), was selected for assessing crop yield losses. This metric estimates a

Table 1 – Health endpoints, C–R coefficients (per 10 $\mu g/m^3$ $PM_{2.5}$) and incidence rates.

Health endpoints	C–R coefficient	Source	Incidence rate		Source
	Mean (95% CI)		City	Rural area	
All-cause mortality	0.0600 (0.0400, 0.0800)	Hoek et al. (2013)	0.0053046	0.0051801	CHSY2007
Hospital admissions for RD	0.0185 (0.0123, 0.0246) *	Aunan and Pan (2004)	0.0061	0.0117	CHSY2009
Hospital admissions for CVD	0.0108 (0.0046, 0.0169) *	Aunan and Pan (2004)	0.0217	0.0108	CHSY2009
Chronic bronchitis	0.0888 (0.0297, 0.1478) *	Jing et al. (2000)	0.0066	0.0071	CHSY2009

CVD: cardiovascular disease; RD: respiratory disease; C–R: concentration–response.
* Calculated from PM_{10} ($PM_{2.5} \approx PM_{10} \times 0.65$).

cumulative ozone exposure over a 3-month growing season and applies a sigmoidal weighting to the hourly ozone concentration (Lefohn et al., 1988; Lefohn and Runeckles, 1987). It used to be considered as the second standard for ecosystem assessments in the U.S.

The W126 general function is

$$W126 = \sum_{i=1}^{n} \frac{[Co_3]_i}{\{1 + 4403\exp[-0.126(Co_3)i]} \quad (4)$$

The C–R functions we selected were derived from large experiments conducted in North America and Europe. However, these experiments did not include rice, because it is not a staple crop in North America and Europe, and the W126 index is not available for rice. Therefore, the M7 index was selected for evaluating the O_3 risk for rice in this study (Adams et al., 1989; Wang and Mauzerall, 2004). M7 (ppb) represents the 7-hr (9:00–15:59 local time) seasonal mean O_3 concentration, which can be expressed as follows:

$$M7 = \frac{1}{n} i = 1n[C_{O_3}]_i \quad (5)$$

Crop production loss (CPL, ton) is calculated based upon the relative yield loss, and the production output data:

$$CPL = \frac{RYL}{1\text{–}RYL} \times CP \quad (6)$$

where, CP (ton) is the annual yield produced for each crop, and RYL is the relative yield loss. The C–R function for crops is listed in Table 2.

1.4. *Determining the economic costs of health effects and crop yield loss*

The value of a statistical life (VSL) is typically used to assess the health effects associated with air pollution. VSL is the sum of the value of an individual's willingness to pay for small risk reductions related to dying (World Bank, 2007). Several methods can be used to determine the VSL, of which the willingness to pay (WTP) method is considered the best for valuing human health (Wang and Mullahy, 2006). When determining the VSL for morbidity, the WTP method is not always appropriate, and the cost of illness (COI) method is often recommended. The COI estimates the total cost associated with disease treatment, as well as lost earnings related to disease. Due to its inability to evaluate pain and suffering related to illness, the COI estimate represents a lower boundary of the WTP (World Bank, 2007). Because only a few VSL studies have been conducted in China, we selected values for health endpoints from an internationally peer-reviewed report of a study in Beijing (Zhang et al., 2007), which was originally based on studies in Chongqing (Wang and Mullahy, 2006) and Shanghai (Kan and Chen, 2004). The benefit transfer approach (BAT) was used to calculate the country average VSL. The BAT equation is as follows:

$$VSL_{country} = VSL_{BJ} \times (I_{country}/I_{BJ})^e \quad (7)$$

where, $VSL_{country}$ and VSL_{BJ} are the average VSL for the country and the VSL for Beijing, respectively, $I_{country}$ (USD) and I_{BJ} (USD) are the personal incomes of the whole country and Beijing, respectively, and e is the elastic coefficient, which is assumed to be 1. The values for selected health endpoints are 797,000 USD for all-cause mortality, 4298 USD for chronic bronchitis, 803 USD for hospital admissions due to RD and 1626 USD for hospital admissions due to CVD, respectively.

Following the approach used in Avnery et al. (2011), Wang and Mauzerall (2004), and Van Dingenen et al. (2009), CPL was translated into economic loss by simply multiplying the national CPL by producer prices for each crop in the year 2006 as given by the FAO Food Statistics Division (FAOSTAT, http://faostat.fao.org/). This was used as a surrogate for domestic market or crop prices. The prices used were 331.1 USD/ton for rice, 177.2 USD/ton for wheat, 252.1 USD/ton for maize, and 412.7 USD/ton for soybeans.

1.5. *Population and crop data*

High-resolution (1 km) population data for the year 2003 (Fig. S1) and county-level crop data for 2005 (Fig. S2) were used to assess the losses due to health effects and crop yield losses in this study. There were 1292 million people living in China in 2003, of which 524 million lived in cities and towns, and 768 million lived in rural areas (National Bureau of Statistics of China, data.stats.gov.cn/easyquery.htm?cn=C01). Approximately 75% of the population is concentrated in an area that accounts for less than 20% of the land surface (Ge and Feng, 2009). Areas with a population density of 501–1000 person/km^{2}account for a population of more than 341 million and are mainly distributed in the North China Plain, Sichuan Basin, and Yangtze River Delta regions, and along the southeast coast of China. Areas with a population density of >1000 person/km^2 are regarded as megacities and big cities, where the total population exceeds 235 million. There are many industrial plants located in these areas, in which consumption of fossil fuel is high. The distribution of the population is similar to that of pollutants (Huang et al., 2015). Considering that the health endpoint incidence rates are different between urban and rural areas, the populations were distinguished using 1 km resolution moderate-resolution imaging spectroradiometer

Table 2 – Concentration-response (C–R) functions for crops.

Crop	Exposure-relative yield relationship	Reference
Rice	RY = $\exp[-(M7/202)^{2.47}] / \exp[-(25/202)^{2.47}]$	Wang and Mauzerall (2004)
Wheat	RY = $\exp[-(W126/51.2)^{1.747}]$	Wang and Mauzerall (2004)
Corn	RY = $\exp[-(W126/93.7)^{3.392}]$	Wang and Mauzerall (2004)
Soybean	RY = $\exp[-(W126/109.75)^{1.2315}]$	Wang and Mauzerall (2004)

RY: relative yield; C–R: concentration–response.

(MODIS) land cover data. The distribution of cities recognized from MODIS data was quite similar to those of the megacities and big cities identified according to the population density in Fig. S1.

China is a large agricultural country, with a total crop yield of 498 million tons in 2006 (National Bureau of Statistics of China, data.stats.gov.cn/easyquery.htm?cn=C01). Rice, wheat, maize, and soybeans are staple foods in China and made up more than 90% of the total crop yield in 2006. These four staple crops are all sensitive to O_3 (Adams et al., 1989; Feng and Kobayashi, 2009; Heck et al., 1984b). County-level crop yield data for 2005 was used in this study, as shown in Fig. S2.

Three major kinds of rice, single-crop rice (SR), double-crop early rice (DER), and double-crop late rice (DLR), are planted mainly in the south and northeast of China (Fig. S2a). Because the three kinds of rice can all grow in south China and have different growing seasons, we used coefficients calculated from province level rice yield data (National Bureau of Statistics of China, data.stats.gov.cn/easyquery.htm?cn=C01) to distinguish among SR, DER, and DLR.

Two major kinds of wheat, winter and spring wheat, are planted in China. The multi-year average winter wheat yield accounts for approximately 95% of the total crop yield, while spring wheat accounts for only 5% (National Bureau of Statistics of China, data.stats.gov.cn/easyquery.htm?cn=C01). The main growing area for wheat is the North China Plain, including Henan, Shandong, Anhui, and Jiangsu provinces (Fig. S2b). However, in some provinces, both kinds of wheat are planted. For simplification, we defined the wheat growing season based on the main kind of wheat grown in the areas where both are planted.

Maize, the second largest crop in China, is planted all over the country, with the exception of Tibet, Qinghai, and part of Xinjiang (Fig. S2c). The main area for growing maize is northeast and central China. Two major types of maize, spring and summer maize, are planted in China. Because there are no statistical data available to distinguish between the two types of maize, we simply defined the growing season based on the date spring maize ripened.

Soybean is an important staple crop that can grow across most of China, except for several western provinces. The main growing area for soybean is northeast China, especially Heilongjiang province (Fig. S2d). The date of soybean ripening in north China is usually from early September to mid-October (Pan et al., 1984). In South China, due to the warm climate, soybean is grown more than once a year. In some provinces, soybean can even grow in all seasons. Considering that the soybean yield in north China accounts for more than 65% of the total yield, we simplified the growing season defined for soybean and specified early October as the date of ripening.

2. Results and discussion

2.1. WRF-Chem model simulation results

2.1.1. $PM_{2.5}$

Fig. S3 shows the distribution of the annual and monthly (January, April, July, and October) average $PM_{2.5}$ concentrations simulated by the WRF-Chem model. The modeled annual concentration (Fig. S3a) indicated regionally high $PM_{2.5}$ concentrations over east-central China and the Sichuan Basin. East-central China, particularly north China, was the most polluted area, with a $PM_{2.5}$ annual average concentration range of 60–120 $\mu g/m^3$ and the highest value of 128 $\mu g/m^3$. Another heavily polluted area was the Sichuan Basin in southwest China, with a $PM_{2.5}$ annual average concentration range of 60–90 $\mu g/m^3$. This simulated $PM_{2.5}$ distribution pattern was in agreement with the anthropogenic emission distribution shown in Huang et al. (2015). Emissions in east-central China and the Sichuan Basin were higher than those in other parts of China, as a result of the dense population and large number of industrial plants, which consume high levels of fossil fuel. The seasonal patterns showed that winter (Fig. S3b) and fall (Fig. S3e) experienced the most pollution, with the highest seasonal average $PM_{2.5}$ concentrations being 150–160 and 130–140 $\mu g/m^3$, respectively. Spring (Fig. S3c) and summer (Fig. S3d) were the least polluted seasons, during which the highest seasonal average concentrations of $PM_{2.5}$ were 80–90 and100–110 $\mu g/m^3$, respectively. The reasons for the seasonal cycle in North China is that, in winter (December, January, and February), more coal is combusted for heating, which together with the low planetary boundary layer height causes air quality degradation, while in spring, dust storms from the northwest often influence the area (Huang et al., 2015). In summer, the $PM_{2.5}$ concentration decreased as a result of reduced emissions from heating, the high planetary boundary layer height, and the large amount of precipitation from the summer monsoon. For the Sichuan Basin, the high $PM_{2.5}$ level was a consequence of local emissions, mild wind speeds, and high temperature and humidity (Yang et al., 2011). South China was found to be relatively clean compared with north China and the Sichuan Basin due to the lower emissions and favorable climatic conditions. However, compared with the satellite-derived aerosol optical depth (AOD), the model underestimated $PM_{2.5}$ in northwest China due to the underestimation of meteorological parameters in northern China (Huang et al., 2015).

2.1.2. Surface O_3

Model-based monthly means of the daily 7-hr average surface O_3 concentration (M7) from January to December are shown in Fig. S4. The model results show that the seasonal cycle and distribution patterns differ among growing areas (Northeast China, North China, and South China), which is quite similar to previous studies (Li et al., 2007; Wang et al., 2011; Xu et al., 2008). Over north China and the Sichuan Basin, monthly M7 exceeded 50 ppb in summer (June, July, and August), with maximum values of 60 to 70 ppb in June across most of this area as a result of weak winds, high temperatures, and strong radiation (Wang et al., 2013). In winter (December, January, and February), the monthly M7 was reduced to less than 10 ppb. An analysis of observation data from Shangdianzi (Lin et al., 2008), Miyun (Wang et al., 2008) and Mount Tai (Li et al., 2007) confirmed the seasonal cycle in north China (Wang et al., 2011). In South China, two peaks were found in spring (March, April, and May) and fall (September, October, and November), respectively. A low surface O_3 level occurred in summer and winter. These results are consistent with observations from Linan (Xu et al., 2008) and Hong Kong (Wang et al., 2009). This is because in summer, the East Asian Monsoon brings clean air from the southern ocean, and rainy and unstable weather promotes the diffusion and removal of pollutants, while in the fall, the outflow from the northern polluted area and stable and warm weather contributed to the O_3 maximum (Wang et al., 2009; Zhou et al., 2013). Over northeast and west China, the M7 peak in spring (30–40 ppb) and the lower concentration in winter (less than 10 ppb) could be attributed to the natural background (Wang et al., 2011).

2.2. Losses due to health effects

Table 3 summarizes the estimated effects for each health endpoint in cities and rural areas at $C_0 = 0\ \mu g/m^3$ and $C_0 = 10\ \mu g/m^3$ due to exposure to outdoor $PM_{2.5}$, while Fig. S6 presents the distribution of all-cause mortality ($C_0 = 0$ and $10\ \mu g/m^3$) induced by outdoor $PM_{2.5}$. It can be seen from Table 3 that when considering no threshold ($C_0 = 0\ \mu g/m^3$), there were around 1.99 (95% CI, 1.42–2.48) million cases of all-cause mortality, 1.4 (95% CI, 0.96–1.84) million hospital admissions for RD, 1.1 (95% CI, 0.47–1.66) million hospital admissions for CVD, and 3.6 (95% CI, 1.46–5.02) million cases of chronic bronchitis, which were induced by $PM_{2.5}$ in China. Even though we only considered the effects of anthropogenic emissions ($C_0 = 10\ \mu g/m^3$), the attributable numbers for all-cause mortality, hospital admissions for RD, hospital admissions for CVD, and chronic bronchitis were 1.70 (95% CI, 1.20–2.14), 1.19 (95%CI, 0.81–1.55), 0.91 (95% CI, 0.40–1.40), and 3.10 (95% CI, 1.24–4.40) million cases, respectively. The level of mortality induced by outdoor $PM_{2.5}$ roughly amounted to 22% and 19% of the total deaths in China at $C_0 = 0\ \mu g/m^3$ and $C_0 = 10\ \mu g/m^3$, respectively. These results show that population health in China has suffered severely due to outdoor $PM_{2.5}$.

The results also show that for morbidity, the total number of chronic bronchitis cases related to $PM_{2.5}$ exposure was far greater than the number of hospital admissions for RD and CVD because of the higher incidence rate and C–R coefficient for chronic bronchitis. The total number of hospital admissions for RD was larger than that for CVD for the same reason. It should be noted that the number of hospital admissions for RD was smaller than that for CVD in cities, while the opposite situation occurred in rural areas. A possible reason for this is that the incidence of hospital admissions for RD was smaller than that for CVD in cities and larger than that for CVD in rural areas. However, our results could not identify if the losses due to health effects related to $PM_{2.5}$exposurewere more severe between cities and rural areas. This is because the urban population based on MODIS land cover data in this study was approximately 287 million, slightly more than the value (235 million in 2000) obtained by Ge and Feng (2009), which indicates that our results can only represent the population of megacities and big cities, but are not able to distinguish population between small cities and rural areas as a result of the underestimation of city areas in the MODIS land cover data (Ran et al., 2009).

As shown in Fig. S5, these premature deaths occurred mainly in the North China Plain and Yangtze River Delta regions, as well as the Sichuan Basin, and especially some megacities within these areas with dense populations and large energy consumptions, resulting in significant anthropogenic emissions.

We compared the results of our study with those of three previous studies focusing on $PM_{2.5}$ (listed in Table 4). These three studies were based on an integrated exposure-response

Table 3 – Estimated results for selected health endpoints in 2006.

Health endpoints	Attributable number of cases (95% CI)					
	$C_0 = 0\ \mu g/m^3$			$C_0 = 10\ \mu g/m^3$		
	Total	City	Rural area	Total	City	Rural area
All-cause mortality	1,988,873	466,276	1,523,183	1,697,970	401,101	1,297,679
	(1,415,803, 2,482,353)	(332,730, 582,239)	(1,086,158, 1,906,593)	(1,202,359, 2,136,065)	(284,271, 504,112)	(920,294, 1,633,708)
Hospital admissions for RD	1,411,458	190,921	1,221,505	1,188,242	161,847	1,028,738
	(960,691, 1,838,907)	(129,821, 248,391)	(831,012, 1,590,829)	(806,023, 1,549,722)	(109,793, 211,041)	(696,411, 1,339,201)
Hospital admissions for CVD	1,083,327	407,719	676,558	910,765	344,623	567,502
	(471,833, 1,657,038)	(177,661, 624,028)	(294,747, 1,037,853)	(395,676, 1,396,431)	(149,810, 528,690)	(246,935, 871,353)
Chronic bronchitis	3,598,221	781,802	2,817,812	3,098,640	678,785	2,422,558
	(1,461,145, 5,022,876)	(318,647, 1,089,708)	(1,144,731, 3,946,045)	(1,235,602, 4,402,761)	(271,240, 962,025)	(967,185, 3,445,341)

CVD: cardiovascular disease; RD: respiratory disease.

Table 4 – Comparison of losses due to health effects with other studies.

Reference	Base year	Urban population	C_0	Pollutant	Mortality
		million			thousand
This study	2006	Whole China	10 μg/m^3	$PM_{2.5}$	1698
This study	2006	280	10 μg/m^3	$PM_{2.5}$	401
GBD2010	2010	Whole China	5.8–8.8 μg/m^3	$PM_{2.5}$	1234
Rohde and Muller (2015)	2014	East China	5.8–8.0 μg/m^3	$PM_{2.5}$	1600
Apte et al. (2015)	2010	Whole China	5.8–8.0 μg/m^3	$PM_{2.5}$	1270
CAEP (2006–2012)	2004–2010	540–670	15 μg/m^3	PM_{10}	357–500

(IER) curve, a threshold of 5.8–8.8 μg/m^3, and surface observation data or a combination of surface observation data, satellite data, and chemical model results, and in these studies, premature deaths from five major diseases related to $PM_{2.5}$ were evaluated. Although the base year in our study was different from those of these three studies, the population-weighted $PM_{2.5}$ exposure in our study was 61 μg/m^3 (C_0 = 10 μg/m^3), while the other results were 59 μg/m^3 (Apte et al., 2015), 52 μg/m^3 (Rohde and Muller, 2015), and 55 μg/m^3 (GBD 2010 study for East Asia, from Brauer et al. (2012)), respectively, which are comparable. As can be seen, our estimate of premature mortality was similar to that of Rohde and Muller (2015), but much higher than that reported in the GBD2010 study and by Apte et al. (2015). For example, our estimate of all-cause mortality due to outdoor $PM_{2.5}$, considering C_0 = 10 μg/m^3, was 1,698,000 premature deaths in 2006, while Rohde and Muller (2015) estimated 1,600,000 premature deaths per year. The GBD 2010 study (Lim et al., 2012) reported 1,234,000 premature deaths in 2010, and Apte et al. (2015) reported 1,270,000 premature deaths in 2010. The biggest difference lies in the C–R functions. In the three studies, the IER function was used, which produced a lower value compared with the other C–R functions, such as the log-linear and power law (Apte et al., 2015). Apte et al. (2015) demonstrated that the IER result was 21% and 10% lower than the log-linear and power law results, respectively. Another possible reason for this result is that the estimated mortality in this study was based on a C–R coefficient reflecting all-cause mortality related to outdoor $PM_{2.5}$, while the results of the three other studies only included six major mortality-related diseases (ischemic heart disease, stroke, chronic obstructive pulmonary disease, lung cancer, and acute lower respiratory infections). We performed a sensitivity analysis using different C–R coefficients from internationally peer-reviewed literature, and the results are summarized in Table 5. The estimated mortality ranged from 1.29 to 2.04 million using the different C–R coefficients, which suggests that the C–R coefficient is one of the decisive factors in this study. More studies need to be conducted to investigate the local C–R coefficients for China. In addition, the choice of C_0 could also influence the estimated results.

In addition, if we simply multiply the CAEP (Chinese Academy for Environmental Planning) study result (listed in Table 4) by a factor of 1.5 ($PM_{2.5}/PM_{10} \approx 0.65$) and then compare the revised result (538–750,000 deaths among 540–570 million people) with that of our study (401,000 deaths among 280 million people), it is apparent that the two results are comparable considering the population scale.

Table 6 lists the economic costs of the losses due to health effects induced by exposure to outdoor $PM_{2.5}$ in China. We estimated that the health costs induced by exposure to the outdoor $PM_{2.5}$ without a threshold were 176.9 (120.7–223.6) billion USD. Health costs induced by the outdoor $PM_{2.5}$ concentrations exceeding background levels due to anthropogenic pollution sources were 151.1 (102.3–192.7) billion USD. Approximately 90% of the total costs were attributed to mortality, with the remaining 10% to morbidity; *i.e.*, the economic loss due to mortality was far more than the loss due to morbidity. For morbidity, the economic losses due to chronic bronchitis were approximately 15.5 and 13.3 billion USD with and without a threshold, respectively, which are much higher than the cost of hospital admissions for RD (1.1 and 1.0 billion USD, respectively) and CVD (1.8 and 1.5 billion USD, respectively).

2.3. *Crop yield losses*

Fig. S6 shows the ozone exposure risks aggregated over the growing season for rice, wheat, maize, and soybean in 2006. Generally for all four crops, the O_3 exposure risks during the growing season were greater in east China and the Sichuan Basin than in the other areas. The O_3 exposure risk metric M7

Table 5 – Health impact assessment (HIA) results with different C–R coefficients.

C–R source	C–R coefficients per 10 μg/m^3 $PM_{2.5}$		All-cause mortality (C_0 = 0 μg/m^3)	All-cause mortality (C_0 = 10 μg/m^3)
Hoek et al. (2013)	0.0600 (0.0400, 0.0800)	Meta-analysis	1,988,873 (1,415,803, 2,482,353)	1,697,970 (12,202,359, 2,136,065)
Pope et al. (2002)	0.0620 (0.016, 0.1100)	Cohort study	2,041,950 (616,091, 3,111,962)	1,744,236 (519,251, 2,697,086)
Krewski et al. (2009)	0.0300 (0.0020, 0.0050)	Re-analysis	1,100,337 (759,196, 1,712,231)	930,711 (639,877, 1,456,869)
Cao et al. (2011)	0.009 (−0.003, 0.018)	China Cohort study, TSP	355,277 (−123,934, 687,957)	298,428 (−103,482, 579,914)
Zhang et al. (2014)	0.4 (0.37, 0.45)	China Cohort study, PM_{10}	5,699,003 (5,580,899, 5,862,407)	5,220,248 (5,091,879, 5,401,618)

Table 6 – Economic cost of health effects of outdoor $PM_{2.5}$ pollution in China.

Health endpoints	Value (billion USD)	
	$C_0 = 0\ \mu g/m^3$	$C_0 = 10\ \mu g/m^3$
All-cause mortality	158.5 (112.8, 197.8)	135.3 (95.8, 170.2)
Hospital admissions for RD	1.1 (0.8, 1.5)	1.0 (0.6, 1.2)
Hospital admissions for CVD	1.8 (0.8, 2.7)	1.5 (0.6, 2.3)
Chronic Bronchitis	15.5 (6.3, 21.6)	13.3 (5.3, 18.9)
Total	176.9 (120.7, 223.6)	151.1 (102.3, 192.7)

CVD: cardiovascular disease; RD: respiratory disease.

is displayed separately for the three kinds of rice. M7 ranged from 20 to 70 ppb in the main growing areas in the south, particularly in Hubei and the south of Anhui Province, with a high value in Sichuan province. In these provinces, the M7 values for SR and DER were 10 ppb higher than that for DLR due to the differences in the growing season for the three kinds of rice. For wheat, the accumulated 3-monthly W126 value was approximately 10–20 ppm in north China, which is also the main growing area for wheat. In part of this area, such as the southern Hebei Province and border areas of Henan and Anhui provinces, the W126 reached 20–30 ppm. The most impacted area was the Sichuan Basin, which showed the highest value of nearly 40 ppm. The distributions of the W126 for maize and soybean were similar to those for wheat. The main differences were that the area with a high O_3 exposure risk for maize was the second most important growing area, while Northeast China is the main growing area for maize and soybean.

Fig. S7 shows the distribution of the yield losses induced by surface O_3 for the four crops, while Table 7 summarizes the yield losses, percentage losses, and economic losses. The distribution patterns of the crop yield losses were produced by combining O_3 exposure risks, crop growing areas, and growing seasons. The estimated total crop yield loss for China in 2006 was 14.4 million tons. Among the four crops, wheat was the most impacted crop with yield losses of approximately 9 million tons, accounting for 9.9% of the total wheat yield in 2006, followed by rice at 4.6 million tons, accounting for 2.5% of the total yield. Our estimated result for wheat is comparable with other studies (Van Dingenen et al., 2009; Wang and Mauzerall, 2004), although the estimated yield loss result for rice was smaller than has been reported in other studies. However, our estimated results for maize (0.44 million tons, 0.3%) and soybean (0.34 million tons, 2.2%) were much smaller than the equivalent values reported in other studies. One possible reason for this is that the most impacted areas for maize and soybean are in the central part of China, including Hebei, Henan, and Sichuan provinces, while the main growing areas for maize and soybean are in Northeast China.

Table 7 – Crop yield losses and economic losses for four crops.

Crop	Yield loss (ton)	Percentage (%)	Economic loss ($\times 10^6$ \$)
Wheat	9,015,671	9.9	1598
Single rice	2,714,937	2.6	899
Double E rice	803,481	2.2	266
Double L rice	1,084,246	2.7	359
Total rice	4,602,664	2.5	1524
Maize	437,983	0.3	110
Soybean	335,107	2.2	138
Total	14,391,425		3370

Our estimated results were compared with previous studies (Avnery et al., 2011; Tang et al., 2013; Van Dingenen et al., 2009; Wang and Mauzerall, 2004) and summarized in Table 8. Generally, our estimated results for crop yield losses agree well with the values reported in other studies, suggesting that surface O_3 pollution has a serious impact on the yield production of staple crops. For wheat, our estimated result was comparable with previously reported results, with the yield loss induced by surface O_3 being 9 million tons, accounting for 9.9% of the total crop yield in 2006. For rice, our estimated loss (4.6 million tons, 2.5%) was lower than that reported in previous studies. The relative production losses for SR, DER, and DLR were 2.6%, 2.2%, and 2.7% in this study, and 4%, 3%, and 5% in Wang and Mauzerall (2004), respectively. Both studies used the same C–R function and O_3 exposure index for rice; therefore the differences in the results could be due to the O_3 exposure risks. In Wang and Mauzerall (2004), the highest M7 for $O_3$was more than 70 ppb, while in our study it was only 67 ppb. Another possible explanation for these results is that the crop yield distribution data were provided at the county-level in our study, which were more detailed than the data used in Wang and Mauzerall (2004). Combined with the different O_3 exposure, this may have impacted the results obtained.

However, there were significant differences in the crop production losses for maize and soybean between this study and previous studies. The comparison showed that our estimated results for these two crops were only approximately 10% of the estimated values reported in previous studies on average. These discrepancies could be ascribed to the different O_3 exposure risk for soybean between our study and previous studies. As shown in Fig. S2, maize and soybean are grown mainly in northeast China, while our model simulation indicated that the most severe O_3 exposure occurred in east and central parts of China.

The estimated economic damage for crop yield loss in mainland China was 3370 million USD in 2006. For wheat, the estimated economic damage was 1598 million USD, followed by rice at 1524 million USD. The economic losses for wheat and rice accounted for more than 92% of the total losses from the four crops.

2.4. Uncertainty

As an integrated assessment, uncertainties accumulated in each step. First, the uncertainties arose due to model uncertainties from the emissions inventory and the modeling systems for both health impact assessment and crop yield loss assessment. Besides, air pollution from outdoor and indoor both could affect human health. Indoor air pollution is even more harmful to human health as people usually spend more time indoor. However, health losses due to indoor air pollution were hard to be evaluated as indoor pollution was not available in our simulated result. Additionally, uncertainties for health impact assessment were derived from the C–R coefficients used in this study. For mortality, we selected the C–R coefficient from a

Table 8 – Comparison of crop production loss (CPL) and relative yield loss (RYL) due to surface O_3 with other studies.

Source	Base year	Crop yield loss								Indices
		Wheat		Rice		Maize		Soybean		
		CPL (Mt)	RYL (%)	CPL (Mt)	RYL (%)	CPL (Mt)	RYL (%)	CPL (Mt)	RYL (%)	
This study	2006	9	9.9	4.6	2.5	0.44	0.3	0.34	2.2	W126/M7
Wang and Mauzerall (2004)	1990	5.5	5.6	8	4.2	8.2	8.5	3.2	29.3	M7/M12
		12.73	12.8	–	–	6.6	6.9	2.6	23.7	SUM06
		12.58	12.7	–	–	2.7	2.8	2	17.8	W126
Van Dingenen et al. (2009)	2000	10.8–23.4	9.8–19.0	6.0–7.7	3.1–3.9	4.9–7.7	4.7–7.1	2.0–4.0	11.4–20.8	AOT40/M7
Avnery et al. (2011)	2000	3.0–19	3–16	–	–	4.5–9.8	4–8	3.7–4.6	21–25	AOT40/M12
Tang et al. (2013)	2000	7.78	6.4	–	–	–	–	–	–	90 days AOT40
		8.89	7.2	–	–	–	–	–	–	75 days AOT40
		19.95	14.9	–	–	–	–	–	–	POD6
		13.01	10.3	–	–	–	–	–	–	POD12

M7/12: mean concentration index; W126/SUM06/AOT40: accumulated concentration index; POD6/POD12: flux index.
–: no data.

meta-analysis based on cohort studies conducted in western developed nations, with lower $PM_{2.5}$ concentration conditions of 5–30 μg/m^3 (Burnett et al., 2014). Whether those results can be extrapolated and used directly in studies for China with high $PM_{2.5}$ levels needs to be investigated further. Although an integrated exposure-response model (Burnett et al., 2014) has been developed to overcome this issue, cohort studies in areas with high pollution levels are still needed to verify the performance of the new model. We also assumed that health effects due to exposure to $PM_{2.5}$ were only related to the $PM_{2.5}$concentration without considering its complex composition, which is usually location and time dependent. Because of the heterogeneity of $PM_{2.5}$ (Hoek et al., 2013), this assumption probably influenced the results. In addition, we used uniform C–R coefficients for the assessment of both cities and rural areas, assuming that there were no differences in the population response to $PM_{2.5}$exposure in cities and rural areas, and we did not consider the heterogeneity of weather, people's activity patterns, and the level of economic activity. This also resulted in uncertainties. Some studies (Yu et al., 2013)have suggested this may overestimate the health impacts in China, because the air quality in rural area areas is usually better than that in cities. In addition, only $PM_{2.5}$ was selected to evaluate the losses due to health effects, whereas other pollutants, such as O_3 and NO_2, are also linked to adverse health effects. This may underestimate the health loss induced by air pollution in China.

Population data for urban and rural areas were determined using MODIS land cover data in the study. The urban population recognized in our study was less than that given in national statistics, which could affect the health assessment results, as the incidences of health endpoints were different between cities and rural areas.

Furthermore, the mortality estimated in this study may have been overestimated due to the harvest effect. Murray (1994) reported that there are limitations in health impact assessments based on mortality and morbidity indices, because air pollution does not cause death directly, and therefore recommended a disability adjusted life years method to evaluate the health impact of air pollution.

For the assessment of crop yield losses, we used cumulative metrics for assessing crops loss for wheat, maize and soybean. As cumulative metrics emphasized high greater weight to elevated O_3 (Lapina et al., 2014), uncertainties exits as ozone peak concentration was not always captured well by modeling (Avnery et al., 2011). C–R coefficients used in the research were based on large-scale experiments developed for North American cultivars. Crops in China may have different sensitivities to surface O_3than those of the North American cultivars (Emberson et al., 2009). Some studies have reported that in China the two different varieties of wheat have different responses to O_3 (Feng et al., 2011). In addition, the C–R coefficients for estimating crop yield losses were derived from open-top field chamber experiments. It has been reported that the environment in the chamber of such controlled experiments could alter the microclimate and then affect the experimental results. The Free-Air Concentration Enrichment system with ozone experiment was conducted to investigate the exposure-response relationship. Furthermore, the definition of the growing season in this study will also affect the results by changing the O_3 exposure period, although some studies have suggested that changing the growing season can only alter the results by less than 5%. Our analysis for soybean showed that moving the date of ripening ahead by 1 month will lead to a doubling of the yield loss. Further investigation is needed to define the growing season accurately, especially for maize and soybean in China.

Despite these uncertainties, our study suggests that air pollution in China has caused major damage to population health and crop yields. The results also indicate that there is a large potential to reduce air pollution, with likely benefits human health and crop yields.

3. Conclusions

In this study, we estimated health effects and crop yield losses due to air pollution in China, using model-based results and C–R functions for human health and crops, combined with population and crop yield data. Simulated results for $PM_{2.5}$ and surface O_3 were compared with the results from other studies, indicating that the modeled results reproduced the spatial distribution and seasonal patterns well.

Our results showed that outdoor $PM_{2.5}$ pollution has caused 1.99 (95%CI 1.41–2.48) million cases of all-cause mortality, 1.41 (95% CI 0.96–1.84) million hospital admissions for RD, 1.08 (95% CI 0.47–1.66) million hospital admissions for CVD, 3.60 (95%CI 1.46–5.02) million cases of chronic bronchitis at $C_0 = 0\ \mu g/m^3$ and 1.70 (95%CI 1.20–2.14) million cases of all-cause mortality, 1.19 (95%CI 0.81–1.40) million hospital admissions for RD, 0.91 (95%CI 0.40–1.40) million hospital admissions for CVD, and 3.10 (95%CI 1.24–4.40) million cases of chronic bronchitis at $C_0 = 10\ \mu g/m^3$. The total economic losses related to the health effects induced by $PM_{2.5}$ were 176.9 (120.7–223.6) billion USD and 151.5 (102.3–192.7) billion USD at two thresholds of $C_0 = 0\ \mu g/m^3$ and $C_0 = 10\ \mu g/m^3$, respectively. The estimated crop yield losses for wheat, rice, maize, and soybean were approximately 9, 4.6, 0.44, and 0.34 million tons, respectively, resulting in an economic loss of 3.4 billion USD. Our results showed that air pollution in China has significant impacts on population health and crop yields, resulting in huge economic losses in 2006. Although the estimated economic damages for crop yield losses was much smaller than that for population health effects, it should not be neglected due to the important impact on food security.

Considering the uncertainties regarding the health impact and crop yield loss assessments, including the emission inventory, model system, C–R coefficients, population exposure assessment, and growing season definition for crops, further work including designing model systems, long-term cohort studies on $PM_{2.5}$ health effects, and field experiments on the crop response to elevated surface O_3 should be conducted.

Appendix A. Supplementary data

Supplementary data to this article can be found online at doi:10.1016/j.jes.2016.08.024.

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