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# Population Exposure to Ambient PM<sub>2.5</sub> at the Subdistrict Level in China\*

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#### **Abstract**

Fine particle pollution is a major public health concern in China. This paper assesses China's potential population exposure to  $PM_{2.5}$  at the subdistrict level, the smallest census unit with public information. Using both ground-based measurements and satellite-based Aerosol Optical Depth retrievals, we estimate subdistrict-level daily  $PM_{2.5}$  concentrations by means of the block cokriging approach. Our results reveal that China's population-weighted annual average  $PM_{2.5}$  concentration during April 08, 2013 and April 07, 2014 is nearly 7 times the annual average level suggested by the World Health Organization (WHO). About 1,322 million people, or 98.6% of China's total population, are exposed to  $PM_{2.5}$  at levels above WHO's daily guideline for longer than half a year. We also simulate the effects of China's most recent action plan on air pollution control. The simulation results demonstrate that the population exposed to  $PM_{2.5}$  above China's daily standard for longer than half a year will be reduced by 85% if the plan can achieve its target by 2017. Nevertheless,  $PM_{2.5}$  will be still at a harmful level to public health, which calls for additional effort in pollution control.

**Keywords**: PM<sub>2.5</sub>, population exposure, MODIS AOD, China.

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#### 1 Introduction

Epidemiological evidence has consistently shown that airborne particulate matter (PM) is associated with adverse health impacts; short- and long-term exposures to PM can impair respiratory and cardiovascular systems (Dominici et al., 2014). Fine particles with aerodynamic equivalent diameter smaller than 2.5  $\mu$ m (PM<sub>2.5</sub>)–including soot, organics and sulphates–are particularly harmful. Compared with coarse particles, PM<sub>2.5</sub> travels farther, is suspended in the air longer, penetrates indoor environments more easily, and is inhaled more deeply into the lungs (Wilson and Suh, 1997). Therefore, many countries, including China, have identified PM<sub>2.5</sub> pollution as a major risk to public health.

After decades of rapid economic growth that heavily relies on fossil fuel consumption, the PM pollution of many Chinese cities has reached a hazardous level (Zhang et al., 2012). Serious air pollution is associated with elevated mortality risk. A recent study shows that long-term exposure to total suspended particulates reduces life expectancies in North China by about 5.5 years (Chen et al., 2013). Although inhalable particles (PM<sub>10</sub>) have been regulated for about two decades, China's PM<sub>2.5</sub> pollution has not drawn national and international attention until very recently. In particular, a series of extreme air pollution episodes triggered the Chinese government to tackle the serious fine particle pollution problem by enacting new air quality standards that incorporate PM<sub>2.5</sub>. The systematic disclosure of PM<sub>2.5</sub> information enables us to assess China's fine particle pollution nationwide at a fine spatiotemporal resolution.

The objective of this paper is to assess China's potential population exposure to  $PM_{2.5}$ , map its spatiotemporal variability, and simulate the effects of various  $PM_{2.5}$  concentration standards and air pollution control policy. To this end, we relate Moderate Resolution Imaging Spectroradiometer (MODIS) Aerosol Optical Depth (AOD) retrievals to ground-based  $PM_{2.5}$  observations. We employ block cokriging (BCK) to improve the spatial interpolation of  $PM_{2.5}$  distribution (Goovaerts, 1997). In addition, we use the subdistrict level population data to estimate and map potential population exposure to  $PM_{2.5}$  pollution in China at the subdistrict level, the smallest census unit that discloses public demographic information.

We find that Chinese people are exposed to severe  $PM_{2.5}$  pollution. During April 08, 2013 and April 07, 2014, China's population-weighted annual average  $PM_{2.5}$  concentration reaches 68.3

 $\mu g/m^3$ , which is nearly 7 times the annual average level recommended by the World Health Organization (WHO). An average Chinese person is exposed to 113 days with PM<sub>2.5</sub> concentrations above China's daily average PM<sub>2.5</sub> standard of 75  $\mu g/m^3$ ; about 223 million people lived in a polluted environment for longer than half a year. If we use WHO's guideline for daily average PM<sub>2.5</sub> concentration of 25  $\mu g/m^3$ , the exposed population is 1,322 million, or 98.6% of China's total population. PM<sub>2.5</sub> pollution exhibits significant spatiotemporal variability: it is generally worse for the areas in the north, inland areas, plains, and basins and the pollution peaks during fall and winter. We also simulate the effects of China's recently proposed effort on air pollution control. The simulation results demonstrate that the population exposure to PM<sub>2.5</sub> above China's daily standard for longer than half a year will be reduced by 85% if the plan can achieve its target by 2017. However, the PM<sub>2.5</sub> level will be still dangerous to public health.

To the best of our knowledge, we are the first to assess China's potential population exposure to  $PM_{2.5}$  on a daily basis at the subdistrict level. Although similar questions have been explored in previous studies, they mostly focus on one major metropolitan area such as Beijing or Tianjin (Zhang et al., 2013; Chen et al., 2010). In comparison, our study covers the whole country at a fine spatial and temporal resolution, taking advantage of the first batch of ground-based  $PM_{2.5}$  observations and satellite remote sensing. This allows us to make more comprehensive and accurate assessment of population exposure to  $PM_{2.5}$  in China.

The remainder of the paper is organized as follows. Section 2 describes the data used for estimating population exposure to  $PM_{2.5}$ . Section 3 elaborates the method for interpolating  $PM_{2.5}$  concentrations from ground-based observations and MODIS AOD images. Section 4 reports the estimation and simulation results. Section 5 discusses the advantages and caveats of the study. Section 6 concludes.

#### 2 Data

**Ground-based PM**<sub>2.5</sub> **Measurements**. China's Ministry of Environmental Protection (MEP) and its local agencies maintain a nationwide network of air quality monitoring stations, which monitor concentrations of particulate and gaseous air pollutants at the ground level. Although fine particles are the most harmful components of particulate matters,  $PM_{2.5}$  has not been regulated until

very recently due to technical and economic constraints. The 2012 *Ambient Air Quality Standards* and *Technical Regulation on Ambient Air Quality Index* require cities to report hourly concentrations of six criteria pollutants including PM<sub>2.5</sub> in real time by January 2013.<sup>1</sup> All provincial capitals and some municipalities in the developed regions are among the first group to disclose PM<sub>2.5</sub> information. By the end of 2013, China has established 945 monitoring stations, increasing from 670 in 2012. We have collected daily average PM<sub>2.5</sub> concentrations during April 08, 2013 and April 07, 2014 from all monitoring stations in 190 cities.<sup>2</sup> The one year of *in situ* observations at daily level for each station are used as a key input for pollution exposure estimation.

Ground-based monitoring stations are sparsely located. Figure 1(a) shows the locations of all monitoring sites. Figure 1(b) is the spatial interpolation of the duration of  $PM_{2.5}$  above China's daily standard, which is obtained by applying the kriging method to the ground-based observations only. We notice that a similar approach has been used by the Chinese government to illustrate the spatial pattern of smog duration.<sup>3</sup> However, the spatial resolution of the estimated  $PM_{2.5}$ , which relies on ground-based observations only, is very coarse.

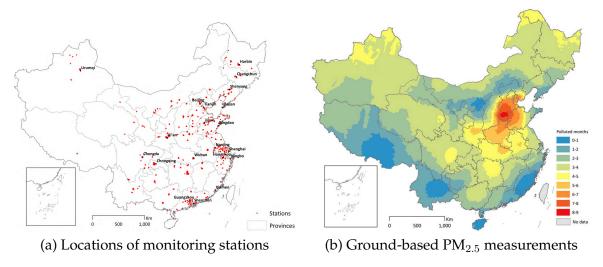


Figure 1: Panel (a): spatial distribution of monitoring stations in 190 Chinese cities. By the end of 2013, 945 stations have disclosed  $PM_{2.5}$  concentrations to the public. Panel (b): the duration of  $PM_{2.5}$  above China's daily standard spatially interpolated by ground-based observations only. We convert the number of pollution days to months by assuming 30 days in a month.

<sup>&</sup>lt;sup>1</sup>Ambient Air Quality Standards (GB3095-2012) (in Chinese): http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/dqhjzlbz/201203/W020120410330232398521.pdf. Technical Regulation on Ambient Air Quality Index (HJ 633-2012) (in Chinese): http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/jcgfffbz/201203/W020120410332725219541.pdf.

<sup>&</sup>lt;sup>2</sup>There are 657 cities in mainland China as of 2012.

<sup>&</sup>lt;sup>3</sup>Source: http://jcs.mep.gov.cn/hjzl/zkgb/2013zkgb/201406/t20140605\_276521.htm (in Chinese).

MODIS AOD Retrievals. Satellite remote sensing has been used to estimate  $PM_{2.5}$  concentrations in the areas lacking ground-level measurements (van Donkelaar et al., 2010; Liu, 2013). The MODIS sensor is one of the first passive satellite radiometers designed to systematically retrieve aerosol properties over both land and ocean on a daily basis (Remer et al., 2005). NASA released global retrievals of MODIS AOD with the nadir resolution of 10 km. The uncertainty of the MODIS derived AOD is expected to be  $\pm (0.05 + 15 \%)$  over the land (Levy et al., 2007). In the MODIS AOD Collection 5 retrieval algorithm, three different channels–0.47, 0.66, and 2.12  $\mu$ m—are primarily employed for over-land aerosol retrievals. These three wavelength channels are simultaneously inverted to finally report AOD values at the wavelength of 0.55  $\mu$ m. More details about the retrievals of the MODIS AOD product are discussed in Remer et al. (2005) and Levy et al. (2010). In this paper, we use the MODIS AOD retrievals to improve daily  $PM_{2.5}$  estimates for the whole country. We obtained the daily MODIS AOD Collection 5 from the Atmosphere Archive and Distribution System.<sup>4</sup> These AOD retrievals were screened from cloud and bright surfaces. We extracted AOD at 0.55  $\mu$ m as the auxiliary information to spatially interpolate  $PM_{2.5}$  levels.<sup>5</sup>

**Population**. The data of population density for each subdistrict are obtained from the 6<sup>th</sup> National Population Census in 2010, which covers the People's Republic of China but not including Hong Kong, Macau, and Taiwan. China has three forms of township-level administrative units: subdistrict (iiedao), town (zhen), and township (xiang). Subdistrict is mainly in cities; its counterpart in suburbs and rural areas is town or township. Hereafter in this paper, we use the term subdistrict to represent all types of township-level administrative units in China. A subdistrict includes dozens of census units and it is the smallest population unit available to the public. As of 2010, China has about 40 thousand subdistricts; average subdistrict population density is close to 1 thousand persons per km<sup>2</sup>. The population is divided into three segments: children (0-14), adults (15-64), and seniors ( $\geq$  65). The age information allows us to assess exposures for the most susceptible members of population such as children and seniors.

City Boundaries. We analyze and rank the population exposure to  $PM_{2.5}$  in each city by aggregating the subdistrict-level data to the city level. The city boundaries data, in the form of 1:4,000,000 maps, are obtained from the National Fundamental Geographical Information System

<sup>&</sup>lt;sup>4</sup>Source: http://ladsweb.nascom.nasa.gov/

 $<sup>^5</sup>$ MODIS variable name: Optical\_Depth\_Land\_And\_Ocean, which is the aerosol optical depth from both the land and ocean models at  $0.55 \, \mu m$ .

of China. Our study covers 654 cities in China, in which 286 cities are at the prefecture level or above and the rest are county-level cities.<sup>6</sup> It is worth noting that a Chinese city proper contains both rural and urban land uses.

#### 3 Methods

#### 3.1 Estimating PM<sub>2.5</sub> Concentrations

One challenge to map high-resolution PM<sub>2.5</sub> concentrations is the sparsely located monitoring stations. Various approaches have been developed such as exposure indicator variables, interpolation methods, dispersion models, and land use regression (LUR) models (Hoek et al., 2008). Among these alternatives, the interpolating methods that incorporate ground-based measurements with satellite-retrieved MODIS AOD are particularly promising. In general, there are two ways to estimate PM<sub>2.5</sub> from ground monitoring stations with satellite-retrieved AOD. One approach uses AOD retrievals as a covariate in regression models to predict ground-level PM<sub>2.5</sub> concentrations (Liu et al., 2009). The other approach uses AOD retrievals as auxiliary information in various types of kriging algorithms (Sampson et al., 2013). In this paper, we adopt the second approach to predict daily PM<sub>2.5</sub> levels by exploiting the spatiotemporal relationship between ground-based observations and MODIS AOD data.

As shown in Figure 1, the sparsely located monitoring sites are insufficient to represent the spatiotemporal variation of PM<sub>2.5</sub> concentrations. Therefore, the spatial interpolation algorithm that relies on ground-based observations only yields a coarse estimate of PM<sub>2.5</sub> concentrations. Because ground-based PM<sub>2.5</sub> concentrations are intrinsically correlated with AOD, the MODIS AOD retrievals provide secondary information about the spatial distribution of particulate matter over the domain. More specifically, we employ block cokriging (BCK) (Goovaerts, 1997) to improve PM<sub>2.5</sub> concentration estimation by combining information from daily MODIS AOD retrievals and ground-level measurements. This geostatistical interpolation technique is useful in predicting PM<sub>2.5</sub> concentrations for each subdistrict in China.

Let  $Z_1$  designate PM<sub>2.5</sub> ground observations and  $Z_2$  designate MODIS AOD retrievals. Since

<sup>&</sup>lt;sup>6</sup>Sansha in Hainan and Beitun in Xinjiang are not included due to the availability of the spatial data. Taiwan, Hong Kong, and Macau are not included in the analysis.

 $Z_1$  and  $Z_2$  are spatially correlated, the spatial variation in  $Z_2$  can be used to predict that of  $Z_1$ . BCK estimates the average value of variable  $Z_1$  over a subdistrict v with covariate  $Z_2$  as

$$\hat{Z}_1(v) = \sum_{i=1}^{n_1} \lambda_{1i}(v) Z_1(s_{1i}) + \sum_{i=1}^{n_2} \lambda_{2i}(v) Z_2(s_{2i}), \tag{1}$$

where  $s_1$  and  $s_2$  denote a set of spatial coordinates,  $n_1$  and  $n_2$  are the number of observations for  $Z_1$  and  $Z_2$  respectively. The above estimator is unbiased if the BCK weights  $\lambda_{1i}(v)$  and  $\lambda_{2i}(v)$  satisfy the following constraints:

$$\sum_{i=1}^{n_1} \lambda_{1i}(v) = 1 \quad \text{and} \quad \sum_{i=1}^{n_2} \lambda_{2i}(v) = 0.$$
 (2)

The system of equation (1) determining the weights in the BCK estimator is obtained by imposing two constraints that require the estimator to be unbiased and efficient (Cressie and Wikle, 2011; Goovaerts, 1997). Using the solution of this system, we can derive the estimates and standard errors for the BCK prediction of  $PM_{2.5}$  concentrations at the subdistrict level. By applying this method to the daily ground-based  $PM_{2.5}$  observations and MODIS AOD retrievals, we obtain 365 maps for the interpolated  $PM_{2.5}$  concentrations at the subdistrict level.

We compare the BCK estimation results with those of ordinary block kriging (BK) using the leave-one-out cross-validation (LOOCV) method. LOOCV works as follows. The model predicts an annual time series of daily  $PM_{2.5}$  concentrations for each station using the observations from its neighboring stations. BCK uses both ground-level observations and MODIS AOD retrievals; BK uses ground-level observations only. The predicted  $PM_{2.5}$  concentration is compared with the actual  $PM_{2.5}$  observation to derive the cross-validation statistics. Model accuracy is assessed using the Pearson's correlation coefficient (COR) and the root-mean-square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\hat{Z}_1(v_i) - Z_1(v_i)\right)^2}.$$
 (3)

In this form, n is the number of observations,  $\hat{Z}_1(v_i)$  is the cross-validation estimate and  $Z_1(v_i)$  is the observed PM<sub>2.5</sub> concentration at station i. The preferred model is the one associated with higher COR and smaller RMSE in model comparisons.

#### 3.2 Potential Population Exposure

According to the guidelines of the US Environmental Protection Agency, exposure is the contact between pollutant and the outer boundary of a human (US EPA, 1992). The magnitude of exposure for an individual is determined by the cumulative exposure concentration over a period of time (pollution duration). Because the information required estimating actual exposure for the total population in China is overwhelming, we use a number of simplified indicators to measure potential population exposure to  $PM_{2.5}$ . Although these indicators are coarser than the ones in the standard exposure assessment, they provide essential information about the relationship between  $PM_{2.5}$  pollution and population.

First of all, we use population-weighted mean  $PM_{2.5}$  concentration to measure the potential exposure for an average Chinese in the study period. We use subdistrict-level  $PM_{2.5}$  concentration, which is derived in the previous section, along with the distribution of population or population segments, to compute means for the country and cities. Another intuitive indicator is formed by the interaction of the number of pollution days and the exposed population. We define a pollution day as its 24-hour average of  $PM_{2.5}$  concentrations exceeding the air quality standard. We consider multiple standards in this paper. China's national ambient air quality standards, which set  $PM_{2.5}$  level at  $75 \,\mu\text{g/m}^3$ , are used as the benchmark. We also consider various stages of standards proposed by the WHO guidelines (WHO, 2006).

Let v index subdistrict, t index day, C designate PM<sub>2.5</sub> concentration, S designate PM<sub>2.5</sub> standard, and N designate the size of population or population segment. The total exposure E for subdistrict v over a period of time  $\tau = t_2 - t_1$  is

$$E_v = \sum_{t=t_1}^{t_2} N_v \cdot 1(C_{vt} \ge S), \tag{4}$$

where 1() is an indicator function indicating whether  $PM_{2.5}$  concentration of a particular day is above the standard. We can use total exposure (person days) to assess the aggregated public health risk of  $PM_{2.5}$  in any given area or period. However, this indicator is not appropriate for the mapping purpose because land areas vary hugely among subdistricts and cities; the large areas will be visually over-represented on the map. Therefore, we propose to use exposure intensity EI

to map PM<sub>2.5</sub> exposure for each subdistrict:

$$EI_v = N_v^{\tau} \frac{P_v}{A_v}.$$
 (5)

In this form,  $A_v$  is the land area of subdistrict v and  $N_v^{\tau} = \sum_{t=t_1}^{t_2} 1(C_{vt} \ge S)$  is the exposure duration (number of pollution days) in period  $\tau$ . Exposure intensity (person days/km²) is determined by population density (persons/km²) and days of pollution. Again this indicator can be assessed separately for different age groups.

We aggregate total exposure and exposure intensity in both temporal and spatial dimensions to gain insights on the spatiotemporal pattern of the  $PM_{2.5}$  pollution risk. Specifically, to illustrate seasonality, the subdistrict-level exposure duration, or the total number of days exceeding China's current ambient  $PM_{2.5}$  standard, is calculated for each month. To show spatial heterogeneity, the exposure of each city is inferred by averaging the  $PM_{2.5}$  estimates of all subdistricts in each city's administrative boundary.

#### 4 Results

We use BCK to combine MODIS AOD retrievals with ground-based observations and estimate daily average  $PM_{2.5}$  concentrations for each subdistrict. Our model is validated by means of the LOOCV method. The yearly mean RMSE for BK and block BCK is  $21.5 \,\mu g/m^3$  and  $19.6 \,\mu g/m^3$ , respectively. The yearly mean COR for BK and BCK is 0.832 and 0.864, respectively. Both statistics indicate that the BCK method improves the accuracy of  $PM_{2.5}$  estimation. Therefore, the following results are based on the estimates from the BCK method.

#### 4.1 Overall Pattern

In our study period during April 08, 2013 and April 07, 2014, China's population-weighted annual average  $PM_{2.5}$  concentration reaches 68.3  $\mu g/m^3$ , which almost doubles China's annual standard of 35  $\mu g/m^3$ . It is nearly 7 times the annual average level (10  $\mu g/m^3$ ) recommended by the WHO. Using China's daily standard of 75  $\mu g/m^3$ , an average Chinese person experienced 113 pollution days in the study year. If we use the WHO's daily guideline of 25  $\mu g/m^3$ , the population-weighted

average number of days above WHO's daily standard increases to 257 days in that year.

Table 1: Potential Exposure to PM<sub>2.5</sub>

	Cumulative Exposure			
Exposure Duration (month)	Area (10,000 km²)	Population (million people)		
≥ 1	745	1,241		
$\geq 2$	470	1,070		
$\geq 3$	243	827		
$\geq 4$	110	550		
$\geq 5$	61	355		
$\geq 6$	35	223		
$\geq 7$	12	90		
$\geq 8$	4	34		
$\geq 9$	0.4	3		

*Notes*: Exposure duration is the total number of days above China's ambient  $PM_{2.5}$  standard, which is converted to the equivalent number of months by a factor of 30.

Using China's daily PM<sub>2.5</sub> standard, the mode of PM<sub>2.5</sub> exposure duration for the Chinese subdistricts is 1-2 months in a year. Since the population centers tend to be more polluted, the mode of exposure duration for the population reaches 3-4 months in a year. We summarize the cumulative PM<sub>2.5</sub> exposure duration for land area and population in Table 1. For example, a total land area of 243 million km<sup>2</sup>, or 25.3% of China's land area, has experienced PM<sub>2.5</sub> pollution for longer than 3 months. In terms of the population exposed, 827 million people, or 62.0% of total population in 2010, have been exposed to PM<sub>2.5</sub> pollution for longer than a quarter of a year.

#### 4.2 Spatial Heterogeneity

To illustrate the spatial variation in  $PM_{2.5}$ , we report the frequency of a subdistrict violating national ambient air quality standards. Please see Figure 2 and the online visualization for more details.<sup>7</sup> Our results highlight three pollution hotspots in China. The most pronounced hotspot is a diamond-shaped large area that sprawls across eastern and central China. The area is anchored by four major metropolitan areas: Beijing in the north, Shanghai in the east, Guangzhou in the south, and Chengdu in the west. The other two hotspots are the Harbin-Shenyang Corridor in Northeast China and northern Xinjiang with Urumqi as the center. These pollution centers are

<sup>&</sup>lt;sup>7</sup>More details are available in the online visualization at the Beijing City Lab: http://www.beijingcitylab.com

formed due to a combination of factors such as fossil fuel combustion, industrial processes, and natural conditions.

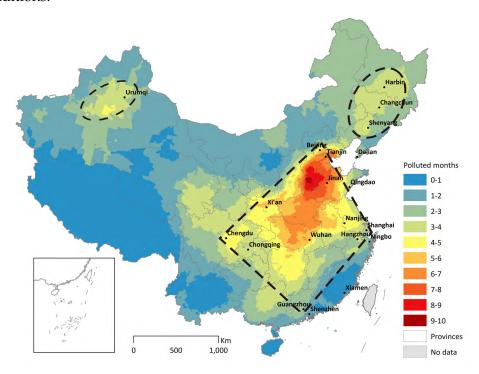


Figure 2: Pollution duration for each Chinese subdistrict during the period of April 2013-April 2014. It measures the total number of days with daily average  $PM_{2.5}$  concentration above the national standard. The number of pollution days is converted to months by a factor of 30.

About 4,100 subdistricts, or nearly 11%, are exposed to PM<sub>2.5</sub> pollution for longer than half a year. The total area of these highly exposed subdistricts is 347,432 km<sup>2</sup>, or approximately 3.65% of mainland China's land area. These highly exposed subdistricts combined have more than 223 million people, almost 17% of the total population in mainland China.<sup>8</sup> Moreover, exposure duration in some subdistricts is over 8 months and even up to 9 months in a year. These most exposed areas cover more than 121,000 km<sup>2</sup> area and 90 million people.<sup>9</sup> By contrast, less than half of the total subdistricts have less than 3 months of pollution. Low exposed subdistricts are mainly in the plateau and alpine regions.<sup>10</sup> Although the low exposed regions cover three-quarters of China's land areas, or 7,097,097 km<sup>2</sup>, they only accommodate 38% of total population.

<sup>&</sup>lt;sup>8</sup>The highly exposed subdistricts are mainly located in Beijing, Tianjin, southern and central Hebei, central and eastern Henan, central and western Shandong, and central Hubei.

<sup>&</sup>lt;sup>9</sup>The most exposed regions are mainly distributed in southern Hebei, northern Henan and western Shandong.

<sup>&</sup>lt;sup>10</sup>The low exposed regions include Tibet and Northwest China, southeastern coastal regions (Fujian, Guangdong, and Hainan), and southwestern border regions (Yunan, part of Guizhou, and Guangxi)

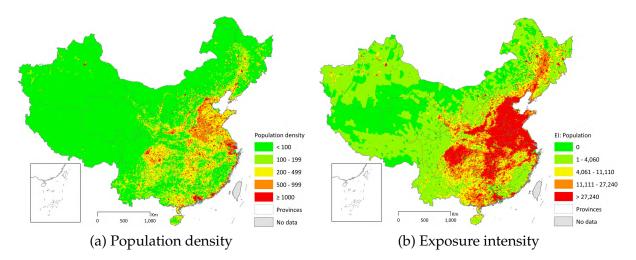


Figure 3: Panel (a): population density (persons per  $\rm km^2$ ). Panel (b): exposure intensity (pollution days\*persons per  $\rm km^2$ ). Exposure intensity is the product of exposure duration and exposed population density. Exposure duration is the total number of days in a year exceeding China's current  $\rm PM_{2.5}$  standard. The spatial resolution is subdistrict.

We calculate exposure intensity based on the exposure duration and population density in each subdistrict according to equation (5). The results are mapped in Figure 3. Because PM<sub>2.5</sub> pollution and population density are positively correlated (see Table S3), nearly all densely populated subdistricts are among the worst polluted regions. In particular, the areas with high exposure intensity almost cover the entire eastern-central China except for east Fujian, the Harbin-Dalian corridor in the northeast, and the Guanzhong and Chengdu Plain in the west. Therefore, exposure intensity is more spatially concentrated compared with population density.<sup>11</sup>

#### 4.3 Seasonality

In order to illustrate the seasonality of  $PM_{2.5}$ , we aggregate the daily pollution level to the monthly level. More specifically, we calculate the percentage of days within a month that exceeds  $PM_{2.5}$  standard. Figure 4 illustrates the spatiotemporal variation of exposure duration without considering population density. Overall, Chinese people are exposed to  $PM_{2.5}$  pollution in almost every month of a year. The seasonal fluctuation spreads and congregates in space due to a complex interplay with weather variability, diffusion conditions, and coal combustion (Fenger, 1999).

 $PM_{2.5}$  pollution in winter half year (from October to March) is generally much more serious

<sup>&</sup>lt;sup>11</sup>Although some subdistricts have relatively low pollution levels, high population density still gives rise to serious exposure intensity. These subdistricts include the Pearl River Delta, eastern Guangdong, southeaster Zhejiang, Guangxi, Hunan, and Sichuan.

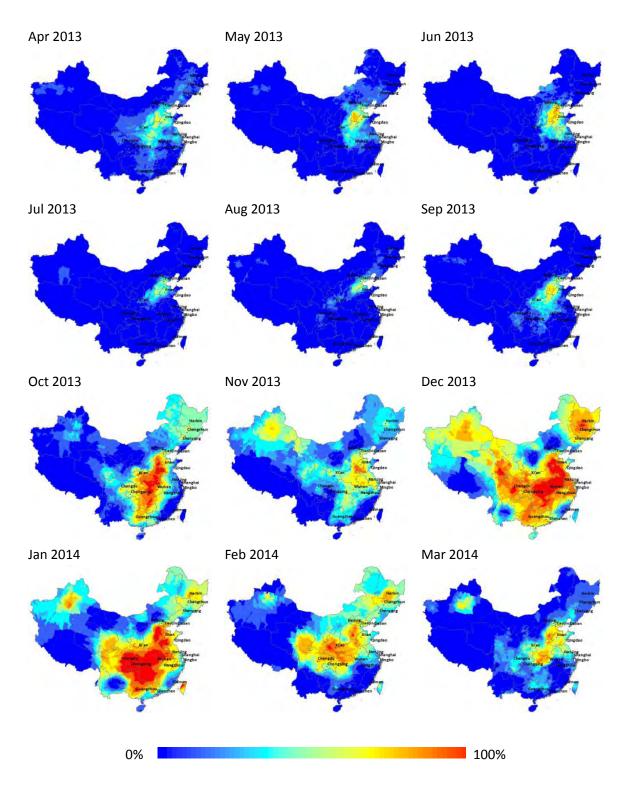


Figure 4: Spatiotemporal variation of  $PM_{2.5}$  pollution. The color ramp depicts the percentage of days with  $PM_{2.5}$  concentration above the national standard for each month between April 2013 and April 2014. China's national standard for daily average  $PM_{2.5}$  concentration is 75  $\mu g/m^3$ . The spatial resolution is subdistrict.

than that of summer half year (from April to September). The whole country is exposed to incredibly high PM<sub>2.5</sub> pollution in winter half year due to the influence of downdraft and coal-fired heating (Zheng et al., 2005; Yang et al., 2011). In December and January, an overwhelming majority of subdistricts are exposed to PM<sub>2.5</sub> pollution for longer than 50% of days in a month. Apart from the regions with low human activities such as forests and plateaus, the southeastern coastal areas like Fujian and Hainan are the only regions with good air quality, although their population density is also high. Pollution starts to abate during February and reaches the bottom level in August. In spring and summer, pollution is limited to a number of areas in the north due to the spring dust storm (He et al., 2001). As demonstrated in Figure 3, the population in North China is still exposed to high PM<sub>2.5</sub> concentrations even between May and September.<sup>12</sup> After August, pollution starts to increase again; it expands from the north to the south gradually until it covers the most part of China in December.

#### 4.4 Urban Areas and City Regions

Since air pollution is primarily an urban challenge, we aggregate the subdistrict pollution level to the city level. Figure S1 in the supplementary appendix illustrates the spatial heterogeneity of  $PM_{2.5}$  pollution across 654 cities. The pollution pattern shows that northern cities are worse than southern cities, inland cities are worse than coastal cities, and plain and basin cities are worse than plateau and hilly cities.

We use total exposure, a product of exposure duration and population, to rank cities in  $PM_{2.5}$  pollution. We report the rank of the best and worst cities in terms of  $PM_{2.5}$  pollution in Table S1 in the supplementary appendix.<sup>13</sup> We find that the worst 20 cities are mostly from central or southern part of Hebei province, which is clustered with the iron and steel industry that heavily relies on coal consumption. Beijing is one of the most polluted cities in terms of total exposure, indicating a huge amount of population is exposed to  $PM_{2.5}$  pollution. The other three megacities–Tianjin,

<sup>&</sup>lt;sup>12</sup>These areas include the Beijing-Tianjin-Hebei (BTH) region, southeastern Shanxi, northern-central Henan, and western Shandong.

 $<sup>^{13}</sup>$ The cities in the Beijing-Tianjin-Hebei (BTH) region , Henan, mid-western Shandong (except cities in the Shandong Peninsula), central Hubei, and central Shaanxi (eg, Xi'an) are ranked the top on the list of most polluted cities. The next tier of polluted cities with exposure between 111 and 158 days include the northeastern Yangtze River Delta (YRD, eg, Nanjing), Chengdu Plain (eg, Chengdu), east Hubei, and Hunan (eg, Wuhan and Changsha). Residents in the major urbanization city-regions like BTH, YRD, Chengdu-Chongqing, and the middle reaches of Yangtze River are exposed to  $PM_{2.5}$  concentrations above the standard for more than 100 days a year. The exception is that the Pearl River Delta (PRD), east Fujian, Shandong Peninsula, and Liaodong Peninsula have relatively less  $PM_{2.5}$  pollution.

Shanghai, and Chongqing–are all on the top list too. Although some cities have a relatively shorter duration of exposure, the risk of pollution is still high because of the concentrated population. In contrast, Tibet, Yunnan, and Fujian have the cleanest cities in China in terms of  $PM_{2.5}$ .

Table 2: PM<sub>2.5</sub> pollution in major city regions

City Region	Exposure duration	Annual average concentration	Rate of compliance
	(day)	$(\mu g/m^3)$	(%)
Beijing-Tianjin-Hebei	219	107	0
Yangtze River Delta	99	64	0
Pearl River Delta	53	44	4.5
South-Central Liaoning	80	56	0
Shandong	146	80	0
Wuhan metropolitan area	161	87	0
Changsha-Zhuzhou-Xiangtan	127	71	0
Chengdu-Chongqing	113	66	0
Fujian	17	37	43.5
North Central Shanxi	128	70	0
Central Shaanxi	132	79	0
Gansu and Ningxia	69	58	0
Northern Xinjiang	89	60	0

*Notes*: Exposure duration is the average number of days above China's ambient  $PM_{2.5}$  standard for the cities in the same city region. Annual average concentration is the simple arithmetic mean of  $PM_{2.5}$  concentration between April 2013 and April 2014. Rate of compliance measures the percentage of cities in the city-region that comply with China's annual  $PM_{2.5}$  standard.

Furthermore, we focus on  $PM_{2.5}$  exposures in the thirteen major city regions that are identified by the Ministry of Environmental Protection of China as the key regions in air pollution control. Table 2 presents various exposure indicators. The results show that half of these city regions experienced over 100 pollution days in the past year. Only Fujian province has a relatively low annual average concentration of  $37 \,\mu g/m^3$ , which is still slightly above the national standard of  $35 \mu g/m^3$ . The percentage of cities in these city regions that comply with China's  $PM_{2.5}$  annual standard is negligible.

#### 4.5 Susceptible Subpopulation

Studies reveal that seniors and children are more susceptible to  $PM_{2.5}$  pollution (Zhang et al., 2002; Ashmore and Dimitroulopoulou, 2009). Therefore, we estimate the exposure intensity for the susceptible subpopulation including children (0-14) and seniors ( $\geq$  65). Figure 5 illustrates the

spatial and temporal variations in exposure intensity for the susceptible groups. We find that the pattern of their exposure intensity to  $PM_{2.5}$  is similar to that of the population in Figure 3.

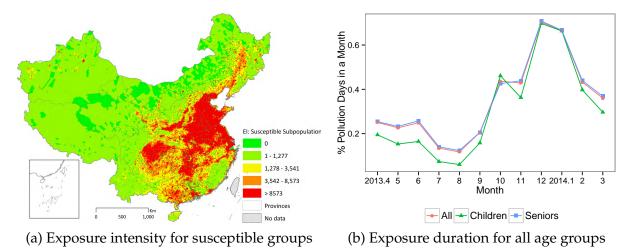


Figure 5: Panel (a): exposure intensity for the susceptible subpopulation across space. Panel (b): exposure duration for all age groups over time. Exposure duration is designated by the percentage of days in a month exceeding the national  $PM_{2.5}$  standard.

The spatial distribution for each population segment is slightly different. The correlation matrix between population density and exposure duration is reported in Table S3. The correlation coefficients show that children on average have higher risk of  $PM_{2.5}$  exposure than the average population. This perhaps attributes to the high birth rate in the populated areas. The condition for the senior subpopulation, however, is better than the average and young population. This might be explained by the fact that seniors tend to stay in the places with better environment. Another possible explanation is that adults between 15 and 64 are likely to migrate to population centers for better job opportunities, where turn out to be also pollution hotspots.

#### 4.6 Simulation Results

Our analysis uses China's ambient  $PM_{2.5}$  standard as the benchmark. For comparison, we simulate the implication of several stages of  $PM_{2.5}$  standard proposed by the World Health Organization (WHO, 2006). The WHO guideline for daily average  $PM_{2.5}$  concentration is 25  $\mu g/m^3$ . WHO also suggests three interim targets: 75  $\mu g/m^3$  (interim-target 1, IT-1), 50  $\mu g/m^3$  (interim-target 2, IT-2), and 37.5  $\mu g/m^3$  (interim-target 3, IT-3). We simulate population exposures under

<sup>&</sup>lt;sup>14</sup>For example, the WHO recommended standard is adopted by Canada and Australia. The adopters of the interim targets include: IT-1 by China, India, and Mexico; IT-2 by EU and Thailand; and IT-3 by the United States, Japan, and

each standard as the counterfactual analysis. The simulation results of population exposure under various hypothetical standards are summarized in Figure 6(a).

Figure 6(a) shows that exposed population increases dramatically as the applicable standard is getting more stringent. Let us take the exposure duration over half a year as an example. The simulation results demonstrate that 223 million people are exposed to  $PM_{2.5}$  above China's ambient  $PM_{2.5}$  standard (or IT-1) for longer than half a year. The exposed population increases to 776 or 1,195 million if the IT-2 or IT-3 standard is used. If we adopt WHO's guideline of 25  $\mu$ g/m³, 1,322 million people, or 98.6% of the Chinese population in 2010, live in an environment exceeding WHO's  $PM_{2.5}$  daily standard for over half a year.

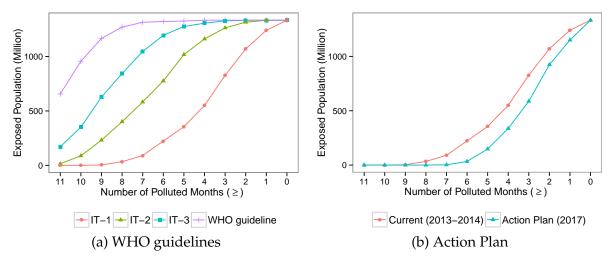


Figure 6: Panel (a): exposure duration and exposed population under various ambient air quality standards. Panel (b): simulation results for the target of China's Action Plan on Prevention and Control of Air Pollution. The x-axis is exposure duration measuring the cumulative time exceeding  $PM_{2.5}$  standard. The y-axis is exposed population. Each standard is represented by one curve. Dot (x,y) on curve S means that y million people are exposed to  $PM_{2.5}$  above the standard S for over x months.

In addition, we simulate the effects of China's most recent air pollution control policy, the Action Plan on Prevention and Control of Air Pollution (hereinafter referred to as Action Plan). The Action Plan is arguably the toughest regulation on air pollution in Chinese history; its main target is to tackle the challenge of  $PM_{2.5}$  pollution.<sup>15</sup> The implementation of the Action Plan sets differentiated targets for three groups of provinces. The three major metropolitan areas–Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta–are required reducing annual average

Singapore.

<sup>&</sup>lt;sup>15</sup>Source: http://www.mep.gov.cn/gkml/hbb/bwj/201407/t20140725\_280516.htm (in Chinese).

 $PM_{2.5}$  concentrations by 25%, 20%, and 15% by 2017 respectively. For example, the target for Beijing is to limit its annual average concentration of  $PM_{2.5}$  to 60  $\mu$ g/m<sup>3</sup> as of 2017 (85  $\mu$ g/m<sup>3</sup> in our study period). The second group is required to reduce annual average  $PM_{10}$  concentrations. The third group has no quantified target but is asked to make continuous improvement. More details about the Action Plan is summarized in Table S5 in the appendix.

The simulation result for the Action Plan is summarized in Figure 6(b). It demonstrates that population exposure to PM<sub>2.5</sub> will be reduced significantly by 2017 if China can successfully achieve its targets in the Action Plan. For instance, 33 million people will be exposed to PM<sub>2.5</sub> exceeding China's current standard for over half a year in 2017, which is a significant improvement compared with 223 million during 2013-2014. The population-weighted average exposure duration reduces from 113 days to 86 days according to China's standard. However, even if the Action Plan can succeed, the PM<sub>2.5</sub> pollution level by 2017 will be still at a dangerous level to public health.

Te simulation of the impact of the Action Plan on air pollution control hinges on the assumption of population density. Specifically, we assume that the population density in 2017 is the same as that in 2010. However, migration and urbanization can shift population densities across space over the period 2010-2017 and hence bias the estimated potential population exposure to PM<sub>2.5</sub>. In order to assess the sensitivity of our results to the assumption on population density, we conduct a robustness check by using 2010 total population and 2000 population density. The result is summarized in Table S4. The counterfactual analysis shows that the shift of population density during 2000-2010 does not significantly affect our estimated population exposure. It implies that our results are robust to the assumption of population density.

#### 5 Discussion

Air pollution data have been widely used to investigate the impact of the environment on public health, property values, labor productivity, and economic growth. However, the application of these studies in China has been hampered by limitations in the availability of pollution data. Although fine particle pollution is of the most relevance to public health,  $PM_{2.5}$  was not officially reported in China until 2013. Air pollution data are published on web pages only, so researchers

have to rely on web scraping techniques. Even worse, the Chinese government pulls back historical pollution data after a short period of disclosure, further reducing the data availability to the public. This study contributes to China's air pollution studies by systematically documenting and sharing the key data and results on-line in the form of tables and maps, providing better information for citizenry, researchers, firms, and decision makers.<sup>16</sup>

The spatial resolution of  $PM_{2.5}$  concentrations is critical for epidemiological, environmental, urban planning, and economic studies. However, ground-based monitors only measure air quality at fixed locations. High monitoring cost prevents cities from establishing dense monitoring sites. For instance, Beijing has only 35 stations although it is one of the world's most populated capital cities. Therefore, the air quality for the area without monitoring stations has to be interpolated by the readings from nearby stations, which introduces measurement errors for the receptors. By applying geostatistical techniques to ground-based observations and satellite-based AOD images, we can improve the estimation of  $PM_{2.5}$  concentrations at a fine spatial resolution. In addition, by linking detailed  $PM_{2.5}$  pollution levels with fine-scale population densities, we can also improve the estimation of population exposure to ambient  $PM_{2.5}$  pollution.

It is worth noting that BCK is only one of the geostatistical techniques that can take advantage of both ground- and satellite-based observations. Other studies have recently used land-use regression (LUR) models to predict local PM<sub>2.5</sub> concentrations with spatially predicting variables (Hoek et al., 2008; Liu et al., 2009). However, most LUR models focus on annual average PM<sub>2.5</sub> concentrations; it is still a challenge to estimate fine-scale spatial distribution of PM<sub>2.5</sub> concentrations in high frequency (e.g. daily). Satellite-retrieved AOD provides a new way that can be calibrated to reflect daily PM<sub>2.5</sub> concentrations; however, they also have missing values due to cloud cover or snow cover (Levy et al., 2010). BCK does not need AOD to cover space exhaustively and it can make full use of PM<sub>2.5</sub> spatial autocorrelation and cross correlation with MODIS AOD to optimally estimate values at each subdistrict.

However, our study has several caveats. The first concern is about the data quality of the ground-based observations. Ghanem and Zhang (2014) found suggestive evidence that about 50% of the cities that were required to disclose daily air pollution levels during 2001-2010 are suspected

<sup>&</sup>lt;sup>16</sup>The maps and data in this paper are publicly available at the Beijing City Lab (BCL): http://www.beijingcitylab.com.

to manipulate the  $PM_{10}$  data around the cutoff for "blue-sky days." Since 2010, the credibility of air pollution data has improved significantly thanks to the direct on-line reporting system that largely prevents data falsification. However, anecdotal information still shows that local government can "fine tune" local pollution data by influencing air quality around the monitoring stations. Therefore, if official  $PM_{2.5}$  measurements do not reflect true air quality, the accuracy of our results, which relies on the ground-based pollution levels, will be impaired and the estimated pollution exposure is biased downward.

Second, the population exposure to  $PM_{2.5}$  pollution in this paper is estimated by simply overlaying pollution to population at subdistrict level without addressing the duration of actual exposure to pollution. Due to the data limitation, we do not take into account avoidance behavior such as reducing outdoor activities, wearing face masks, and installing air purifiers. The behavioral adaptation will reduce actual pollution exposure and hence mitigate the negative health impact of  $PM_{2.5}$  pollution. In addition, we are only concerned with the ambient pollution levels without discussing indoor air quality. A more realistic estimate has to account for the duration of indoor and outdoor activities. Therefore, our estimates measure potential pollution exposure, which is the upper bound of actual exposure.

Third, our estimates of pollution exposure are associated with large uncertainty in the locations where ground-level measurements are sparse. Over four hundred Chinese cities have no monitoring stations. Their  $PM_{2.5}$  concentrations are heavily determined by the MODIS AOD images. The best approach to improve the estimates in these cities is to increase the number of monitoring stations, which requires significant investment from the central and local governments.

#### 6 Conclusion

This paper assesses China's potential population exposure to  $PM_{2.5}$ . We estimate daily  $PM_{2.5}$  concentrations by combining ground-based measurements and MODIS AOD images at the subdistrict level. We map  $PM_{2.5}$  concentration for each subdistrict to gain knowledge of the overall pattern and spatiotemporal variations. We also simulate the potential population exposure under various hypothetical scenarios, in particular the effects of China's most recent effort on air pollution control. Our results show that the vast majority of the Chinese population is exposed to serious  $PM_{2.5}$ 

pollution. Even if the ambitious Action Plan can achieve its target in reducing particulate matters, the population exposure to  $PM_{2.5}$  will still stay at a high level, which calls for further actions to mitigate the pollution of fine particles.

The output of this paper–maps, data, and results–can be used in other studies. One direction is to link the fine-scale PM<sub>2.5</sub> concentration estimates with the time-stamped and geocoded health data like hospital admission and discharge data. The merged data set can allow us to evaluate the health consequence of PM<sub>2.5</sub> pollution by utilizing very fine spatiotemporal variation. Existing studies tend to focus on a city with available air pollution records like Shanghai or Beijing. Since our estimates of pollution levels cover the whole country, it enables us to study the PM<sub>2.5</sub>-health relationship at a national level, which provides more complete information for policy makers to design environmental and health policies. Another direction is to analyze the driving factors of PM<sub>2.5</sub> pollution, for example the factors related to urban form. Our estimates of PM<sub>2.5</sub> concentrations with high resolution are essential to understand intra-urban heterogeneities, which can inform planners to design better urban form to improve environmental quality.

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### **Supplementary Appendix**

Table S1: Top 20 best and worst Chinese cities in  $PM_{2.5}$  exposure duration

T	op 20 worst citi	es		Top 20 best citie	es
	Population	Exposure duration		Population	Exposure duration
City	(million)	(day)	City	(million)	(day)
Xingtai	0.7	279	Fuqing	1.2	15
Shahe	0.5	260	Fuzhou	2.9	15
Nangong	0.5	255	Ruili	0.2	14
Handan	1.4	253	Yongan	0.3	14
Linqing	0.7	253	Putian	1.9	12
Shijiazhuang	2.6	252	Kunming	3.5	11
Jizhou	0.4	252	Shishi	0.6	11
Gaocheng	0.8	250	Longhai	1	11
Jinzhou	0.5	248	Chuxiong	0.6	11
Anyang	0.6	246	Longyan	0.7	11
Xinji	0.6	245	Jinjiang	1.9	10
Wuan	0.8	244	Zhangping	0.2	10
Hengshui	0.5	241	Zhangzhou	0.5	10
Dezhou	0.6	240	Quanzhou	1.5	9
Xinle	0.5	239	Xiamen	3.5	8
Luquan	0.4	238	Nanan	1.4	8
Shenzhou	0.6	238	Yuxi	0.5	7
Liaocheng	1.1	238	Anning	0.3	6
Anguo	0.4	238	Lhasa	0.3	2
Yucheng	0.5	238	Shigatse	0.1	2

*Notes*: The population is for the whole county if a city is a county-level city. For other cities with higher administrative rank, the population is for the city proper.

Table S2: Ranking of Chinese cities in potential population exposure to  $PM_{2.5}$  pollution

City	Population (million)	Exposure duration (day)	Total exposure (million people*day)	Annual average concentration $(\mu g/m^3)$	Area (km²)
Beijing	18.9	161	3,048	84	12,163
Tianjin	10.4	204	2,130	94	7,158
Shanghai	22.4	88	1,964	60	5,476
Wuhan	9.7	158	1,535	85	8,583
Chengdu	7.4	150	1,114	81	2,171
Chongqing	11.4	97	1,104	61	15,385
Xi'an	6.5	162	1,056	91	3,569
Nanjing	7.2	138	991	76	4,736
Jinan	4.1	213	873	98	3,070
Zhengzhou	4.1	201	832	96	1,015
Guangzhou	11.1	65	723	50	3,412
Shenyang	6.3	108	676	64	3,471
Harbin	5.8	115	668	69	7,016
Tangshan	3.2	205	653	96	3,253
Shijiazhuang	2.6	252	645	136	379
Hangzhou	6.3	98	619	66	3,344
Zibo	3.1	188	589	91	2,984
Suzhou	5.3	109	581	68	4,606
Foshan	7.4	75	551	52	3 <i>,</i> 798
Xuzhou	3.1	148	451	80	3,038

*Notes*: The area is for the administrative boundary of each city, rather than the urban built-up area.

Table S3: Pearson correlation matrix for population density and exposure duration

Variable	Population	Population	Population	Exposure
	density	density	density	duration
		(0-14)	(≥65)	
Population density	1	0.942	0.949	0.116
Population density (0-14)		1	0.829	0.120
Population density (≥65)			1	0.109
Exposure duration				1

 $\it Notes:$  all correlation coefficients are significant at the 1% level.  $\it N=39,007.$ 

Table S4: Exposure estimation using 2010 and 2000 population density

	Cumulative Population Exposed (million)		
Exposure Duration	2010 Population	2000 Population	
(month)	Density	Density	
$\geq 0$	1,334	1,334	
$\geq 1$	1,241	1,244	
$\geq 2$	1,070	1,084	
$\geq 3$	827	848	
$\geq 4$	550	560	
$\geq 5$	355	357	
$\geq 6$	223	226	
$\geq 7$	90	90	
$\geq 8$	34	33	
$\geq 9$	3	3	
$\geq 10$	0	0	
$\geq 11$	0	0	

*Notes*: Exposure duration measures the cumulative time exceeding China's current  $PM_{2.5}$  standard. The second column used the census data in 2010. The third column is a counterfactual analysis that uses total population in 2010 and population density in 2000.

Table S5: Provincial targets under the Air Pollution Prevention and Control Action Plan

Regions	Target
Group A: annual average PM <sub>2.5</sub> concentrations	
Beijing, Tianjin, Hebei	-25%
Shanxi, Shanghai, Jiangsu, Shandong, Zhejiang	-20%
Guangdong (Pearl River Delta, PRD), Chongqing	-15%
Inner Mongolia	-10%
Group B: annual average PM <sub>10</sub> concentrations	
Henan, Shaanxi, Qinghai, Xinjiang	-15%
Hubei, Gansu	-12%
Liaoning, Jilin, Anhui, Hunan, Guangdong (non-PRD), Sichuan, Ningxia	-10%
Heilongjiang, Fujian, Jiangxi, Guangxi, Guizhou	-5%
Group C: requirement of continuous improvement	

Hainan, Yunnan, Tibet

Notes: The data are assembled from the implementation details of the Action Plan: the Responsibility Agreement on Air Pollution Control Targets signed between the Ministry of Environmental Protection and provinces. In the simulation, for the provinces with  $PM_{10}$  targets only, we assume that  $PM_{2.5}$  is reduced proportionally with  $PM_{10}$ . In addition, daily concentration reduction is proportional to annual reduction. For the provinces without quantified target, we assume its  $PM_{2.5}$  concentration stays at the same level.

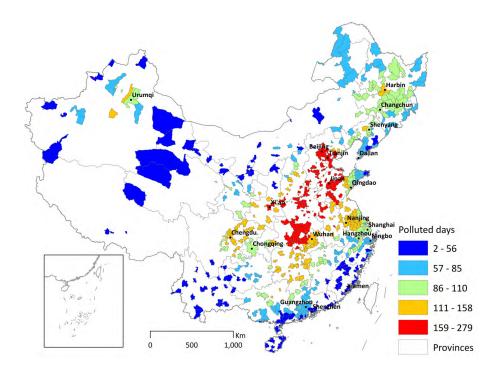


Figure S1: Exposure duration (polluted days) at the city level. Exposure duration is the total number of days in a year exceeding China's current  $PM_{2.5}$  standard.

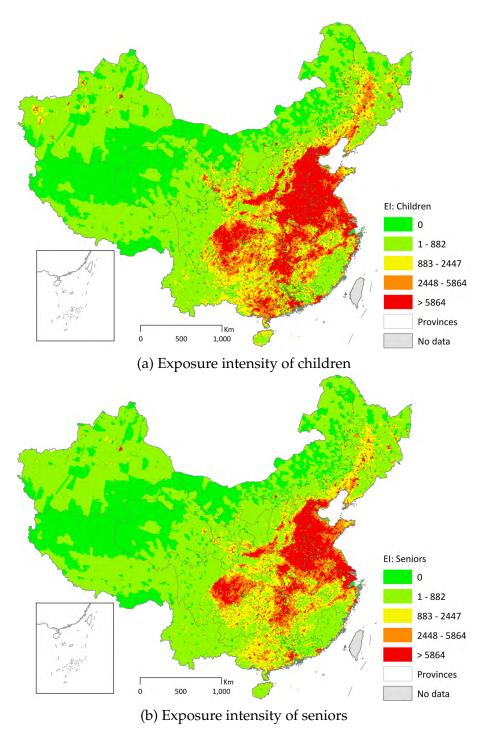


Figure S2: Exposure intensity of two susceptible age groups: children ( $\leq$  14) and seniors ( $\geq$  65). Exposure intensity is the product of exposure duration and exposed population density. Exposure duration is the total number of days in a year exceeding China's current PM<sub>2.5</sub> standard. The spatial resolution is subdistrict.