GeoHealth

RESEARCH ARTICLE
10.1029/2021GH000531

Special Section:
Atmospheric PM2.5 in China: indoor, outdoor, and health effects

Key Points:

- $PM_{2.5}$ showed a significant decrease but still severe impacts on human health
- Ozone (O_3) is posing an increasingly serious threat to human health and economic loss in China
- Coordinated control of $PM_{2.5}$ and O_3 is essential

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:
C. Cheng and H. Zhao,
chengcx@bnu.edu.cn;
zhaohui_nuist@163.com

Citation:
Zhang, X., Cheng, C., & Zhao, H. (2022). A health impact and economic loss assessment of O_3 and $PM_{2.5}$ exposure in China from 2015 to 2020. *GeoHealth*, *6*, e2021GH000531. https://doi.org/10.1029/2021GH000531

Received 7 OCT 2021
Accepted 27 FEB 2022

Author Contributions:
Conceptualization: Xiangxue Zhang
Data curation: Xiangxue Zhang
Funding acquisition: Changxiu Cheng
Methodology: Xiangxue Zhang
Software: Xiangxue Zhang
Supervision: Changxiu Cheng, Hui Zhao
Visualization: Hui Zhao
Writing – original draft: Xiangxue Zhang

A Health Impact and Economic Loss Assessment of O_3 and $PM_{2.5}$ Exposure in China From 2015 to 2020

Xiangxue Zhang[1,2], Changxiu Cheng[1,2,3], and Hui Zhao[4]

[1]State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, China, [2]Key Laboratory of Environmental Change and Natural Disaster, Ministry of Education, Beijing Normal University, Beijing, China, [3]National Tibetan Plateau Data Center, Beijing, China, [4]Department of Environmental Science and Engineering, Fudan University, Shanghai, China

Abstract China is in a critical air quality management stage. Rapid industrial development and urbanization has resulted in non-ignorable air pollution, which seriously endangers human health. Assessment of the health impacts and economic losses of air pollution is essential for the prevention and control policy formulation. Based on ozone (O_3) and fine particulate matter concentration ($PM_{2.5}$) monitoring data in 331 Chinese cities from 2015 to 2020, this study evaluated the health effects and the corresponding economic losses of O_3 and $PM_{2.5}$ pollution on three health endpoints. The ratio of population exposed to O_3 levels that exceeded the Chinese Ambient Air Quality Standards (CAAQS) increased from 13.35% in 2015 to 14.15% in 2020, which resulted in 133,415 (2015) - 156,173 (2020) all-cause deaths, 88,941 (2015) - 104,051 (2020) cardiovascular deaths, and 28,614 (2015) - 33,456 (2020) respiratory deaths. The ratio of population exposed to $PM_{2.5}$ levels that exceeded the CAAQS decreased, but in many regions, especially in North China and the Yangtze River Delta, the $PM_{2.5}$ concentration remained high. By 2020, nearly half of the population in China was still exposed to $PM_{2.5}$ levels that exceeded the CAAQS, and the corresponding economic losses reached CNY 3.46 and 3.05 billion, respectively. These results improved the understanding of the spatial-temporal variation trends of major air pollutants at city scale in China, and emphasize the continued coordination urgently needed for controlling O_3 and $PM_{2.5}$ following the implementation of the 2013 policy to mitigate air pollution to protect human health.

Plain Language Summary Based on ozone (O_3) and fine particulate matter concentration monitoring data in 331 Chinese cities from 2015 to 2020, this study adopted the health impact assessment model to evaluate the health effects of O_3 and $PM_{2.5}$ pollution on three health endpoints: premature, cardiovascular and respiratory mortality.

1. Introduction

In recent years, air pollution problems have become increasingly severe worldwide, have a negative influence on human health, the climate, and economic development (Fang et al., 2013; Lelieveld et al., 2015; Shang et al., 2013). Among atmospheric pollutants, the most commonly reported include particulate matter with an aerodynamic diameter smaller than 2.5 microns ($PM_{2.5}$) and 10 microns (PM_{10}), nitric dioxide, sulfur dioxide, and ozone (O_3; Shen et al., 2020). Notably, both long- and short-term atmospheric pollutants are related to acute and chronic impacts on human health (Jerrett et al., 2009; Philip et al., 2014; Shang et al., 2013).

In recent decades, rapid urbanization has been closely related to air pollution and human health worldwide (Ferreri et al., 2018; Guan et al., 2019; Lim et al., 2012; Wang et al., 2018). In China, rapid development of cities has created various environmental pollution problems (Huang et al., 2014; Zhang et al., 2020), which pose a notable threat to human health and cause substantial economic losses. The Chinese government has implemented a range of measures to improve air quality, such as the 2012 National Ambient Air Quality Standard and the 2013 Air Pollution Prevention and Control Action Plan (APPCAP). These efforts have realized great achievements, particularly in the remarkable reduction in $PM_{2.5}$ pollution in many cities in China, as reported in several previous studies (Gui et al., 2019; Zhao et al., 2021). However, O_3 concentration exhibits an overall increasing trend, contrary to $PM_{2.5}$ concentration. Zhao et al. (2021) demonstrated that the maximum daily 8-hr average O_3 concentration (MDA8 O_3) increased 3.4 μg m^{-3} per year from 2015 to 2018 in China. Maji and Sarkar (2020) reported that, in the summertime, the mean MDA8 O_3 value increased from 91.6 to 103.1 μg/m^3 from 2015 to

Writing – review & editing: Changxiu Cheng, Hui Zhao

2018 in China. Notably, studies have revealed that $PM_{2.5}$ reduction promotes O_3 enhancement (Li et al., 2019; Sicard et al., 2020).

O_3 poses increasingly adverse effects on human health and can cause systemic oxidative stress and harm to the cardiovascular and respiratory systems (Gabehart et al., 2015; McDonnell et al., 1997; Salonen et al., 2018). Zhang et al. (2019) indicated that O_3 pollution can also cause a variety of diseases and social phenomena, including asthma emergencies, hospitalization, and absenteeism from school. Previous studies have provided valuable insights into O_3 risk assessment for protecting human health. On both regional and global scales, atmospheric chemistry models and remote sensing data have been adopted to estimate the potential health risks of O_3 exposure. Based on an atmospheric chemistry-general circulation model and satellite data, the global premature and cardiovascular mortality and lung cancer attributable to O_3 and $PM_{2.5}$ pollution in 2005 were estimated to reach approximately 773 thousand/year, 186 thousand/year, and 2000 thousand/year, respectively (Lelieveld et al., 2013). Anenberg et al. (2010) used a global atmospheric chemical transport model to calculate the global mortality associated with O_3 in 2000, and found that the annual respiratory mortality attributable to O_3 was estimated to be 0.7 ± 0.3 million. In addition to negative effects on human health, O_3-related economic losses are greatly increasing. Several previous studies have estimated these losses. Feng et al. (2019) found that the costs of morbidity regarding respiratory diseases and nonaccidental mortality reached US$ 690.9 billion and US$ 7.5 billion, respectively. Previously, Maji et al. (2019) calculated that the national economic loss in 2016 due to exposure to O_3 was approximately US$ 7.6 billion.

Moreover, although the concentration of $PM_{2.5}$ has declined in recent years, its impact on people's health and economic losses remains notable. Therefore, $PM_{2.5}$ pollution and related issues still receive global attention. The mortality, cardiovascular and respiratory mortality related to $PM_{2.5}$ in 2013 were estimated to be 763,595, 149,754, and 446,035, respectively, according to measured data (Song et al., 2016). Based on satellite data, Liu et al. (2017) examined the national deaths from stroke, lung cancer, and ischemic heart disease caused by $PM_{2.5}$ pollution, and the number increased from approximately 800 thousand in 2004 to over 1,200 thousand in 2012. With a global atmospheric chemical transport model, Anenberg et al. (2010) found that the annual global mortality due to $PM_{2.5}$ in 2000 was estimated to reach 3.5 ± 0.9 million cardiopulmonary deaths and 220 ± 80 thousand lung cancer deaths. Song et al. (2017) suggested that in 2015, $PM_{2.5}$ accounted for more than 40.3% of the total stroke deaths and 33.1%, 26.8%, and 15.5% of all acute respiratory system, ischemic heart disease, and all-cause deaths, respectively. With the use of monitoring data, the mortality related to $PM_{2.5}$ in China in 2016 was calculated to reach 964 thousand deaths, which accounted for 9.98% of the total deaths. Specifically, the morbidity of respiratory and cardiovascular diseases was 605 thousand and 364 thousand, respectively (Maji et al., 2018). More importantly, the $PM_{2.5}$-related economic losses remain very high, as X. Lu et al. (2017) revealed that the highest economic loss caused by $PM_{2.5}$ pollution in southern China occurred in 2012, at US$ 4.6 billion, which is approximately 6.1% of the local total gross domestic product. Xie et al. (2017) predicted that China will suffer economic losses of US$ 4.2 billion and equivalent life losses of US$ 285 billion due to $PM_{2.5}$ pollution in 2030 without a control policy.

Since 2013, the air conditions in China have shown a combined pollution characterized by high concentrations of $PM_{2.5}$ and O_3, it is a top issue to understand their adverse effects on human health in the atmospheric environment field. Due to a lack of data, many previous studies were mostly conducted based on atmospheric chemistry models or satellite products (Anenberg et al., 2010; Lelieveld et al., 2013; Lin et al., 2018; Xie et al., 2016; Zhao et al., 2017). In recent years, with the establishment of air quality monitoring sites, it becomes possible to quantify the health risks of $PM_{2.5}$ and O_3 based on monitoring data. However, it must be point out that, although some studies have used monitoring data to investigate the link between $PM_{2.5}$ and O_3 and their associated diseases, most of these studies have focused on either a region (e.g., Beijing-Tianjin-Hebei, Yangtze River Delta (YRD)) or a single pollutant (e.g., $PM_{2.5}$ or O_3; Maji & Namdeo, 2021; Maji et al., 2018; Song et al., 2016). Moreover, a recent study revealed that the decline in $PM_{2.5}$ in recent years has enhanced surface photochemical reactions, thereby exacerbated O_3 pollution (Li et al., 2019). Notably, it remains unclear whether the reduction in health risk due to decreased $PM_{2.5}$ is offset by the increase in health risk due to increased O_3 concentrations. Therefore, it is valuable to analyze the human health effects of $PM_{2.5}$ and O_3 simultaneously.

The objectives of this study are to (a) identify the long-term spatiotemporal variation trends and heterogeneity in O_3 and $PM_{2.5}$ pollution of 331 cities in China from 2015 to 2020 based on monitoring data, (b) quantify the

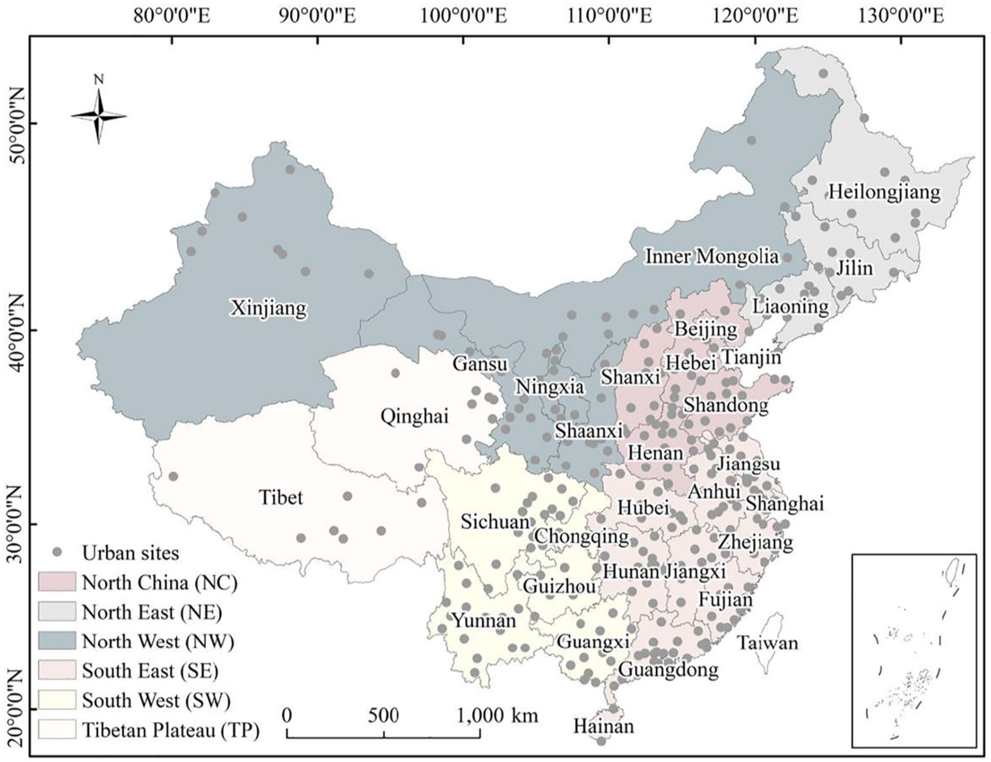

Figure 1. Geographic distribution of the 331 cities in China.

impacts of O_3 and $PM_{2.5}$ pollution on human health, and (c) estimate the economic losses related to O_3 and $PM_{2.5}$ pollution in China.

2. Data and Methods

2.1. Data

There are notable climatic variations in the eastern, western, southern, and northern areas of China due to geographical effects. Given these differences, six representative regions were divided, as follows: (a) North China (Beijing, Tianjin, Hebei, Shanxi, Henan, and Shandong); (b) Northeast China (Heilongjiang, Jilin, and Liaoning); Northwest China (Inner Mongolia, Ningxia, Gansu, Shaanxi, and Xinjiang); Southeast China (Jiangsu, Anhui, Shanghai, Hubei, Hunan, Jiangxi, Guangdong, Fujian, Zhejiang, and Hainan); Southwest China (Guangxi, Chongqing, Sichuan, Yunnan and Guizhou); and the Tibetan Plateau (Qinghai and Tibet; Figure 1).

Monitoring data on the MDA8 O_3 and $PM_{2.5}$ from 1 January 2015, to 31 December 2020, that pertain to 367 cities were collected from the China National Environmental Monitoring Centre, 2020 (https://quotsoft.net/air/; Figure 1). Due to the acute lack of data in certain cities, 331 cities eventually participated in the following calculations. Moreover, considering the missing values and outliers in the data, a rigorous quality control of the data was performed using the method proposed by Barrero et al. (2015) to ensure the reliability of the study results. The annual mean values per city were calculated by averaging the daily data retrieved from all stations in this city.

Population data (>30 years for O_3, all age groups for $PM_{2.5}$) from the 6th Population Census in 2010 in each city were obtained from China's economic and social big data research platform, 2020 https://data.cnki.net/yearbook/Single/N2021050059. In recent decades, the population of China has grown slowly. Therefore, in this study, no further adjustments were applied to the obtained population data.

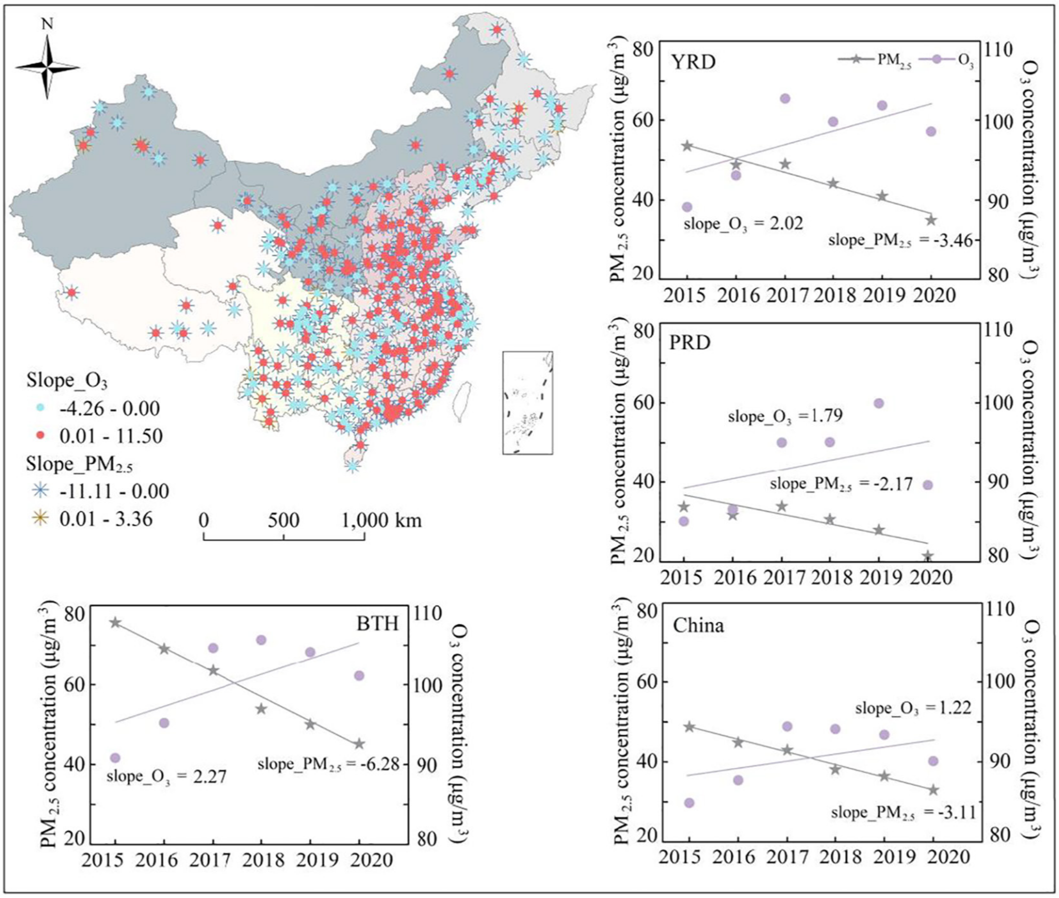

Figure 2. Spatiotemporal variation trends of the annual mean MDA8 O_3 and $PM_{2.5}$ concentrations from 2015 to 2020 in China. BTH represents Beijing-Tianjin-Hebei region, YRD represents Yangtze River Delta, PRD represents Pearl River Delta.

2.2. The Univariate Linear Regression Model

The slope calculated by the univariate linear regression model in this study was used to explore and test the long-term interannual variation rate of $PM_{2.5}$ and O_3 pollution. That indicates, how many units of $PM_{2.5}$ and O_3 are increasing or decreasing per year overall. The spatial patterns of the temporal variation trends (slope values) of the O_3 and $PM_{2.5}$ concentration were calculated for each city in China from 2015 to 2020 (Figure 2). The slope in the unitary linear regression model represents the annual rate of change, which has been analyzed by several previous studies (Hammer et al., 2020; Lu et al., 2020; Zhang et al., 2020). When the absolute value of the slope is larger, the increasing (positive slope values)/decreasing temporal trend (negative slope values) is stronger, which is a common method and the corresponding equation can be found in D. Lu et al. (2017).

2.3. Health Impacts

Log-linear (LL) exposure-response functions were used in this study, which were drawn from Hubbell et al. (2009). If the level of air pollutants exceeds the safe threshold, then the exposure-response coefficient can be used to calculate the change in health risk for one person with every 1 μg m^{-3} increase in concentration (Liao et al., 2017). Furthermore, if the population of each city is known, then we can estimate the health effects.

In this study, the LL method was adopted to evaluate the health impacts of O_3 and $PM_{2.5}$ pollution regarding three health endpoints, as:

$$\mathrm{RR} = \exp\left[\beta \times (C - C_0)\right] \tag{1}$$

$$\mathrm{E} = f_p \times P \times \left[(RR - 1)/RR\right] \tag{2}$$

Table 1
The Long-Term Exposure-Response Coefficient (β), RR, and Baseline Mortality for $PM_{2.5}$ and Ozone (10 μg/m³)

Parameter	All-cause	Cardiovascular	Respiratory
β ($PM_{2.5}$)	0.00336 (0.00076, 0.00504)	0.00068 (0.00043, 0.00093)	0.00109 (0, 0.00221)
(Sources)	1, 2, 3, 4, 5	1, 4, 5	1, 4, 5
RR ($PM_{2.5}$)	1.0342 (1.0076, 1.0517)	1.0068 (1.0043, 1.0093)	1.0110 (1.0000, 1.0223)
(Sources)	1, 2, 3, 4, 5	1, 5, 6	1, 5, 6
C_0	10 μg/m³	10 μg/m³	10 μg/m³
f_p ($PM_{2.5}$)	0.00614	0.00546	0.01022
β (O_3) (Sources)	0.00198 (0.001, 0.00392)	0.00296 (0.001, 0.00583)	0.00392 (0, 0.00862)
	Turner et al., 2016	Lim et al., 2019	Lim et al., 2019
RR (O_3)	1.0200 (1.0100, 1.0400)	1.0300 (1.0100–1.0600)	1.0400 (1.0000–1.0900)
	Turner et al., 2016	Lim et al., 2019	Lim et al., 2019
C_0	26.7 ppb	26.7 ppb	26.7 ppb
f_p (O_3)	0.00654	0.00296	0.00072

Note. 1. Aunan & Pan, 2004; 2. Burnett et al., 2014; 3. Kan & Chen, 2002; 4. Xie et al., 2010; 5. Xie et al., 2009.

where β is the exposure-response coefficient indicating that, based on an increase of 1 μg m^{-3} per pollutant, the percentage increase in the health impact (Liao et al., 2017) is derived from the relative risks. In this study, exposure-response coefficient (β) related O_3 pollution was estimated from the long-term epidemiological study by Turner et al. (2016) and cardiovascular and respiratory mortality from Lim et al. (2019), also a long-term study (Table 1). Meanwhile, β related long-term $PM_{2.5}$ pollution was estimated from the previous studies (Aunan and Pan., 2004; Burnett et al., 2014; Kan and Chen., 2002; Xie et al., 2009, 2010) (Table 1). C is the annual average pollutant concentration, and C_0 represents the minimum risk exposure level, which is set to 26.7 ppb for O_3 (Turner et al., 2016) and 10 μg/m³ for $PM_{2.5}$ (WHO, 2006). The number of cases (E) that consider three endpoints related to O_3 and $PM_{2.5}$ is evaluated by using Equation 2. P is the exposed population, and f_p is the baseline mortality rate, which was obtained from the China Health Statistical Yearbook (https://data.cnki.net/yearbook).

2.4. Economic Impacts

The cost of illness (COI) model is applied to monetize the economic cost of each health endpoint, thereby estimating the socioeconomic loss caused by air pollution (Maji et al., 2018; Zhang et al., 2017).

The economic losses caused by O_3 and $PM_{2.5}$ pollution in this study are calculated with the COI method, which mainly refers to the additional health expenditures of residents attributed to air pollution, such as hospitalization and outpatient expenses. Based on the per capita medical expenses (MEs) in the China Health Statistics Yearbook (2015–2020), the economic loss in each city from 2015 to 2020 is estimated, as follows:

$$\mathrm{HE} = \sum E_i \times RP_i \tag{3}$$

where i denotes the health endpoint, and RP_i denotes the per capita MEs for the category i health endpoint, which was collected from the China Health Statistics Yearbook 2015–2020. The RP values for cardiovascular disease in 2015, 2016, 2017, 2018, 2019, and 2020 were CNY 23,997.56, 23,784.00, 24,949.80, 23,607.90, 27,579.12, and 27,579.12, respectively, and the RP values for respiratory disease were CNY 7,604.90, 7,663.60, 7,905.30, 7,975.60, 8,150.00, and 8,150.00, respectively.

3. Results

3.1. Annual Variations in the O_3 and $PM_{2.5}$

The slope values of the annual $PM_{2.5}$ concentration for 2015–2020 shows higher values in the more industrial and populated areas, such as NC and the YRD (Figure 2). $PM_{2.5}$ experienced a continuous and significant decrease across China, and decreased from 48.7 μg/m^3 in 2015 to 33.0 μg/m^3 in 2020 at a rate of 3.11 μg/m^3 from 2015 to 2020. The BTH, YRD and PRD regions showed a decreased trend in the annual $PM_{2.5}$ concentrations, which decreased at rates of 6.28, 3.46, and 2.17, respectively (Figure 2).

The spatial distribution of O_3 concentration in China is similar to that of $PM_{2.5}$. However, different from $PM_{2.5}$, O_3 concentration shows a sustained increase at an average annual rate of 1.22 μg/m^3 from 84.9 μg/m^3 in 2015 to 90.1 μg/m^3 in 2020, which indicates that humans suffer from more severe health risks associated with O_3 exposure. The increase was greater in BTH, YRD, and PRD regions (2.27 μg/m^3, 2.02 μg/m^3 and 1.79 μg/m^3, respectively), than the national average of 1.22 μg/m^3 (Figure 2).

3.2. Population Exposure to O_3 and $PM_{2.5}$

$PM_{2.5}$ is decreasing and O_3 is increasing, which means China is currently experiencing complex and severe $PM_{2.5}$ and O_3 pollution. In this study, according to the annual average O_3 and $PM_{2.5}$ concentration and the population data of 331 cities in China and the above six representative regions, the cumulative population exposure level to O_3 and $PM_{2.5}$ is calculated (Figures 3 and 4).

For O_3, it is reported that at Level II of the CAAQS, the limits of MDA8 O_3 and the daily maximum 1 hr O_3 concentration are 160 μg/m^3 (used in the study) and 200 μg/m^3, respectively. In general, NC was the most severe region, followed by SE (including the YRD region), while the number of people exposed to excessive O_3 concentration in the TP was low (Figure 3). The proportion of people exposed to O_3 above the CAAQS in summer is higher than that in spring and autumn. In the summers of 2015, 2016, 2017, 2018, 2019 and 2020, 175.51 million (13.35%), 193.13 million (14.69%), 273.20 million (20.78%), 291.34 million (22.16%), 286.35 million (21.78%), and 186.03 million (14.15%) people in China were exposed to O_3 pollution that exceeded the CAAQS. All of these results indicate that in recent years, especially in the summer, the risk of O_3 exposure is high; therefore, it is necessary to analyze its impact on health.

For $PM_{2.5}$, the cumulative population exposed to $PM_{2.5}$ above the CAAQS (15 and 35 μg/m^3) decreases along with the decrease in $PM_{2.5}$ from 2015 to 2020 (Figure 4). In 2015, 2016, 2017, 2018, 2019 and 2020, the number of people in China living with $PM_{2.5}$ levels higher than 35 μg/m^3 was 1,111.39 million, 1,034.52 million, 1,008.96 million, 880.27 million, 837.23 million, and 647.71 million, respectively, which accounted for approximately 84.53%, 78.69%, 76.74%, 66.95%, 63.68%, and 49.27%, respectively, of the total population. Notably, overall, NC was the most severely affected region, where approximately 90% of people lived in areas where concentrations of $PM_{2.5}$ greater than 35 μg/m^3. However, notably, in 2020, nearly 50% of the population still experienced air problems. Therefore, although $PM_{2.5}$ has exhibited a downward trend in recent years, there remains a need to further reduce $PM_{2.5}$ pollution.

3.3. Health Impacts of O_3 and $PM_{2.5}$

In this study, the spatiotemporal distributions of three health endpoints mortality in adults (>30 years) attributed to O_3 and $PM_{2.5}$ exposure in 331 cities across China from 2015 to 2020 are shown in Figures S1-S4 in Supporting Information S1. For O_3, in China, the all-cause mortality was 133,415 [95% confidence interval (CI): 67,927–259,873] in 2015 and 156,173 (95% CI: 79, 562–303,843) in 2020 at a threshold of 26.7 ppb (Table 2). In 2015, the estimated cardiovascular mortality was 88,941 (95% CI: 30,585–171,304), while respiratory mortality was 28,614 (95% CI: 0–60,511). These numbers increased to 104,051 (95% CI: 35,824–200,055) and 33,456 (95% CI: 0–70,548) in 2020. Cardiovascular and respiratory mortality accounted for 55.7% and 21.4% of all-cause mortality, respectively. From 2015 to 2020, all-cause, cardiovascular, and respiratory deaths attributable to O_3 exposure increased by 17.1%, 17.0%, and 16.9%, respectively (Figures S1 and S2 in Supporting Information S1). The cities with the highest six-year average all-cause mortality due to O_3 were Shanghai [4,101 (95% CI: 2,093–7,446)], Beijing [3,432 (95% CI: 1,750–6,668)], Linyi (Shandong) [1,887 (95% CI: 964–3,650)], Chengdu (Sichuan) [1,874 (95% CI: 954–3,648)], Chongqing [1,826 (95% CI: 926–3,587)] and Baoding (Hebei) [1,774 (95% CI:906–3,436)] (Figure S1 in Supporting Information S1). The provinces with high health impacts from 2015 to 2020 at the three health endpoints were Shandong, Jiangsu, Henan, Guangdong, and Hebei, and these results suggest that the relevant authorities should focus on O_3 pollution control in these regions (Table 2). Overall,

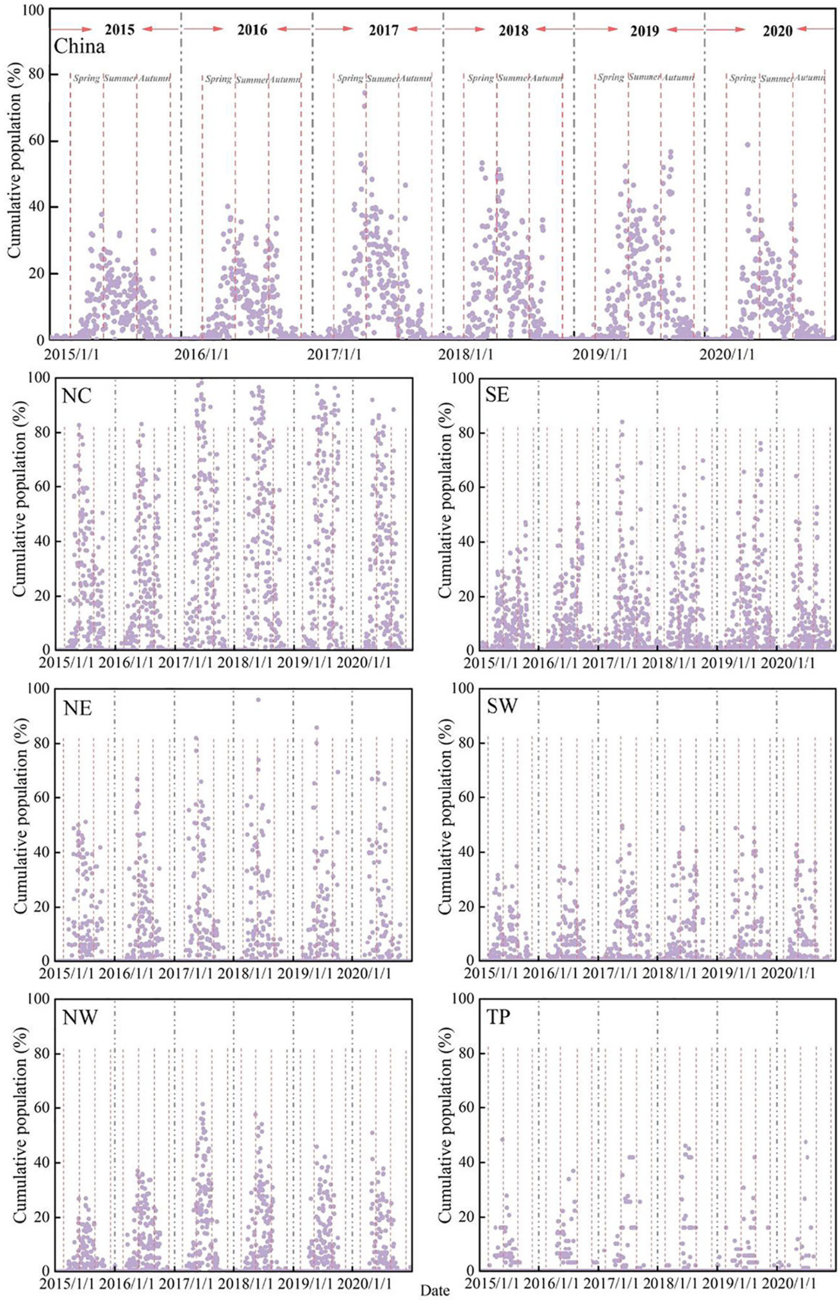

Figure 3. Population exposure to O_3 in China and six representative regions.

the health impacts-related O_3 exposure are strongly correlated with the level of O_3 pollution and the size of the exposed population, such that several provinces, such as Shandong, Henan, Hebei, and Jiangsu, which have high O_3 levels, experience high numbers of premature deaths due to their large population. Guangdong has relatively low levels of O_3 pollution; however, it has the highest population in China, which caused the health effects attributed to long-term O_3 exposure to be higher than in other provinces (Figure S2 in Supporting Information S1).

It is estimated that approximately 920 million people (70% of the total population) are living in areas with a six-year average $PM_{2.5}$ greater than 35 μg/m^3. The cause-specific premature deaths and differences between 2016 and 2020 and 2015 due to long-term $PM_{2.5}$ exposure in each city were therefore examined (Figures S3 and S4 in Supporting Information S1). Table 3 reports the details on three health endpoints in China and the five

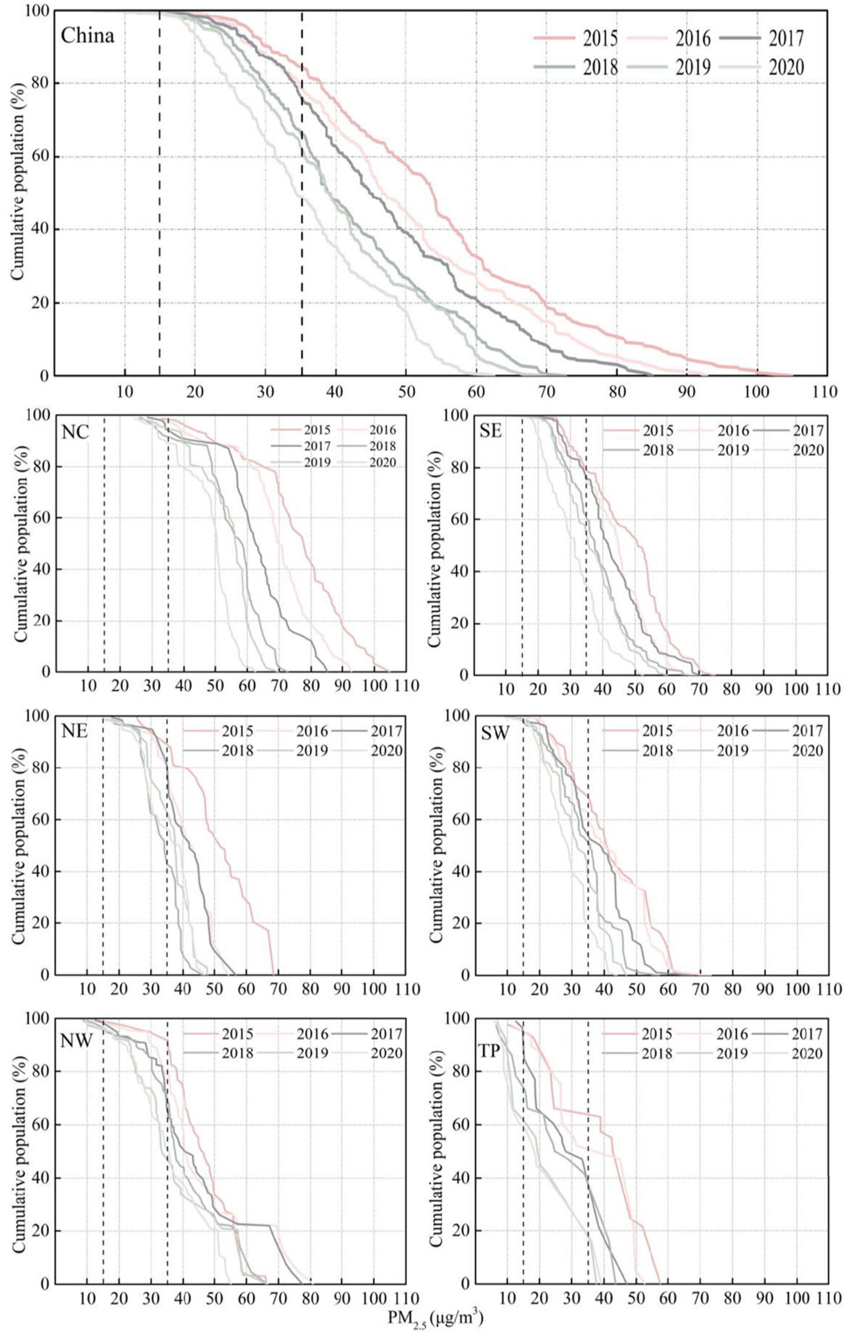

Figure 4. Population exposure to $PM_{2.5}$ in six representative regions and China.

provinces with high premature deaths from 2015 to 2020. In China, all-cause deaths decreased by 39.4%, from 1,105,089 (95% CI: 267,049–1,590,192) in 2015 to 669,555 (95% CI: 157,576–979,324) in 2020, and the highest value was found in 2015 (Figure S4 in Supporting Information S1). During the study period, cardiovascular and respiratory mortality decreased by 41.0%, from 212,917 (95% CI: 135,515–289,319) in 2015 to 125,529 (95% CI: 79,686–171,020) in 2020, and by 40.8%, from 632,101 (95% CI: 0–1,245,414) in 2015 to 374,265 (95% CI: 0–745,934) in 2020. From the provincial perspective, the number of all-cause premature deaths during the study period was higher in Henan (11.0%) [2015: 121,506; 2020: 76,673], Shandong (9.9%) [2015: 116,004; 2020: 69,265], and Hebei (8.4%) [2015: 94,543; 2020: 53,726] (Table 3). A larger decreasing trend in premature deaths was identified for the provinces of Zhejiang (55.9%), Hubei (46.4%), Guangdong (46.8%), Guizhou

Table 2
The Estimated Three Premature Deaths Related to Long-Term Exposure to O_3 in China and Provinces With High Premature Deaths From 2015 to 2020

Region	Year	All-cause	Cardiovascular	Respiratory
China	2015	133,415 (67,927–259,873)	88,941 (30,585–171,304)	28,614 (0–60,511)
	2016	145,188 (73,933–282,711)	96,773 (33,290–186,295)	31,116 (0–65,774)
	2017	175,735 (89,315–340,091)	116,570 (40,215–223,500)	37,445 (0–78,603)
	2018	172,845 (88,132–335,707)	115,060 (39,683–220,670)	36,964 (0–77,633)
	2019	171,249 (87,316–332,630)	114,002 (39,315–218,661)	36,625 (0–76,934)
	2020	156,173 (79,562–303,843)	104,051 (35,824–200,055)	33,456 (0–70,548)
Shandong	2015	14,887 (7,598–28,859)	9,901 (3,421–18,934)	3,178 (0–6,643)
	2016	15,308 (7,814–29,663)	10,178 (3,519–19,455)	3,266 (0–6,822)
	2017	17,964 (9,184–34,707)	11,927 (4,135–22,697)	3,821 (0–7,926)
	2018	17,072 (8,732–32,955)	11,329 (3,932–21,533)	3,629 (0–7,510)
	2019	18,533 (9,479–35,776)	12,299 (4,268–23,376)	3,939 (0–8,153)
	2020	17,460 (8,924–33,754)	11,596 (4,018–22,087)	3,717 (0–7,720)
Jiangsu	2015	11,358 (5,797–22,017)	7,553 (2,610–14,445)	2,424 (0–5,068)
	2016	11,053 (5,639–21,442)	7,353 (2,539–14,078)	2,361 (0–4,944)
	2017	12,324 (6,297–23,838)	8,187 (2,835–15,607)	2,625 (0–5,459)
	2018	11,146 (5,688–21,613)	7,414 (2,561–14,184)	2,380 (0–4,978)
	2019	12,085 (6,172–23,403)	8,033 (2,779–15,338)	2,577 (0–5,373)
	2020	11,347 (5,791–22,004)	7,548 (2,607–14,441)	2,423 (0–5,069)
Henan	2015	10,502 (5,348–20,451)	7,000 (2,408–13,477)	2,252 (0–4,758)
	2016	13,259 (6,763–25,737)	8,824 (3,045–16,907)	2,834 (0–5,942)
	2017	15,674 (8,009–30,319)	10,413 (3,606–19,849)	3,338 (0–6,943)
	2018	16,093 (8,226–31,109)	10,687 (3,704–20,354)	3,425 (0–7,113)
	2019	15,976 (8,165–30,889)	10,611 (3,676–20,214)	3,401 (0–7,066)
	2020	14,185 (7,240–27,498)	9,434 (3,260–18,041)	3,028 (0–6,330)
Guangdong	2015	9,561 (4,865–18,647)	6,378 (2,190–12,307)	2,053 (0–4,355)
	2016	8,957 (4,553–17,498)	5,980 (2,050–11,568)	1,927 (0–4,103)
	2017	11,709 (5,963–22,792)	7,803 (2,685–15,015)	2,510 (0–5,298)
	2018	11,888 (6,056–23,132)	7,921 (2,727–15,232)	2,547 (0–5,372)
	2019	12,852 (6,552–24,971)	8,557 (2,950–16,420)	2,749 (0–5,779)
	2020	10,276 (5,229–20,037)	6,854 (2,355–13,220)	2,206 (0–4,676)
Hebei	2015	8,164 (4,157–15,897)	5,442 (1,872–10,475)	1,750 (0–3,698)
	2016	9,074 (4,623–17,655)	6,046 (2,082–11,624)	1,944 (0–4,099)
	2017	12,015 (6,137–23,258)	7,985 (2,763–15,237)	2,561 (0–5,335)
	2018	12,544 (6,411–24,253)	8,331 (2,887–15,872)	2,670 (0–5,549)
	2019	11,718 (5,984–22,693)	7,789 (2,694–14,874)	2,499 (0–5,211)
	2020	10,813 (5,517–20,978)	7,194 (2,484–13,774)	2,310 (0–4,837)

(44.9%), Hebei (43.2%), Shandong, Jiangsu, Fujian, Guangxi, and Yunnan (40.0%–45.0%). In 2015, five cities had the highest all-cause mortality, that is, Beijing [28,997 (95% CI: 7,154–41,180)], Chongqing [25,607 (95% CI: 6,130–37,050)], Shanghai [19,385 (95% CI: 4,638–28,056)], Baoding [18,770 (95% CI (4,784–26,135)], and Tianjin [14,475 (95% CI: 3,533–20,691)]. By 2020, the all-cause mortality in Chongqing [14,212 (95% CI: 3,315–20,904)], Beijing [12,730 (95% CI: 2,985–18,658)], Shanghai [9,784 (95% CI: 2,275–14,419)], and Tianjin [9,710 (95% CI: 2,308–14,110)] remained the highest.

Table 3
The Estimated Three Premature Deaths Related to Long-Term Exposure to $PM_{2.5}$ in China and Provinces With High Premature Deaths From 2015 to 2020

Region	Time	All-cause	Cardiovascular	Respiratory
China	2015	1,105,089 (267,049–1,590,192)	212,917 (135,515–289,319)	632,101 (0–1,245,414)
	2016	999,538 (239,961–1,444,093)	191,280 (121,664–260,087)	568,472 (0–1,123,254)
	2017	939,871 (224,650–1,361,527)	179,050 (113,835–243,563)	532,504 (0–1,054,194)
	2018	810,276 (192,155–1,179,521)	153,112 (97,269–208,443)	455,945 (0–905,723)
	2019	774,314 (183,241–1,128,637)	146,001 (92,731–198,802)	434,914 (0–864,733)
	2020	669,555 (157,576–979,324)	125,529 (79,686–171,020)	374,265 (0–745,934)
Shandong	2015	116,004 (28,681–164,567)	22,884 (14,598–31,026)	67,687 (0–132,047)
	2016	100,613 (24,551–143,880)	19,580 (12,474–26,581)	58,039 (0–113,876)
	2017	85,792 (20,692–123,568)	16,496 (10,497–22,420)	48,991 (0–96,610)
	2018	72,971 (17,419–105,774)	13,883 (8,825–18,887)	41,297 (0–81,804)
	2019	78,912 (18,894–114,169)	15,059 (9,576–20,482)	44,776 (0–88,580)
	2020	69,265 (16,479–100,614)	13,132 (8,345–17,872)	39,085 (0–77,535)
Jiangsu	2015	71,576 (17,216–164,567)	13,724 (8,730–31,026)	40,776 (0–132,047)
	2016	60,361 (14,379–143,880)	11,459 (7,283–26,581)	34,100 (0–113,876)
	2017	57,377 (13,658–123,568)	10,884 (6,917–22,420)	32,392 (0–96,610)
	2018	55,884 (13,278–105,774)	10,580 (6,723–18,887)	31,498 (0–81,804)
	2019	51,300 (12,127–114,169)	9,662 (6,136–20,482)	28,788 (0–88,580)
	2020	42,424 (9,956–100,614)	7,931 (5,033–17,872)	23,656 (0–77,535)
Henan	2015	121,506 (30,059–172,276)	23,984 (15,300–32,516)	70,936 (0–138,352)
	2016	108,689 (26,618–155,063)	21,231 (13,531–28,813)	62,899 (0–123,216)
	2017	98,023 (23,805–140,574)	18,982 (12,087–25,782)	56,311 (0–110,717)
	2018	92,623 (22,385–133,223)	17,847 (11,359–24,252)	52,986 (0–104,398)
	2019	87,560 (21,084–126,227)	16,808 (10,694–22,848)	49,931 (0–98,534)
	2020	76,673 (18,314–111,091)	14,596 (9,279–19,857)	43,417 (0–85,979)
Guangdong	2015	48,942 (11,423–71,954)	9,097 (5,770–12,404)	27,160 (0–54,327)
	2016	44,751 (10,420–65,894)	8,298 (5,262–11,317)	24,783 (0–49,624)
	2017	46,860 (10,923–68,949)	8,699 (5,517–11,863)	25,977 (0–51,989)
	2018	41,678 (9,685–61,445)	7,713 (4,890–10,521)	23,042 (0–46,176)
	2019	36,898 (8,544–54,518)	6,803 (4,312–9,283)	20,337 (0–40,817)
	2020	26,056 (5,993–38,666)	4,771 (3,022–6,515)	14,277 (0–28,738)
Hebei	2015	94,543 (11,423–133,319)	18,841 (5,770–25,520)	55,641 (0–108,080)
	2016	86,279 (10,420–122,381)	17,023 (5,262–23,079)	50,351 (0–98,219)
	2017	80,695 (10,923–114,925)	15,812 (5,517–21,452)	46,820 (0–91,597)
	2018	67,270 (9,685–96,720)	12,972 (4,890–17,626)	38,508 (0–75,846)
	2019	61,021 (8,544–88,082)	11,691 (4,312–15,895)	34,739 (0–68,610)
	2020	53,726 (5,993–77,933)	10,209 (3,022–13,891)	30,376 (0–60,199)

3.4. Economic Loss Attributable to O_3 and $PM_{2.5}$ Pollution

For the convenience of calculation, we assume that the population incurs no per capita MEs related to premature deaths. This study estimates only the economic losses associated with cardiovascular and respiratory diseases caused by O_3 and $PM_{2.5}$. Figure S5 in Supporting Information S1 shows city-specific economic loss associated with cardiovascular and respiratory diseases attributable to O_3 and $PM_{2.5}$ pollution in China by using the COI method with different C_0 values (for O_3: 26.7 ppb; for $PM_{2.5}$: 10 μg/m^3). Economic losses attributable to the O_3

10.1029/2021GH000531

Table 4
The Economic Loss Related to Long-Term Exposure to O_3 and $PM_{2.5}$ in China and Provinces With High Premature Deaths From 2015 to 2020

Pollutants	Time	Cardiovascular (billion)	Respiratory (billion)
O_3	2015	2.13 (0.73–4.11)	0.22 (0–0.46)
	2016	2.30 (0.79–4.43)	0.24 (0–0.50)
	2017	2.91 (1.00–5.58)	0.30 (0–0.62)
	2018	2.72 (0.94–5.21)	0.29 (0–0.62)
	2019	3.14 (1.08–6.03)	0.30 (0–0.63)
	2020	2.87 (0.99–5.52)	0.27 (0–0.57)
$PM_{2.5}$	2015	5.11 (3.25–6.94)	4.81 (0–9.47)
	2016	4.55 (2.89–6.18)	4.35 (0–8.61)
	2017	4.47 (2.84–6.07)	4.21 (0–8.33)
	2018	3.61 (2.30–4.92)	3.64 (0–7.22)
	2019	4.03 (2.56–5.48)	3.54 (0–7.05)
	2020	3.46 (2.20–4.71)	3.05 (0–6.08)

increased from 2015 to 2020 and reached a maximum at different times in different cities. There was an increasing trend of economic losses from cardiovascular and respiratory mortality, which increased from 2.13 billion CNY (95% CI: 0.73–4.11 billion) in 2015 to 2.87 billion CNY (95% CI:0.99–5.52 billion) in 2020 and from 0.22 billion CNY (95% CI: 0–0.46 billion) in 2015 to 0.27 billion CNY (95% CI: 0–0.57 billion) in 2020 (Table 4 and Figure S5 in Supporting Information S1). In 2020, the cities with the highest economic losses from cardiovascular diseases due to long-term O_3 exposure were Shanghai [66.52 (95% CI: 22.93–127.64) million], Beijing [57.52 (95% CI: 19.80–110.63) billion], Tianjin [37.19 (95% CI: 12.83–71.27) million], Linyi (Shandong) [36.49 (95% CI: 12.66–69.42) million], and Chengdu (Sichuan) [30.63 (95% CI: 10.52–59.14) million]. In contrast, Nujiang (Yunnan) [161,471 (95% CI: 54,751–317,418)] and Linzhi (Tibet) [205,143 (95% CI: 70,068–398,992)] had the lowest economic losses, which were approximately 0.28% and 0.36% of those in Beijing, respectively. Economic losses in 2020 due to cardiovascular mortality accounted for approximately 91.3% of the total economic losses attributable to O_3 exposure, which is much higher than those due to respiratory mortality.

The economic losses of cardiovascular and respiratory mortality related to long-term $PM_{2.5}$ exposure decreased from 5.11 billion CNY (95% CI: 3.25–6.94) in 2015 to 3.46 billion (95% CI: 2.20–4.71) in 2020 and from 4.81 billion CNY (95% CI: 0–9.47) in 2015 to 3.05 billion CNY (95% CI: 0–6.08) in 2020 (Table 4 and Figure S5 in Supporting Information S1). In 2015, the cities with the highest economic loss of cardiovascular diseases-- related to long-term $PM_{2.5}$ exposure were Beijing [136.96 (95% CI: 87.34–185.74) million], Chongqing [117.24 (95% CI: 74.55–159.47) million], Shanghai [88.71 (95% CI: 56.41–120.67) million], Baoding (Hebei) [91.68 (95% CI (58.66–123.93) million], and Tianjin [67.63 (95% CI: 43.08–91.80) million]. By 2020, the economic losses in Chongqing [72.80 (95% CI: 46.17–99.28) million], Beijing [65.58 (95% CI: 41.62–89.38) million], Shanghai [49.96 (95% CI: 31.68–68.14) million], and Tianjin [50.73 (95% CI: 32.24–69.05) million] remained the highest. From the provincial perspective, economic losses during the study period were higher in Henan (11.62%) [2015: 1.12; 2020: 0.76 billion], Shandong (10.45% of total economic loss in 2020) [2015: 1.06; 2020: 0.68 billion], and Hebei (8.13%) [2015: 0.88; 2020: 0.53 billion] (Figure S6 in Supporting Information S1).

4. Discussion

This study assessed the health impacts and economic loss-related long-term exposure to MDA8 O_3 and $PM_{2.5}$ in China during the study period of 2015–2020. This study showed that the O_3 concentration and the deaths of three health endpoints and economic loss cause by long-term O_3 exposure increased significantly in China, which is similar to the results of other studies (Lu et al., 2020; Maji & Namdeo, 2021). At the same time, the $PM_{2.5}$ concentration and corresponding premature mortality decreased significantly in most cities; however, they still exceed the CAAQS in many regions. China is facing new challenges from the complex and increasing mix of O_3 and $PM_{2.5}$ pollution.

Some prior studies examined the health effects attributed to O_3 exposure from a national perspective predominantly based on atmospheric chemistry models or satellite data (Lelieveld et al., 2013; Lin et al., 2018). Because the accuracy of health impact assessments attributable to O_3 can be greatly influenced by the O_3 data source, the monitoring data can help to obtain a more accurate result. Maji and Namdeo. (2021) reported the impact of long-term O_3 exposure on human health by using a model consistent with this study (LL model) in which data from 2015 to 2019 were examined. Their results showed that in 2019, when 26.7 ppb was used as the threshold (C_0) for MDA8 O_3, the mortality for the all-cause, cardiovascular, and respiratory was 181 thousand (95% CI: 91.5–352 thousand), 112 thousand (95% CI: 38.1–214 thousand) and 33.8 (95% CI: 0–71.4 thousand), respectively, which is generally consistent with the results of this study; however, when the (C_0) for MDA8 O_3 was set to 0 ppb, the mortality was 487 thousand (95% CI: 249–922 thousand), 298 thousand (95% CI: 104–552 thousand), and 89,000 (95% CI: 0–178,000), respectively, which is much larger than the results of this study; these differences suggest that the selection of the O_3 threshold results in widely varying estimates of long-term premature mortality. Recently, Guan et al. (2021) conducted a nationwide study of 338 cities in China which generated much higher estimated health risks from O_3 than did our study. The difference between the results of these two studies may be that this study used exposure-response coefficient (β) from Lim et al. (2019) and Turner et al. (2016), whereas the study by Guan et al. (2021) used β from Jerrett et al. (2009). Notably, the selection of β also has a significant impact on the assessment of health impacts. Malley et al. (2017) used different RR values, from Jerrett et al. (2009) and Turner et al. (2016) to estimate mortality caused by O_3 pollution in China, with large differences in the results. The differences among these studies indicate that the health impact assessment-related O_3 is primarily related to the O_3 threshold (C_0), exposure-response coefficient (β), and the data source of O_3. Additionally, the selection of the O_3 indicator has a great impact on the health assessment-related to O_3 exposure (Feng et al., 2019).

Recently, Burnett et al. (2018) and Yin et al. (2020) estimated that there were 1.11 million in 2015 and 850,000 in 2017 deaths from all-cause deaths due to long-term $PM_{2.5}$ exposure, respectively, and our results were slightly lower than that reported in Burnett et al. (2018), but higher than that reported in Yin et al. (2020). Notably, the factors which influenced O_3-related health risk assessment can also affect that of $PM_{2.5}$. For example, Song et al. (2016) reported that there were 763,595 all-cause, 149,754 cardiovascular, and 446,035 respiratory deaths caused by $PM_{2.5}$ pollution in 2013, which were slightly lower than that in this study. One possible reason is that their study region contains only 190 cities, which is far less than this study. Furthermore, there is a significant decrease in $PM_{2.5}$ concentration in recent years. According to the study of Kuerban et al. (2020), in 2015, $PM_{2.5}$ pollution caused 436,260, 149,755, and 94,397 deaths from all-cause, respiratory, and cardiovascular diseases, and the three health endpoints death numbers in 2018 are 344,177, 109,326, and 70,982, respectively using LL model with much lower estimated health risks than our results. The differences may because the selection of the exposed population, this study used the all population as the exposed population, but Kuerban et al. (2020) considered only the population of cities with monitoring stations, which resulted in a lower value. Based on LL model, Maji et al. (2018) showed that the total all-cause deaths attributed to $PM_{2.5}$ in China was 1.258 (95% CI: 1.053, 1.420) million in 2016, which were slightly higher than our results. The reason for the difference may lie in the different selection of coefficients: this study used β and f_p from the previous studies (Aunan and Pan., 2004; Burnett et al., 2014; Kan and Chen., 2002; Xie et al., 2009, 2010), whereas the study by Maji et al. (2018) used β and f_p from Li et al. (2013), Qiu et al. (2013) and NBSC. (2016). Although these studies used the same LL model, the number of deaths related to $PM_{2.5}$ were different, indicating that the $PM_{2.5}$-related health impact assessment is also influenced by the exposed population, coefficients (f_p and β), and number of cities.

According to previous studies (Burnett et al., 2015; Yin et al., 2017), the estimated RRs with LL and IER models are relatively consistent. Maji et al. (2018) demonstrated that the number of all-cause deaths attributed to $PM_{2.5}$ in China was 0.964 (95% CI: 0.447, 1.355) million using IER model (the sum of four type of mortality: cerebrovascular, chronic obstructive pulmonary, ischemic heart disease, and lung cancer), whereas the all-cause deaths was 1.258 (95% CI: 1.053, 1.420) million based on LL model (the sum of five health endpoints: hospital admission due to cardiovascular disease, hospital admission due to respiratory disease, asthma attack, chronic bronchitis and emergency room visits for respiratory disease). It indicates that the LL model results have a slightly higher value of $PM_{2.5}$-related deaths due to the different coefficients and selection of health endpoints. Moreover, IER were employed to estimate limited health endpoints during $PM_{2.5}$ related exposure-response assessment (Yin et al., 2017), which is not suitable for our aims to directly obtain the mortality corresponding to the three health endpoints (all-cause, cardiovascular, and respiratory diseases) caused by $PM_{2.5}$ and O_3 pollution. Furthermore, there are no robust cohort studies to suggest which risk model is more appropriate for China (Maji et al., 2018). A recent cohort study showed that the RR values estimated in areas of high $PM_{2.5}$ concentration in China were not consistent with those specified in the IER model. The China-specific cohort studies contribute to narrow the gap in RR values in the high concentration areas, but are not appropriate for IER, suggesting that IER may underestimate the effect of high $PM_{2.5}$ levels in China (Pope et al., 2018). Therefore, considering reasons mentioned above, this study applied the LL model to estimate the number of deaths from the three health endpoints, which has been widely adopted by many other studies (Kuerban et al., 2020; Maji & Namdeo, 2021; Yin et al., 2017).

We applied the COI method to quantify the medical expenditure of each city by considering each health endpoint attributable to O_3 and $PM_{2.5}$ pollution from 2015 to 2020. High O_3- and $PM_{2.5}$ related economic losses were found in Beijing, Tianjin, Hebei, Anhui, Henan, Shandong, Jiangsu, Sichuan, Guangdong and Zhejiang Provinces. Some studies have shown that the adverse health effects of air pollution can cause significant economic losses

(Nansai et al., 2020; World Bank, 2016). Maji et al. (2019) used the value of a statistical life (VSL) model to assess the economic loss caused by O_3 pollution in 338 cities in China, and the results showed that there was an economic loss of US$7.6 billion in 2016. Wang et al. (2021) estimated the MEs and the VSL caused by the health burden of $PM_{2.5}$ and O_3 in 31 Chinese provinces from 2010 to 2050, and their results indicated that the MEs due to $PM_{2.5}$ and O_3 was approximately US$ 6.3 billion and that the VSL was approximately US$ 112.1 billion in 2010. The results of these two studies are higher than those of this study, and the differences may lie in the selection of the models and the sources of pollutant data, which may lead to dramatic differences in the results. Moreover, Lanzi et al. (2018) predicted that $PM_{2.5}$ pollution will cause US$ 2.26 trillion economic loss in 2030 without any control. Xie et al. (2017) showed that if there is no control policy, China will suffer US$ 4.2 billion in economic losses and US$ 285 billion in human loss in 2030. Therefore, we should continue to give more attention to air quality improvement, especially coordinated control for O_3 and $PM_{2.5}$ pollution.

Several uncertainties are involved in this study. First, we assumed that the total population of each city is exposed to the same average O_3 and $PM_{2.5}$ concentrations, although the exposure environment of each person varies greatly in space and time (Maji et al., 2018). Second, the air quality monitoring stations are mainly distributed in urban areas, but the population of each city is not located only across these areas, which can introduce some uncertainty. Studies have revealed that the O_3 is significantly higher in suburban areas than in urban areas (Sicard et al., 2016). Therefore, in this study, the health effects estimated using the average concentration over all areas in each city may smaller than the actual effects.

5. Conclusions

This study analyzed the temporal and spatial heterogeneity of long-term O_3 and $PM_{2.5}$ pollution in 331 cities across China from 2015 to 2020. It was found that $PM_{2.5}$ concentrations continued to decrease in almost all Chinese cities, especially in cities located in NC and the YRD; conversely, O_3 showed an overall increasing trend. The population exposed to high $PM_{2.5}$ decreased from 2015 to 2020, but notably, although there was a substantial reduction in $PM_{2.5}$ due to the implementation of the APPCAP in recent years, it was still high in many cities. By 2020, approximately half of the population lived in areas where $PM_{2.5}$ exceeded the CAAQS; therefore, further control of $PM_{2.5}$ pollution will still be necessary in the future. Meanwhile, the ratio of the population exposed to O_3 continued to increase from 13.35% in 2015% to 14.15% in 2020; it peaked at 22.16% in 2018 and caused all-cause, cardiovascular, and respiratory mortality of 156,173 [95% CI: 79,562–303,843], 104,051 (95% CI: 35,824–200,055), and 33,456 (95% CI: 0–70,548) in 2020, respectively. According to these increases and the results of this study, it is imperative to urgently propose and adopt strict measures to control the continued rise of O_3 pollution in the future.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data sets for this study are publicly available. Data on ozone concentration are available via the China National Environmental Monitoring Centre (https://quotsoft.net/air/), and Population data (>30 years and all age group) obtained from the 6th Population Census (https://data.cnki.net/yearbook/Single/N2021050059).

Acknowledgments
This work was supported by the National Key Research and Development Plan of China (2019YFA0606901); the Visiting Fellowship from China Scholarship Council (No. 202106040072); China Postdoctoral Science Foundation (2020M681157).

References

Anenberg, S. C., Horowitz, L. W., Tong, D. Q., & West, J. J. (2010). An estimate of the global burden of anthropogenic ozone and fine particulate matter on premature human mortality using atmospheric modeling. *Environmental Health Perspectives*, *118*(9), 1189–1195. https://doi.org/10.1289/ehp.0901220

Aunan, K., & Pan, X. C. (2004). Exposure-response functions for health effects of ambient air pollution applicable for China e a meta-analysis. *The Science of the Total Environment*, *329*(1–3), 3–16. https://doi.org/10.1016/j.scitotenv.2004.03.008

Barrero, M. A., Orza, J. A. G., Cabello, M., & Canton, L. (2015). Categorisation of air quality monitoring stations by evaluation of PM10 variability. *The Science of the Total Environment*, *524–525*, 225–236. https://doi.org/10.1016/j.scitotenv.2015.03.138

Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C. A., et al. (2018). Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(38), 9592–9597. https://doi.org/10.1073/pnas.1803222115

Burnett, R. T., Pope, C. A., Ezzati, M., Olives, C., Lim, S. S., Mehta, S., et al. (2014). An integrated risk function for estimating the global burden of disease attributable to ambient fine particulate matter exposure. *Environmental Health Perspectives*, *122*(4), 397–403. https://doi.org/10.1289/ehp.1307049

Burnett, R. T., Pope, C. A., III. Ezzati, M., Olives, C., Lim, S. S., Mehta, S., et al. (2015). *An integrated risk function for estimating the Global Burden of Disease attributable to ambient fine particulate matter exposure*. University of British Columbia.

China National Environmental Monitoring Centre. (2020). National Air Quality Forecast Information Dissemination System [Dataset]. Monitoring Data. Retrieved from https://quotsoft.net/air/

China's economic and social big data research platform. (2020). The 6th Population Census [Dataset]. Retrieved from https://data.cnki.net/yearbook/Single/N2021050059

Fang, Y., Naik, V., Horowitz, L. W., & Mauzerall, D. L. (2013). Air pollution and associated human mortality: The role of air pollutant emissions, climate change and methane concentration increases from the preindustrial period to present. *Atmospheric Chemistry and Physics*, *13*(3), 1377–1394. https://doi.org/10.5194/acp-13-1377-2013

Feng, Z., De Marco, A., Anav, A., Gualtieri, M., Sicard, P., Tian, H., et al. (2019). Economic losses due to ozone impacts on human health, forest productivity and crop yield across China. *Environmental International*, *131*, 104966. https://doi.org/10.1016/j.envint.2019.104966

Ferreri, J. M., Peng, R. D., Bell, M. L., Ya, L., Li, T., & Anderson, G. B. (2018). The January 2013 Beijing "Airpocalypse" and its acute effects on emergency and outpatient visits at a Beijing hospital. *Air Quality Atmosphere & Health*, *11*(3), 301–309. https://doi.org/10.1007/s11869-017-0538-0

Gabehart, K., Correll, K. A., Loader, J. E., White, C. W., & Dakhama, A. (2015). The lung response to ozone is determined by age and is partially dependent on toll-Like receptor 4. *Respiratory Research*, *16*(1), 117. https://doi.org/10.1186/s12931-015-0279-2

Guan, Y., Kang, L., Wang, Y., Zhang, N. N., & Ju, M. T. (2019). Health loss attributed to $PM_{2.5}$ pollution in China's cities: Economic impact, annual change and reduction potential. *Journal of Cleaner Production*, *217*, 284–294. https://doi.org/10.1016/j.jclepro.2019.01.284

Guan, Y., Xiao, Y., Wang, Y., Zhang, N., & Chu, C. (2021). Assessing the health impacts attributable to $PM_{2.5}$ and ozone pollution in 338 Chinese cities from 2015 to 2020. *Environmental Pollution*, *287*, 117623. https://doi.org/10.1016/j.envpol.2021.117623

Gui, K., Che, H., Wang, Y., Wang, H., Zhang, L., Zhao, H., et al. (2019). Satellite-derived $PM_{2.5}$ concentration trends over Eastern China from 1998 to 2016: Relationships to emissions and meteorological parameters. *Environmental Pollution*, *247*, 1125–1133. https://doi.org/10.1016/j.envpol.2019.01.056

Hammer, M. S., Donkerlaar, A. V., Li, C., Lyapustin, A., Sayer, A. M., Hsu, N. C., et al. (2020). Global estimates and long-term trends of fine particulate matter concentrations (1998–2018). *Environmental Science & Technology*, *54*(13), 7879–7890. https://doi.org/10.1021/acs.est.0c01764

Huang, R. J., Zhang, Y., Bozzetti, C., Ho, K. F., Cao, J. J., Han, Y., et al. (2014). High secondary aerosol contribution to particulate pollution during haze events in China. *Nature*, *514*(7521), 218–222. https://doi.org/10.1038/nature13774

Hubbell, B., Fann, N., & Levy, J. I. (2009). Methodological considerations in developing local-scale health impact assessments: Balancing national, regional, and local data. *Air Quality Atmosphere & Health*, *2*, 99–110. https://doi.org/10.1007/s11869-009-0037-z

Jerrett, M., Burnett, R. T., Pope, C. A., II., Ito, K., Thurston, G., Krewski, D., et al. (2009). Long-term ozone exposure and mortality. *New England Journal of Medicine*, *360*(11), 1085–1095. https://doi.org/10.1056/nejmoa0803894

Kan, H. D., & Chen, B. H. (2002). Analysis of exposure response relationships of air particulate matter and adverse health outcomes in China. *Journal of Environment and Health*, *19*, 422–424.

Kuerban, M., Waili, Y., Fan, F., Liu, Y., Qin, W., Dore, A. J., et al. (2020). Spatio-temporal patterns of air pollution in China from 2015 to 2018 and implications for health risks. *Environmental Pollution*, *258*, 113659. https://doi.org/10.1016/j.envpol.2019.113659

Lanzi, E., Dellink, R., & Chateau, J. (2018). The sectoral and regional economic consequences of outdoor air pollution to 2060. *Energy Economics*, *71*, 89–113. https://doi.org/10.1016/j.eneco.2018.01.014

Lelieveld, J., Barlas, C., Giannadaki, D., & Pozzer, A. (2013). Model calculated global, regional and megacity premature mortality due to air pollution. *Atmospheric Chemistry and Physics*, *13*(14), 7023–7037. https://doi.org/10.5194/acp-13-7023-2013

Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., & Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*, *525*(7569), 367–+. https://doi.org/10.1038/nature15371

Li, K., Jacob, D. J., Liao, H., Shen, L., Zhang, Q., & Bates, K. H. (2019). Anthropogenic drivers of 2013-2017 trends in summer surface ozone in China. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(2), 422–427. https://doi.org/10.1073/pnas.1812168116

Li, P., Xin, J., Wang, Y., Wang, S., Li, G., Pan, X., et al. (2013). The acute effects of fine particles on respiratory mortality and morbidity in Beijing, 2004–2009. *Environmental Science & Pollution Research*, *20*(9), 6433–6444. https://doi.org/10.1007/s11356-013-1688-8

Liao, Z., Gao, M., Sun, J., & Fan, S. (2017). The impact of synoptic circulation on air quality and pollution-related human health in the Yangtze River Delta region. *The Science of the Total Environment*, *607*, 838–846. https://doi.org/10.1016/j.scitotenv.2017.07.031

Lim, C. C., Hayes, R. B., Ahn, J., Shao, Y., Silverman, D. T., Jones, R. R., et al. (2019). Long-term exposure to ozone and cause-specific mortality risk in the United States. *American Journal of Respiratory and Critical Care Medicine*, *200*(8), 1022–1031. https://doi.org/10.1164/rccm.201806-1161oc

Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair Rohani, H., et al. (2012). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: A systematic analysis for the global burden of disease study 2010. *Lancet*, *380*(9859), 2224–2260.

Lin, Y., Jiang, F., Zhao, J., Zhu, G., He, X., Ma, X., et al. (2018). Impacts of O_3 on premature mortality and crop yield loss across China. *Atmospheric Environment*, *194*, 41–47. https://doi.org/10.1016/j.atmosenv.2018.09.024

Liu, M., Huang, Y., Ma, Z., Jin, Z., Liu, X., Wang, H., et al. (2017). Spatial and temporal trends in the mortality burden of air pollution in China: 2004-2012. *Environment International*, *98*, 75–81. https://doi.org/10.1016/j.envint.2016.10.003

Lu, D., Xu, J., Yang, D., & Zhao, J. (2017). Spatio-temporal variation and influence factors of $PM_{2.5}$ concentrations in China from 1998 to 2014. *Atmospheric Pollution Research*, *8*(6), 1151–1159. https://doi.org/10.1016/j.apr.2017.05.005

Lu, X., Lin, C., Li, Y., Yao, T., Fung, J. C. H., & Lau, A. K. H. (2017). Assessment of health burden caused by particulate matter in southern China using high-resolution satellite observation. *Environment International*, *98*, 160–170. https://doi.org/10.1016/j.envint.2016.11.002

Lu, X., Zhang, L., Wang, X., Gao, M., Li, K., Zhang, Y., et al. (2020). Rapid increases in warm-Season surface ozone and resulting health impact in China since 2013. *Environmental Science and Technology Letters*, *7*(4), 240–247. https://doi.org/10.1021/acs.estlett.0c00171

Maji, K. J., & Namdeo, A. (2021). Continuous increases of surface ozone and associated premature mortality growth in China during 2015-2019. *Environmental Pollution*, *269*, 116183. https://doi.org/10.1016/j.envpol.2020.116183

Maji, K. J., & Sarkar, C. (2020). Spatio-temporal variations and trends of major air pollutants in China during 2015-2018. *Environmental Science & Pollution Research*, *27*(27), 33792–33808. https://doi.org/10.1007/s11356-020-09646-8

Maji, K. J., Ye, W. F., Arora, M., & Nagendra, S. M. S. (2018). $PM_{2.5}$-related health and economic loss assessment for 338 Chinese cities. *Environment International*, *121*, 392–403. https://doi.org/10.1016/j.envint.2018.09.024

Maji, K. J., Ye, W. F., Arora, M., & Nagendra, S. M. S. (2019). Ozone pollution in Chinese cities: Assessment of seasonal variation, health effects and economic burden. *Environmental Pollution*, *247*, 792–801. https://doi.org/10.1016/j.envpol.2019.01.049

Malley, C. S., Henze, D. K., Kuylenstierna, J. C. I., Vallack, H. W., Davila, Y., Anenberg, S. C., et al. (2017). Updated global estimates of respiratory mortality in adults 30 Years of age attributable to long-term ozone exposure. *Environmental Health Perspectives*, *125*(8), 087021. https://doi.org/10.1289/ehp1390

McDonnell, W. F., Stewart, P. W., Andreoni, S., Seal, E., Kehrl, H. R., Horstman, D. H., et al. (1997). Prediction of ozone-induced FEV1 changes: Effects of concentration, duration, and ventilation. *American Journal of Respiratory and Critical Care Medicine*, *156*(3), 715–722. https://doi.org/10.1164/ajrccm.156.3.9611044

Nansai, K., Tohno, S., Chatani, S., Kanemoto, K., Kurogi, M., Fujii, Y., et al. (2020). Affluent countries inflict inequitable mortality and economic loss on ASIA via PM2.5 emissions. *Environment International*, *134*, 105238. https://doi.org/10.1016/j.envint.2019.105238

NBSC. (2016). China statistical Yearbook 2016. National Bureau of Statistical of China. [Dataset]. Retrieved from http://www.stats.gov.cn/tjsj/ndsj/2016/indexeh.htm

Philip, S., Martin, R. V., van Donkelaar, A., Lo, J. W. H., Wang, Y., Chen, D., et al. (2014). Global chemical composition of ambient fine particulate matter for exposure assessment. *Environmental Science & Technology*, *48*(22), 13060–13068. https://doi.org/10.1021/es502965b

Pope, C. A., Cohen, A. J., & Burnett, R. T. (2018). Cardiovascular disease and fine particulate matter. *Circulation Research*, *122*(12), 1645–1647. https://doi.org/10.1161/circresaha.118.312956

Qiu, H., Yu, I. T., Wang, X., Tian, L., Tse, L. A., & Wong, T. W. (2013). Differential effects of fine and coarse particles on daily emergency cardiovascular hospitalizations in Hong Kong. *Atmospheric Environment*, *64*, 296–302. https://doi.org/10.1016/j.atmosenv.2012.09.060

Salonen, H., Salthammer, T., & Morawska, L. (2018). Human exposure to ozone in school and office indoor environments. *Environment International*, *119*, 503–514. https://doi.org/10.1016/j.envint.2018.07.012

Shang, Y., Sun, Z., Cao, J., Wang, X., Zhong, L., Bi, X., et al. (2013). Systematic review of Chinese studies of short-term exposure to air pollution and daily mortality. *Environment International*, *54*, 100–111. https://doi.org/10.1016/j.envint.2013.01.010

Shen, F., Zhang, L., Jiang, L., Tang, M., Gai, X., Chen, M., & Ge, X. (2020). Temporal variations of six ambient criteria air pollutants from 2015 to 2018, their spatial distributions, health risks and relationships with socioeconomic factors during 2018 in China. *Environment International*, *137*, 105556. https://doi.org/10.1016/j.envint.2020.105556

Sicard, P., De Marco, A., Agathokleous, E., Feng, Z., Xu, X., Paoletti, E., et al. (2020). Amplified ozone pollution in cities during the COVID-19 lockdown. *The Science of the Total Environment*, *735*, 139542. https://doi.org/10.1016/j.scitotenv.2020.139542

Sicard, P., Serra, R., & Rossello, P. (2016). Spatiotemporal trends in ground-level ozone concentrations and metrics in France over the time period 1999–2012. *Environmental Research*, *149*, 122–144. https://doi.org/10.1016/j.envres.2016.05.014

Song, C., He, J., Wu, L., Jin, T., Chen, X., Li, R., et al. (2017). Health burden attributable to ambient $PM_{2.5}$ in China. *Environmental Pollution*, *223*, 575–586. https://doi.org/10.1016/j.envpol.2017.01.060

Song, Y., Wang, X., Maher, B. A., Li, F., Xu, C., Liu, X., et al. (2016). The spatial-temporal characteristics and health impacts of ambient fine particulate matter in China. *Journal of Cleaner Production*, *112*, 1312–1318. https://doi.org/10.1016/j.jclepro.2015.05.006

Turner, M. C., Jerrett, M., Pope, C. A., Krewski, D., Gapstur, S. M., Diver, W. R., et al. (2016). Long-term ozone exposure and mortality in a large prospective study. *American Journal of Respiratory and Critical Care Medicine*, *193*(10), 1134–1142. https://doi.org/10.1164/rccm.201508-1633oc

Wang, Q., Wang, J., He, M. Z., Kinney, P. L., & Li, T. (2018). A county-level estimate of $PM_{2.5}$ related chronic mortality risk in China based on multi-model exposure data. *Environment International*, *110*, 105–112. https://doi.org/10.1016/j.envint.2017.10.015

Wang, Y. Y., Hu, J. L., Zhu, J., Li, J. Y., Qin, M. M., Liao, H., et al. (2021). Health Burden and economic impacts attributed to $PM_{2.5}$ and O_3 in China from 2010 to 2050 under different representative concentration pathway scenarios. *Resources, Conservation and Recycling*, *173*, 105731. https://doi.org/10.1016/j.resconrec.2021.105731

WHO. (2006). *WHO air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide*. Retrieved from http://apps.who.int/iris/bitstream/10665/69477/1/WHO_SDE_PHE_OEH_06.02_eng.pdf

World Bank. (2016). *The cost of air pollution: Strengthening the economic case for action*. World Bank Group.

Xie, P., Liu, X. Y., Liu, Z. R., Li, T. T., & Bai, Y. H. (2009). Study of exposure-response relationship of air particulate pollution in China. *China Environmental Science*, *29*, 1034–1040.

Xie, P., Liu, X. Y., Liu, Z. R., Li, T. T., Zhong, L. J., & Xiang, Y. R. (2010). Impact of exposure to air pollutants on human health effects in Pearl River Delta. *China Environmental Science*, *30*(7), 997–1003.

Xie, Y., Dai, H., Dong, H., Hanaoka, T., & Masui, T. (2016). Economic impacts from $PM_{2.5}$ pollution-related health effects in China: A provincial-level analysis. *Environmental Science & Technology*, *50*(9), 4836–4843. https://doi.org/10.1021/acs.est.5b05576

Xie, Y., Dai, H., Zhang, Y., Tatsuya, H., & Toshihiko, M. (2017). Health and economic impacts of ozone pollution in China: A provincial level analysis. *Atmospheric Chemistry and Physics*, *1–63*.

Yin, H., Pizzol, M., & Xu, L. (2017). External costs of $PM_{2.5}$ pollution in Beijing, China: Uncertainty analysis of multiple health impacts and costs. *Environmental Pollution*, *226*, 356–369. https://doi.org/10.1016/j.envpol.2017.02.029

Yin, P., Brauer, M., Cohen, A. J., Wang, H. D., Li, J., Burnett, R. T., et al. (2020). The effect of air pollution on deaths, disease burden, and life expectancy across China and its provinces, 1990-2017: An analysis for the global burden of disease study 2017. *Lancet planetary health*, *4*(9), E386–E398. https://doi.org/10.1016/s2542-5196(20)30161-3

Zhang, D., Bai, K., Zhou, Y., Shi, R., & Ren, H. (2019). Estimating ground-level concentrations of multiple air pollutants and their health impacts in the Huaihe River Basin in China. *International Journal of Environmental Research and Public Health*, *16*(4), 579. https://doi.org/10.3390/ijerph16040579

Zhang, X., Ou, X., Yang, X., Qi, T., Nam, K. M., Zhang, D., et al. (2017). Socioeconomic burden of air pollution in China: Province-level analysis based on energy economic model. *Energy Economics*, *68*, 478–489. https://doi.org/10.1016/j.eneco.2017.10.013

Zhang, X. X., Gu, X. C., Cheng, C. X., & Yang, D. Y. (2020). Spatiotemporal heterogeneity of $PM_{2.5}$ and its relationship with urbanization in North China from 2000 to 2017. *The Science of the Total Environment*, *744*, 140925. https://doi.org/10.1016/j.scitotenv.2020.140925

Zhao, H., Chen, K., Liu, Z., Zhang, Y., Shao, T., & Zhang, H. (2021). Coordinated control of $PM_{2.5}$ and O_3 is urgently needed in China after implementation of the "Air pollution prevention and control action plan". *Chemosphere*, *270*, 129441. https://doi.org/10.1016/j.chemosphere.2020.129441

Zhao, L., Liang, H. R., Chen, F. Y., Chen, Z., Guan, W. J., & Li, J. H. (2017). Association between air pollution and cardiovascular mortality in China: A systematic review and meta-analysis. *Oncotarget*, *8*(39), 66438–66448. https://doi.org/10.18632/oncotarget.20090