Tracking short-term health impacts attributed to ambient PM$_{2.5}$ and ozone pollution in Chinese cities: an assessment integrates daily population

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Received: 30 March 2022 / Accepted: 13 July 2022 / Published online: 26 July 2022
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Abstract
Joint and synergistic control of PM$_{2.5}$ and ozone pollution is an urgent need in China and a global-wide concerned issue. Health impact assessment could provide a comprehensive perspective for PM$_{2.5}$-ozone coordinated control strategies. For a detailed understanding of the seasonality and regionality of the health impacts attributed to PM$_{2.5}$ and ozone in China, this study extended the classic health impact function by daily population and assessed the short-term (daily) health impacts in 335 Chinese cities in 2021. Population migration indexes from Baidu were introduced to estimate the cities’ daily population. Using this method, we quantitatively investigated the influence of population on short-term health impact assessment and identified which was significant in the Pearl River Delta (PRD) region and other populous cities. Although the annual sums of PM$_{2.5}$- and ozone-related daily health impacts were close for all Chinese cities, the PM$_{2.5}$-related health impact was equivalent to 333.96% and 32.07% of that ozone-related, during the cold and warm periods. The correlation and local spatial association analysis found significant city-specific and city-cluster associations of daily health impacts during the warm period and in Beijing-Tianjin-Hebei and surrounding regions (BTHS) and the Yangtze River Delta (YRD). Policymakers could promote period- and pollutant-targeted control actions for the major city groups, especially the BTHS, YRD, and PRD. Our methods and findings investigated the various influences of the population on short-term health impact assessment and proposed the PM$_{2.5}$-ozone collaborative control idea for key regions and city groups.

Keywords Baidu population migration index · City · Daily health impact · Ozone · PM$_{2.5}$

Abbreviations
BTHS Beijing-Tianjin-Hebei and surrounding areas
BQI Baidu population migration
CC Chongqing and Chengdu
CVD cardiovascular disease
DALY disability-adjusted life year
DMA8 daily averaged and maximum 8-hour average
FWP Fen-Wei plain
HE health impact estimation
HIF health impact function
IQI population inflow index
LISA local indicator of spatial association
MYR Middle Reaches of Yangtze River
NO$_2$ nitrogen dioxide
OQI population outflow index
PAF population attributable fraction
PI population influence coefficient
PM$_{2.5}$ fine particulate matter
PM$_{10}$ inhalable particulate matter
PRD Pearl River Delta
RD respiratory disease
SQI national migration scale index
YRD Yangtze River Delta
Introduction

Ambient fine particulate matter (PM$_{2.5}$) and ozone pollution are health risk factors of worldwide concerns (Murray et al. 2020; Owusu and Sarkodie 2020) while have been associated with considerable health risks (IHME, 2020). In recent years, China has effectively controlled PM$_{2.5}$ but suffering from increasing ambient ozone pollution (Wang et al. 2020; Zhao et al. 2021). Previous studies revealed opposing trends in PM$_{2.5}$ and ozone-related health impacts across China and in key regions/cities, decline, and growth, respectively (Guan et al. 2021a; Kuerban et al. 2020; Liu et al. 2021a; Xiao et al. 2022; Wang et al. 2021a). Nevertheless, the PM$_{2.5}$-related health impact still could not be ignored (Maji 2020; McDuffie et al. 2021). A collaborative and joint control of PM$_{2.5}$ and ozone pollution in China is needed and being discussed (Duan et al. 2022; Liu et al. 2021b, 2021c; Zhao et al. 2021). The seasonality of ozone pollution and associated health impacts are more significant in the warm season (Gao et al. 2020; Lu et al. 2020), which is relatively opposite of PM$_{2.5}$ (Xiao et al. 2022; Zhao et al. 2020). Moreover, the temporal-spatial heterogeneity of PM$_{2.5}$ and ozone in China is significant due to the vast territory and the uneven population distribution (Guan et al. 2021b). Therefore, a shorter-term assessment of PM$_{2.5}$ and ozone-related health impacts, at the daily, month, or season level, could support a systematic and detailed understanding of China’s ozone-related health impacts while guiding the PM$_{2.5}$-ozone joint control.

Long-term health impacts attributed to PM$_{2.5}$ and ozone, assessed by year and peak season, respectively, have drawn more attention. Although previous studies proposed that PM$_{2.5}$ and ozone exposure in short-term episodes were related to acute health effects (Orellano et al. 2020; Sorek-Hamer et al. 2020), the short-term health impacts were generally estimated and discussed in the long-term, such as year, also considered as long short-term health impacts. We collected and sorted the assessing scope information from recent literature, reflecting the timescale selection in existing health impact assessments (Appendix. 1). Some studies shortened the timescales of health impact assessment and provided informative results. For instance, Janssen et al. (2013) performed a daily mortality analysis of PM$_{2.5}$ in the Netherlands without exposure-response assessing. PM$_{2.5}$-related health impacts have been assessed by month and episode in Chinese cities and regions (Song et al. 2019; Wang et al. 2021b). Wang et al. (2021a) assessed the monthly health impacts attributed to PM$_{2.5}$ and ozone simultaneously in 74 air pollution primarily controlled cities of China. Liu et al. (2021a) estimated the daily all-cause mortality attributable to PM$_{2.5}$ and ozone short-term exposures in China from 2013 to 2018. Nevertheless, the short-term health impacts, especially the short-term trends and spatial characteristics of health impacts in China, have rarely been evaluated and discussed. Some studies that simulated and analyzed short-term (hourly or daily) PM$_{2.5}$ and ozone concentrations would turn to long-term or long short-term assessment when calculating the related health impacts (see Appendix 1 for details). Another issue to be aware of is that previous studies generally use constant population data when assessing short-term health impacts.

Referring to the health impact function (HIF), the population is influential during health impact assessment (Anenberg et al. 2010; Lelieveld et al. 2013). Li et al. (2021) suggested that health impacts and controlling benefits might be suitable for evaluating ozone mitigation and regional cooperation while highlighting the importance of population in the evaluation. Other studies have also attempted to apply short-term population data into health impact assessments. Guo et al. (2018) pertinently selected rush hours with intensive and frequent human activities as the research period and examined the associations between air pollutants and mortalities in Chengdu, China. Although the study did not develop a comprehensive health risk assessment considering the short-term population and pollution, the authors pointed out the insufficiency of averaged air pollutant concentrations to represent the exposure level due to the variations of pollution level and human activity. In addition, internet-related data have also been excavated to obtain dynamic population data. Using Weibo (a Chinese social media) user data, Song et al. (2019) tracked the monthly population and performed a short-term assessment for PM$_{2.5}$-related health impact in the Beijing-Tianjin-Hebei region. Guan et al. (2021b) simulated the seasonal population for 100 Chinese cities based on the quarterly population attractiveness indexes released by Baidu Map. The study furtherly estimated short-term health impacts attributed to PM$_{2.5}$ and ozone for fourteen seasons revealing the inter-city differentiations of seasonal population influences. With the rapid urbanization and transportation development, China’s population migration has become more long-distance and high-intensity while expected to cause the spatial relocation of air pollution and associated health risks (Gaughan et al. 2016; Shi et al. 2020). The inter-city differentiation and variation of PM$_{2.5}$- and ozone-related health impacts will be more complicated at the short-term level. A systematical assessment could help us analyze the distributional characteristics of short-term ozone-related health impacts for cities and city clusters.

This study aims to assess the short-term health impacts attributed to PM$_{2.5}$ and ozone at the city level. The assessment integrates the daily PM$_{2.5}$ and ozone pollution levels and city population. Specifically, the objectives are (1) to develop the classic HIF to the daily level by integrating
Baidu’s daily population migration index data; (2) to assess the daily short-term health impacts attributed to PM$_{2.5}$ and ozone in “365 days × 335 Chinese cities” in 2021; (3) to discuss daily population changes as a determinant in the HIF quantitatively; and (4) to investigate the heterogeneity of spatial correlation between PM$_{2.5}$ and ozone-related daily health impacts. It is the first attempt to integrate daily population into the health risk evaluation for air pollutants, especially for ozone, an ambient pollutant with significant seasonality and spatiality. The extended HIF and application of daily floating population data (in the method section for details) could support an accurate and dynamic understanding of short-term health risks attributed to air pollution. The method could be applied at several levels, from daily to annual. The findings for Chinese cities can support the precise policy-making in ozone control key regions and periods. Moreover, the coordinated and simultaneous control of PM$_{2.5}$ and ozone-related health risks is needed and concerned in other countries and regions (Faridi et al. 2018; Hao et al. 2015; Karambelas et al. 2018; Sicard et al. 2021; Yazdi et al. 2019); the methods and findings could provide references for evaluating short-term health risks and developing control strategies and policies.

**Methods and data**

**Estimate short-term health impacts attributed to PM$_{2.5}$ and ozone**

This study primarily focuses on the daily health impact and short-term exposure. We follow the classic framework of HIF, which has been widely used for short-term health impact assessment, and perform a log-linear concentration-response function for calculation (Anenberg et al. 2010; Lelieveld et al. 2013; Dedoussi et al. 2020; Guan et al. 2021b; Li et al. 2020; Wang et al. 2021a). The equation is:

\[ \Delta \text{Mort} = \left( \frac{y_0}{365} \right) \times \text{PAF} \times \text{Pop} \]  

(1)

\[ \text{PAF} = 1 - \exp (-\beta \Delta C) \]  

(2)

where the \( \Delta \text{Mort} \) is the health impact due to a given PM$_{2.5}$ and ozone levels; \( \text{PAF} \) is the population attributable fraction, an epidemiologic measure widely used to assess the public health impact of exposures in populations (Mansournia and Altman 2018). The \( \Delta C \) is the excess of monitoring concentration to the threshold. PM$_{2.5}$ and ozone concentration use the daily averaged and maximum 8-h average (DMA8) value. This study only considers ambient/outdoor pollution. The threshold value is 15μg/m$^3$ and 70μg/m$^3$ for PM$_{2.5}$ and ozone, respectively, referring to WHO (2021) and previous studies (Orellano et al. 2020; Vicedo-Cabrera et al. 2020). We use disability-adjusted life years (DALYs) to measure the health impact as recommended by the WHO (2012) and IHME (2020). Some studies also used DALYs to characterize the health impacts calculated by HIF while providing informative references for this study (Owusu and Sarkodie 2020; Wang et al. 2022). The \( y_0 \) is the annual baseline DALY rate and is assumed evenly distributed every day. We use the province-specific results of Zhou et al. (2019), a systematic analysis for the Global Burden of Disease Study 2017, as the \( y_0 \) data source. We assume that the DALY rates of all cities in a province are the same. Causality determination for health impacts attributed to PM$_{2.5}$ and ozone is according to systematic review studies (Orellano et al. 2020; Vicedo-Cabrera et al. 2020; Zhang et al. 2021) and the reports of the US Environmental Protection Agency and IHME. Among them, the study of Orellano et al. (2020), a systematic review of all-cause and cause-specific mortality for short-term exposure to PM$_{2.5}$, PM$_{10}$, ozone, and nitrogen dioxide (NO$_2$) referenced by the WHO, has been primarily considered. For PM$_{2.5}$, we estimate the health impacts for all-cause, cardiovascular disease (CVD) and respiratory disease (RD). For ozone, health impacts for all-cause and RD are considered (see Appendix 2 for details). The \( \beta \) is the concentration-response function parameter, while the value was obtained from the systematic review studies. The \( \text{Pop} \) is the population. The calculation using Equations (1) and (2) is performed city- and daily-specifically.

**Studied cities and data acquisition**

This study considers 335 Chinese cities, covering more than 99% of China’s population (Appendix 3). The city-specific PM$_{2.5}$ and DMA8 ozone concentration data are calculated based on the original monitoring data released by the China National Environmental Monitoring Center (http://www.cnemc.cn/) in real time. The monitoring data were collected by hour continuously in national ambient air quality monitoring sites from January 1 to December 31, 2021. We converted the hour- and site-specific data into daily averaged PM$_{2.5}$ and DMA8 ozone concentrations for each city. During the data processing, we eliminated the invalid data points referring to related regulations (Appendix 4). Through the processing and filtering, 53 and 45 city-daily data points were invalid and eliminated for PM$_{2.5}$ and ozone, respectively.

We obtain daily population data by processing the Baidu population migration index (BQI). The BQI data was obtained daily on the website http://qianxi.baidu.com/ and has been widely used in sociological and epidemiological research on China (Aleta et al. 2020; Lai et al. 2020; Liu et al. 2020). In a recent study, Liu et al. (2021d) assessed the spatial aggregations of COVID-19 incidences and associated factors (including environmental factors such as air...
pollution) in China from December 2019 to April 2020. The reliability and usability of the data have been tested by previous research. This study uses several sub-indexes of BQI, including the population inflow index (IQI), population outflow index (OQI), and the national migration scale index (SQI). The IQI and OQI are city-specific and characterize the relative size of the inflow and outflow population. The SQI reflects the overall size (also relative size) of the floating population within all cities from the time series. From Baidu (Baidu MAP 2021), there are:

\[Pop_i = Pop_{2020} + \Delta Pop_i \]

\[\Delta Pop_i = (IQ_i - OQ_i) \times Popf_i \]

\[Popf_i = \frac{Pop_f}{n} \times [SQ_i / \text{Average}^n (SQ_i)]\]

where \(i\) refers to the specific date. The \(Pop_{2020}\) is the residential population in 2020, a baseline for calculating the daily population in 2021. The 2020 population is from China’s Seventh National Population Census, a reliable data-set providing city population data accurate to single digit. The \(\Delta Pop_i\) refers to the net inflow population in date \(i\). The \(Popf_i\) and \(Popf\) refer to the average floating population of all cities in date \(i\) and the nation-overall size of the floating population, respectively. In this study, the \(PopfB\) value used China’s total floating population in 2020 (also obtained from the Census-7th). The \(n\) is the city number. The \(BQI\) data on December 3 is not available because Baidu did not release on that day. Therefore, this study includes 121,887 and 121,895 data points for PM$_{2.5}$ and ozone.

### Results and discussion

#### Overview of PM$_{2.5}$- and ozone-related daily health impacts

By adding up, the daily health impact attributed to PM$_{2.5}$ was more severe during the cold period of the year, for both all-cause and cause-specific estimates. Conversely, ozone-related daily health impact was higher during the warm period. Measured by all-cause and respiratory results, the long daily health impacts attributed to PM$_{2.5}$ and ozone were roughly equivalent across China in 2021 (Table 1). For collaborative controlling the health impacts, season- and pollutant-targeted strategies should first be implemented. Severe health risks concentrated in the major city groups of China, including the BTHS and FWP, YRD, MYR, PRD, and CC (Table 1, Figs 1 and 2). Public health of cities within the BTHS and populous cities in the Yangtze River Basin (such

| Cause | Region (number of cities) | PM$_{2.5}$ (range for cities × days) | Ozone | Cold period | Warm period |
|-------|---------------------------|--------------------------------------|-------|-------------|-------------|
|       |                           | Cold period                          |       |             |             |
|       |                           | Warm period                          |       |             |             |
| All-cause | 335 cities          | 3,499.10 (0–1.51)                    | 1,074.75 (0–1.16) | 1,030.42 (0–0.94) | 3,213.17 (0–1.45) | 103.31 (0–0.30) | 700.95 (0–0.78) |
| BTHS (28) |                          | 714.62 (0–1.45)                      | 249.51 (0–0.74)  | 18.59 (0–0.24) | 155.09 (0–0.72) |
| FWP (11) |                            | 187.72 (0–1.29)                      | 53.13 (0–0.44)  | 129.30 (0–0.40) | 409.30 (0–0.76) |
| YRD (27) |                            | 287.15 (0–0.71)                      | 108.84 (0–0.40) | 100.04 (0–0.38) | 276.40 (0–0.72) |
| MYR (28) |                            | 363.25 (0–0.91)                      | 108.84 (0–0.40) | 100.04 (0–0.38) | 276.40 (0–0.72) |
| PRD (9) |                             | 66.57 (0–0.66)                       | 17.13 (0–0.23)  | 105.11 (0–0.63) | 116.59 (0–0.72) |
| CC (2) |                              | 161.08 (0–1.51)                      | 45.22 (0–0.56)  | 18.49 (0–0.94) | 114.93 (0–1.45) |
| CVD | 335 cities | 1,168.93 (0–0.56) | 351.32 (0–0.44) | / | / |
| BTHS | 270.43 (0–0.56) | 95.38 (0–0.30) |
| FWP | 66.52 (0–0.44) | 18.92 (0–0.16) |
| YRD | 71.96 (0–0.16) | 26.87 (0–0.08) |
| MYR | 121.90 (0–0.30) | 34.41 (0–0.12) |
| PRD | 15.87 (0–0.16) | 4.09 (0–0.05) |
| CC | 43.94 (0–0.42) | 12.35 (0–0.15) |
| RD | 335 cities | 316.72 (0–0.21) | 93.66 (0–0.16) | 107.92 (0–0.15) | 321.30 (0–0.23) |
| BTHS | 50.14 (0–0.10) | 17.49 (0–0.05) | 8.43 (0–0.03) | 55.72 (0–0.06) |
| FWP | 13.57 (0–0.09) | 40.31 (0–0.16) | 1.52 (0–0.02) | 12.68 (0–0.06) |
| YRD | 24.03 (0–0.05) | 9.10 (0–0.03) | 12.31 (0–0.04) | 38.99 (0–0.07) |
| MYR | 36.38 (0–0.09) | 10.23 (0–0.04) | 11.44 (0–0.05) | 31.21 (0–0.07) |
| PRD | 5.92 (0–0.06) | 1.52 (0–0.02) | 10.62 (0–0.06) | 11.76 (0–0.07) |
| CC | 22.26 (0–0.21) | 6.26 (0–0.08) | 2.91 (0–0.15) | 18.06 (0–0.23) |
as Shanghai, Wuhan, Changsha, Chongqing, Chengdu) was threatened most by ambient pollution, almost all year. Some cities in southern China, involving Guangdong, Fujian, and Guangxi, have been plagued by ozone-related health risks for a relatively long time. Meteorological factors, especially the longer warm seasons, might be a driver. PM$_{2.5}$-related health impacts were significantly high in some cities of Xinjiang during the cold months (Figs 1 and 2). Daily health impacts were relatively low on most days and cities (Fig. A2), implying the importance of health risk control for key periods and cities (regions and city clusters). Referring to the recent study that tracked PM$_{2.5}$- and ozone-related health burden in China (Xiao et al. 2022), we set the cold period as January to March and October to December while the warm period as April to September. The warm period is consistent with the peak season suggested as the assessing period for ozone-related health impact assessment (Huangfu and Atkinson 2020).
City disproportion and correlation between PM$_{2.5}$- and ozone-related daily health impacts

The statistical distribution of city-level daily health impact results for all-cause and cause-specific was relatively consistent. There are linear fitting relationships between all-cause and cause-specific estimates (scatter of all cities × days results). For PM$_{2.5}$- (all-cause vs. CVD+RD) and ozone-related daily health impacts (all-cause vs. RD), the $R^2$ was 0.984 and 0.909, respectively (Fig. A2 and A3). For clarity and conciseness, the following discussion is based on all-cause results. Figure 3 presents the comparison between two health impacts and the proportion of health impacts during the high-risk day at the city level. From the all-year perspective, daily health impacts in the east and central region, southwest except Yunnan, northwest, and northeast region were generally PM$_{2.5}$-dominated, for a total of 178 cities. PM$_{2.5}$-dominated health risks during the cold period would expand almost entire China (for 283 cities) except the southern coastal region and Qinghai-Tibet Plateau. The situation during the warm period was the opposite. In January and December, the dominance of PM$_{2.5}$-related health impacts was the most significant (Fig. A5). We identified daily health impact higher than 500 DALYs as a high-risk day. For all 335 cities, PM$_{2.5}$ and ozone pollution have accounted for 528 (in 53 cities) and 220 (in 18 cities) high-risk days in 2021, respectively. The time distribution of ozone-related daily health impacts was more even than those PM$_{2.5}$-related, considering their sums of relatively small difference. We calculated the health impacts during the high-risk days as a proportion of the yearly sum. In most cities of the BTHS, PM$_{2.5}$-related health impacts during the high-risk days accounted for a high proportion, especially in the cold period. We can find similar high proportions in other megacities and regional centers. Differently, only in megacities and regional centers, ozone-related health impacts have shown the high-risk day aggregating trends (Fig. 3 and A6).

Correlation analysis is an effective tool for further understanding the characteristics of daily health impacts. Figure 4 presents the correlation coefficients between PM$_{2.5}$- and ozone-related daily health impacts for 335 cities while finding different period patterns. During the warm period, the variations in PM$_{2.5}$- and ozone-related daily health impacts were positively correlated in more cities (coefficients in 285 and 196 cities were positive during the warm and cold periods, respectively), covering almost all cities east of the
Hu Huanyong Line (Fig. A7), involving most of China’s population and highly urbanized areas (Chen et al. 2016). The positive correlations could be due to the shared sources and the similar meteorological effects on PM$_{2.5}$ and ozone in warm months (Xiao et al. 2022). During the cold period, PM$_{2.5}$- and ozone-related daily health impacts were positively correlated in south, northeast, and FWP cities but were negatively correlated in central and northwest China. In the BTHS, correlations were relatively insignificant in warm and cold periods, implying the complexity of health risks. PM$_{2.5}$-ozone joint control policies should be developed and implemented specifically for cities, pollutants, and seasons.

Spatial autocorrelation analysis has been widely used and discussed in China’s air pollution research (Song et al. 2020; Zhao et al. 2019). We used the Global Moran’s $I$ to measure the spatial relationships of PM$_{2.5}$ and ozone-related daily health impacts.

| Health impact PM$_{2.5}$/Ozone | 0-0.2 | 0.2-0.5 | 0.5-1.0 | 1.0-3.0 | 3.0-5.0 | >5.0 |
|-------------------------------|-------|---------|---------|---------|---------|------|

**Fig. 3** The equivalent ratios of PM$_{2.5}$/ozone-related health impacts and the proportions of health impacts during high-risk days
health impacts at the city level. The Global Moran’s I module was operated on GeoDa software (https://geodacenter.github.io/) using the Gaussian kernel method and Euclidean distance. Table A5 presents the Global Moran’s I results. The univariate spatial autocorrelation of ozone-related daily health impacts at the city level was more significant than PM$_{2.5}$-related, revealing a more concentrative distribution. The Global Moran’s I of city-level PM$_{2.5}$-related daily health impacts were stable, while that ozone related in cold and warm periods were higher than the annual. Indicatively, the spatial aggregation direction of ozone-related daily health impacts might be relatively opposite during the cold and the warm periods. In the warm period, the bivariate spatial correlation between PM$_{2.5}$- and ozone-related daily health impacts was more significant, consistent with the correlation results.

Furthermore, a local indicator of spatial association (LISA) analysis reveals the spatial correlation between PM$_{2.5}$- and ozone-related daily health impacts (Fig. 5). Table A6 presents the explanation for classifying the bivariate LISA between PM$_{2.5}$- and ozone-related daily health impacts. For example, a low$_{\text{PM}_{2.5}}$-high$_{\text{ozone}}$ city is a city with a lower PM$_{2.5}$-related daily health impact value while clustered by higher ozone-related values nearby (Anselin et al. 2002; Song et al. 2020). During the warm period, the high$_{\text{PM}_{2.5}}$-high$_{\text{ozone}}$ and high ozone-high$_{\text{PM}_{2.5}}$ cities roughly coincided in the BTHS, indicating a homology and joint control potential for the two health risks. Differently, the high$_{\text{PM}_{2.5}}$-high$_{\text{ozone}}$ types only appeared in several cities within BTHS and the south area adjacent to it during the cold period, revealing that PM$_{2.5}$ mainly drove the health impact. Similar aggregation could be found in the northern part of YRD during the warm period. Considering the source, it might be due to the agglomerated petrochemical and chemical industries in areas between BTHS and YRD. In addition, different industrial staggered production policies in the BTHS, YRD, and the cities between might also be a driving factor. For cities in and around Guangdong, we can observe the high$_{\text{ozone}}$-low$_{\text{PM}_{2.5}}$ aggregation during the cold period, while high PM$_{2.5}$-related daily health impacts in Guangzhou and Shenzhen were correlated with the nearby high ozone-related daily health impacts. Combining with Fig. 4 and A8, policy implications could be proposed that the regionally joint control strategies for PM$_{2.5}$ and ozone could be developed firstly in the BTHS and YRD. During the warm period, pollution sources related to PM$_{2.5}$ and ozone simultaneously should be controlled in BTHS, while control of ozone-related health risks should be strengthened in the YRD. PM$_{2.5}$ should be intensively prevented during the cold period in BTHS, while cities between BTHS and YRD should launch PM$_{2.5}$-ozone joint control actions. Moreover, the joint control policies for other regions and city groups should focus on megacities and regional centers.

**Influence of daily population on health impact assessment**

This study integrates the daily population into the classic HIF framework. Quantitatively analyzing the contribution
of daily population fluctuations on short-term health impact variations can provide a deeper understanding of the characteristics of health risks in China. First, we performed a correlation analysis between daily PAF (see Equation 2) and population. The results (Fig. A9) show that correlations between daily PAFs and populations were generally at a low level. Especially in the major city groups, the correlations were relatively insignificant. By comparison, the correlations were higher for PAF_{PM2.5} vs. population and PAF_{ozone} vs. population during the cold and warm periods, respectively. Second, we defined a population influence coefficient of daily pollution and the health impact estimates as:

\[ \text{PI} = \left| \frac{H_{\text{daily}} - H_{\text{2020}}}{H_{\text{2020}}} \right| \]  

(6)

where PI is the population influence coefficient, characterizing the influence of daily population on health impact estimation. The \( H_{\text{daily}} \) and \( H_{\text{2020}} \) are PM_{2.5} and ozone-related health impacts estimated using daily population and 2020 residential population, respectively. All variables in Equation 6 are city- and day-specific.
Figure 6 presents the population influence coefficient results. The daily average \( PI \) for PM\(_{2.5}\) and ozone-related daily health impact estimates were 1.76\% (0.01–5.88\% for specific city) and 1.72\% (0.22–6.82\%), respectively. During the cold and warm periods, the \( P_{PI\text{PM}_{2.5}} \) were 2.19\% (0.02–9.17\%) and 1.34\% (0–5.98\%), while the \( P_{PI\text{ozone}} \) were 1.67\% (0.13–8.85\%) and 1.77\% (0.23–9.79\%), respectively. In general, the population contributed 0–10\% of fluctuation to daily health impact estimation. The \( PI \) trends for PM\(_{2.5}\) and ozone-related estimates were similar, but we could also find that the average \( P_{PI\text{PM}_{2.5}} \) and \( P_{PI\text{ozone}} \) were higher during the cold and warm periods, respectively. High \( PI \) mainly appeared in three types of cities: one, the megacities and regional centers, such as the municipalities and provincial capitals; two, the cities with small local populations and large floating populations, such as Hainan, Tibet, and Qinghai; and three, the PRD and the surrounding cities. Contrary to PM\(_{2.5}\)-related daily health impact estimates (including the high-risk days), only several BTHS cities have high \( P_{PI\text{PM}_{2.5}} \), revealing the relatively insignificant influence of the daily variations in the population. From the model perspective and referring to the Baidu population migration indexes (Fig. A10), we considered that the persistently high PM\(_{2.5}\) levels in BTHS have reduced the influence of population migrations on health impact estimation. Similarly, \( P_{PI\text{PM}_{2.5}} \) of the PRD and the surrounding cities were relatively low during the warm period due to the low-level PM\(_{2.5}\) at that time. The extremely high value of \( PI \) occurs at the beginning or end of major Chinese holidays, such as October 1 (Chinese National Day), May 1 (International Labor Day), February 18 (Chinese New Year), and April 3 (Qingming Festival), implying that large-scale population travel during holidays may cause disturbances to the prevention of health risks in specific days.

For policy implications, high population influence would increase the complexity for controlling air pollution and the related health risk in the PRD and its surrounding cities. Synergistic and simultaneous reduction of the PM\(_{2.5}\) and ozone levels in this area should be accurate and short-term, especially during the cold-warm alternating seasons. At present, China has formed the technical capability of daily PM\(_{2.5}\) and ozone concentration prediction and has applied it at the provincial and city levels. However, relevant institutions and enterprises have not accumulated sufficient short-term population data from the national level. We propose establishing a multi-year and daily (or hourly) population movement database first in the PRD (the most economically developed and technologically advanced city group in China) while integrating the data to form a technical framework for population migration prediction. On this basis and using the ideas provided by this study, a real-time PM\(_{2.5}\) and ozone health risks forecast and early warning system could be developed while providing a reference for public travel and decision-making. Megacities and regional centers should strengthen the anthropogenic pollution sources control in high-risk days and periods, such as labor-intensive polluting industries and vehicles. Contrarily, health risks in the BTHS should be controlled regionally due to the high pollutant levels and relatively slight influence of population fluctuations. For provinces and cities with small populations, the influx of tourists and holidaymakers and the outflow of laborers on specific days may be the reason for the higher \( PI \). Period-specific control measures, especially for ozone during the warm, could be implemented.

### Uncertainty and limitations

Though we established the methods referring to high-quality and widely followed studies while using reliable data, some limitations and uncertainty still exist. Specifically, we used the provincial DALY rate in 2017 as a baseline and assumed it was constant and evenly distributed among cities and days (Xiao et al. 2022; Xue et al. 2019). Nevertheless, the baseline rate has a significant driving effect on health impact assessment (He et al. 2022). Evaluation for the difference in daily health impacts among cities and days would be biased. Second, the Baidu population indexes and baseline population data were obtained from different monitoring and investigation systems. Inaccuracies and uncertainties for the combination of them exist objectively. The assumption, considering the DALY rate is evenly distributed across cities in a province and throughout each day, would also add to this uncertainty. The health impact estimates might be biased if the DALY rate data in 2020 can be obtained and used in this study. Though the daily population results estimates are highly available, we could not verify the difference between these estimates and reality. Even so, daily population estimation can partially help the short-term PM\(_{2.5}\)-related health impact assessment and reflect the variations due to population changes. Third, the daily health impact assessment only considered ambient PM\(_{2.5}\) and ozone while ignoring indoor pollution, which would underestimate the health impacts. Fourth, the long short-term health impact estimates for PM\(_{2.5}\) and ozone (all-cause) were roughly equivalent across China. The amount comparison of short-term health impacts (between PM\(_{2.5}\) and ozone) is different from that for long-term results. As found in previous studies, the long-term health impacts attributed to PM\(_{2.5}\) were significantly higher than those ozone attributed in China (Guan et al. 2021a; Wang et al. 2021a; Xiao et al. 2022). This study provides a supplementary idea for the joint control of PM\(_{2.5}\) and ozone from the perspective of short-term health impact but does not provide a more comprehensive discussion of the results of long-term and short-term health impact assessments.
Fig. 6 Influence coefficient for health impact estimates during the cold and warm periods
Conclusion

This study innovatively extended the classic ambient pollution health impact function by integrating Baidu population migration indexes. The improved method can simulate the daily population at the city level. Using this method, we draw a city-level map of daily health impacts attributed to PM$_{2.5}$ and ozone in China while providing a more accurate and meticulous understanding of city-level health risks. The results investigate the spatiotemporal differentiation and correlations of PM$_{2.5}$ and ozone and highlight the need and city/region-specific potential for synergistic control of PM$_{2.5}$ and ozone, especially for short-term health effects. Specifically, the daily health impacts attributed to PM$_{2.5}$ and ozone showed significant regionality and seasonality. PM$_{2.5}$- and ozone-related daily health impacts were more severe during the cold and warm periods, respectively. The correlation between the two health impacts was more significant during the warm period. We also perform the bivariate local association between PM$_{2.5}$- and ozone-related health impacts while showing different typologies in the BTHS and YRD and the cities between them. Finally, daily population influenced the health impact estimation significantly in PRD and surrounding cities and populous cities including provincial capitals and regional centers.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11356-022-22067-z.

Availability of data and materials Not applicable.

Author contribution All authors contributed to the study conception and design. Conceptualization, methodology, investigation, writing-original draft preparation, writing-reviewing and editing, software, and validation were performed by Yang Guan and Nannan Zhang. The first draft of the manuscript was written by Yang Guan, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding This work was supported by the Assessment Method of “Beautiful China’s Ecological Construction,” National Key Research and Development Project of China (grant numbers 2019YFC0507803).

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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