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Assessment of health benefit of PM$_{2.5}$ reduction during COVID-19 lockdown in China and separating contributions from anthropogenic emissions and meteorology

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ABSTRACT

The national lockdown policies have drastically disrupted socioeconomic activities during the COVID-19 pandemic in China, which provides a unique opportunity to investigate the air quality response to such anthropogenic disruptions. And it is meaningful to evaluate the potential health impacts of air quality changes during the lockdown, especially for PM$_{2.5}$ with adverse health effects. In this study, by using PM$_{2.5}$ observations from 1388 monitoring stations nationwide in China, we examine the PM$_{2.5}$ variations between the COVID-19 lockdown (February and March in 2020) and the same period in 2015–2019, and find that the national average of PM$_{2.5}$ decreases by 18 μg/m$^3$, and mean PM$_{2.5}$ for most sites (about 75%) decrease by 30%–60%. The anthropogenic and meteorological contributions to these PM$_{2.5}$ variations are also determined by using a stepwise multiple linear regression (MLR) model combined with the Kolmogorov–Zubenko filter. Our results show that the change of anthropogenic emissions is a leading contributor to those widespread PM$_{2.5}$ reductions, and meteorological conditions have the negative influence on PM$_{2.5}$ reductions for some regions, such as Beijing–Tianjin–Hebei (BTH). Additionally, the avoided premature death due to PM$_{2.5}$ reduction is estimated as a predicted number based on a log-linear concentration-
response function. The total avoided premature death is 9952 in China, with dominant contribution (94%) from anthropogenic emission changes. For BTH, Yangtze River Delta, Pearl River Delta and Hubei regions, the reductions of PM$_{2.5}$ are 24.1, 24.3, 13.5 and 29.5 μg/m$^3$, with the avoided premature deaths of 1066, 1963, 454 and 583, respectively.

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**Introduction**

Coronavirus disease 2019 (COVID-19) has spread rapidly and was declared a global pandemic by the World Health Organization on 11 March 2020 (Le Quéré et al., 2020). COVID-19 has caused over 2.95 million infections and 1931,000 deaths globally by 28 April 2020 (Li et al., 2020). Various measures are taken by world governments to control the spread of the virus, and include social distancing, cluster lockdowns, mass quarantines and extensive travel bans (Le Quéré et al., 2020). During the outbreak of COVID-19, China government imposed stringent measures and required its people to stay at home beginning from late January 2020 (Tian et al., 2020), resulting in sweeping disruptions of social and economic activities.

Such measures to control the virus in China dramatically affected industrial, construction and transportation activities (Li et al., 2020; Shi and Brasseur, 2020), and thus provide a good opportunity to investigate the response of air quality to these large disruptions of socioeconomic activities during the lockdown. Given that ambient fine particulate matter air pollution (<2.5 μm in aerodynamic diameter; PM$_{2.5}$) has numerous negative effects on human health (Burnett et al., 2018) and a relatively high level of PM$_{2.5}$ is observed in China (van Donkelaar et al., 2016), some recent studies have examined PM$_{2.5}$ variation during the lockdown in China (Huang et al., 2020; Le et al., 2020; Li et al., 2020; Shi and Brasseur, 2020; Wang et al., 2020). These studies, however, only focused on PM$_{2.5}$ changes themselves and have not assessed their health impacts. Thus, one important objective of this study is to evaluate the potential health impact due to PM$_{2.5}$ change during the lockdown in China.

Most of the recent studies on PM$_{2.5}$ change during the lockdown in China compared PM$_{2.5}$ levels between lockdown and pre-lockdown period, and these studies rarely quantified the contributions of anthropogenic and meteorological factor to the PM$_{2.5}$ variations. Since PM$_{2.5}$ concentrations generally decrease from pre-lockdown to lockdown period in China from a climatology perspective (Chen et al., 2020) and the effects of anthropogenic emissions on PM$_{2.5}$ variations may be significantly confounded by meteorological conditions (Zhai et al., 2019), it is necessary to compare PM$_{2.5}$ concentrations during the lockdown with correspondingly climatological values and further separate anthropogenic and meteorological contributions to PM$_{2.5}$ change, which is another focus of this study.

Here, we analyze the PM$_{2.5}$ variations between the COVID-19 lockdown (February and March in 2020) and the same period in 2015–2019 in China using surface measurements from 1388 monitoring stations nationwide. Additionally, the anthropogenic and meteorological contributions to these PM$_{2.5}$ variations are separated based on a statistical method. Finally, we examine the potentially health impact due to the PM$_{2.5}$ changes during the lockdown.

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1. **Data and methods**

1.1. **Data sets**

1.1.1. **Ground-based PM$_{2.5}$ measurements**

Hourly PM$_{2.5}$ concentrations at monitoring stations nationwide from the 1st January 2015 to the 31st March 2020 are obtained from the website of China National Environmental Monitoring Center (CNEMC, http://www.cnemc.cn). Hourly measurement < 1 μg/m$^3$ are removed because it is below the instruments’ limit of detection (Xiao et al., 2017). Daily mean PM$_{2.5}$ values are then computed from the hourly time series when more than 18 measurements in a day (Barrero et al., 2015). The analyses only use those stations with at least 80% of data coverage for February and March in each year. It finally includes 1388 stations nationwide and the locations of these stations are shown in Fig. 1.

1.1.2. **Meteorological data**

Meteorological data used in this study are derived from ERA5, which is the latest atmospheric reanalysis from ECMWF (5th generation). ERA5 provides hourly products with a spatial resolution of 0.25° x 0.25° based on previous studies (Liu et al., 2019a; Shen et al., 2018; Xiao et al., 2017), meteorological parameters associated with surface PM$_{2.5}$ are selected and include the surface atmospheric pressure (P, hPa), total column water (TCW, kg/m$^2$), 10 m u-wind (U$_{10}$) and v-wind (V$_{10}$) component, air temperature at an altitude of 2 m (T, K), total column ozone (TCO, kg/m$^2$), relative humidity (RH,%), and planetary boundary layer height (PBLH, m). The meteorological data are collocated to PM$_{2.5}$ observations for each station.

1.1.3. **Population and mortality data**

The study area covers 349 cities in China. The city-level population data are collected from statistical yearbooks for each province. Among these 349 cities, data on city-level annual mortality rate for all causes are available for 320 cities (92%) from the city statistical yearbooks, and mortality data for the remaining cities are assigned to the provincial average from provincial statistical yearbook. Note that 14 out of the 349 cities miss PM$_{2.5}$ observations and city-level PM$_{2.5}$ values for these 14 cities are also assigned to the provincial average. Since the latest statistical yearbook can only provide data for 2018, population and mortality data are not available for the
whole time period. Thus, population and mortality for each city are assumed to remain static from 2015 to 2020, and are confined to 2018. It is better to use mortality data with higher time resolution. However, daily or monthly mortality data for each city are unavailable, and we evenly convert the annual mortality rate to the short-term rate (the period from February to March).

1.2. Methods

1.2.1. KZ Filter and Multiple Linear Regression

To better understand the role of anthropogenic emission and meteorological condition to PM$_{2.5}$ variability, a statistical model combining stepwise multiple linear regression (MLR) and Kolmogorov–Zurbenko (KZ) filter is used to separate these influences. Specifically, we firstly use KZ filter to separate time series of PM$_{2.5}$ and meteorological data into short-term and baseline components given that the processes occurring at different time scales are caused by different physical phenomena: the short-term component is attributable to weather and short-term fluctuations in precursor emissions, baseline component to changes in the solar angle, emissions and climate (Rao et al., 1997). MLR is subsequently applied to quantify the effects of variabilities in anthropogenic emission and meteorology on PM$_{2.5}$ at the different time scales.

Note that the statistical analysis in this paper is based on daily data, unless otherwise stated. The KZ$_{m,p}$ filter is a low-pass filter produced through a moving average of length $m$ and obtained after $p$ iterations (Rao et al., 1995; Rao and Zurbenko, 1994), is defined by Eq. (1):

$$Y_i = \frac{1}{m} \sum_{j=-k}^{k} X_{i+j}$$  \hspace{1cm} (1)

where, $X$ is the input time series and $m = 2k+1$ stands for the window length. Then the output of the first pass becomes the input for the next pass and so on (Rao et al., 1995; Rao and Zurbenko, 1994). By adjusting $m$ and $p$ it can control the filtering of different scales of motion. The effective filter width is determined by the following criterion (Milanchus et al., 1998):

$$m \times p^{1/2} \leq N$$  \hspace{1cm} (2)

where, $N$ is the period of the smallest frequency removed. The KZ filter is widely applied to separate the components of air quality and meteorological data in previous studies (Ibarra-Berastegi et al., 2001; Wise and Comrie, 2005a, 2005b) given that this method is relatively simple and can be directly use to
time series with missing data. In current study, a \(KZ_{(m=15, p=3)}\) filter is designed to remove cycles of \(< 26\) days. Then the baseline component is the filtered time series that result from the use of \(KZ_{(m=15, p=3)}\) filter, and denoted \(M_0(t)\) and \(PM_0(t)\) for meteorological and \(PM_{2.5}\) time series, respectively.

The baseline component is defined as the sum of seasonal variation and long-term trend, and is mainly due to changes in the solar angle, emissions and climate (Rao et al., 1997). The short-term component, controlled mainly by weather and short-term fluctuations in precursor emissions (Wiscombe, 2005b), is calculated by subtracting the baseline from the original time series:

\[ PM_2(t) = PM(t) - PM_0(t) \] (3)

\[ M_2(t) = M(t) - M_0(t) \] (4)

where, \(PM(t)\) and \(M(t)\) are the original time series for \(PM_{2.5}\) and meteorological parameters, respectively. \(PM_0(t)\) and \(M_0(t)\), the baseline components, are filtered results by application of the \(KZ_{(m=15, p=3)}\) filter. \(PM_2(t)\) and \(M_2(t)\) are the short-term components.

After the short-term and baseline components are obtained, the MLR model is then used to examine meteorological and anthropogenic influence on \(PM_{2.5}\) variability following previous studies (Li et al., 2019; Zhai et al., 2019).

\[ PM(t) = PM_0(t) + PM_2(t) = \left[ a_0 + \sum_{i=1}^{8} a_i M_0(t) \right] + \left[ b_0 + \sum_{i=1}^{8} i b_i M_0(t) \right] + (\epsilon_S + \epsilon_P) \] (5)

where, \(M_0(t)\) and \(M_0(t)\) are the time series of meteorological variable \(i\) for short-term and baseline components respectively. \(a_0\) and \(b_0\) are the intercepts. The regression coefficients \(a_i\) and \(b_i\) are determined by a stepwise method adding and deleting terms based on their independent statistical significance to obtain the best model fit. The sum of residuals \(\epsilon_S\) (for short-term part) and \(\epsilon_P\) (for baseline part) can represent the fraction of \(PM(t)\) attributable to changes in anthropogenic emissions; the first two items on the right side of Eq. (5) can represent the contribution of meteorological variability to \(PM(t)\) (Ibarra-Berastegi et al., 2001; Li et al., 2019).

The above-mentioned procedures are applied to each site-based time series of \(PM_{2.5}\) and meteorological parameters, covering the period January 2015 to March 2020. We estimate the average \(PM_{2.5}\) variation during the COVID-19 lockdown (February-March 2020) compared to the same period in 2015–2019, and further obtain anthropogenic and meteorological contributions.

### 1.2.2 Health impact assessment

To assess the health impact of \(PM_{2.5}\) variation during the COVID-19 lockdown in China, we use concentration-response (C-R) functions to estimate short-term additional deaths attributable to \(PM_{2.5}\). A log-linear C-R function used in this study is shown below (Fann et al., 2009):

\[ \Delta M_i = Y_i \times POP_i \times (1 - e^{-\beta_i C_i - C_0}) \] (6)

where, \(\Delta M_i\) is the short-term \(PM_{2.5}\)-related additional deaths in city \(i\), \(Y_i\) is the baseline mortality rate for all causes in city \(i\), \(POP_i\) is the exposed population in city \(i\). The C-R function coefficient \(\beta\) is estimated based on relative risk reported in the epidemiological reference. The short-term mean \(PM_{2.5}\) for city \(i\) \((C_i)\) is calculated by averaging \(PM_{2.5}\) observations for monitoring stations in the corresponding city. \(C_0\) is the threshold concentration.

Following a review study about short-term exposure to air pollution and mortality (Shang et al., 2013), we use the relative risk from their results: an increase of \(10 \mu g/m^3\) in \(PM_{2.5}\) would cause a 0.38% (95% Confidence Intervals (CI): 0.31% – 0.45%) increase in total mortality. The C-R function coefficient \(\beta\) is then obtained by \(\beta = \ln(\text{RR})/\Delta C\) and equals \(3.8 \times 10^{-4}\) (95% CI: \(3.1 \times 10^{-4} - 4.5 \times 10^{-4}\)). Additionally, we assume there is no threshold concentration in this study since no obvious thresholds of \(PM_{2.5}\) are found in China (Liu et al., 2019b). Note that there may be a time lag between exposure to \(PM_{2.5}\) and health output (Tie et al., 2009), and we do not consider the effect of the time lag on health assessment given that the time lag structure for each city is unavailable.

For each city in China, the short-term \(PM_{2.5}\) mean concentration is based on the \(PM_{2.5}\) observations during the lockdown in 2020 for stations in the corresponding city, and the mean value during the same period between 2015 and 2019 is used as the reference. Then we estimate avoided (excess) premature death due to decrease (increase) in \(PM_{2.5}\) by applying Eq. (6). These short-term health impact assessments at city level are finally summed up to province level.

### 2 Results

#### 2.1 MLR model performance

For most stations, the variance of daily time series of \(PM_{2.5}\) is mainly attributable to short-term component, as shown in Fig. 1b. However, the relative contribution of baseline component is non-negligible, especially for stations in central China (Fig. 1a). For baseline component, the MLR model (the second item on the right side of Eq. (5)) performs well given that values of coefficient of determination \((R^2)\) are about or higher than 0.5 for 85% of stations (Fig. 1c). Nevertheless, \(R^2\) values are generally low for MLR model using short-term component, and mainly concentrated between 0.2 and 0.35 (Fig. 1d). One possible reason for these low \(R^2\) values is that short-term fluctuations in emissions may play an important role in variability of short-term component of \(PM_{2.5}\). Another possible reason is that some potential meteorological factors are not considered in the process of model building for short-term component, such as vertical wind profile. Additionally, the method itself may also affect the performance of the MLR model. For instance, the MLR model can hardly explain the nonlinear relationship between \(PM_{2.5}\) and meteorology in terms of short-term component.

The overall performance of the prediction of the MLR model with the KZ filter is shown in Figs. 2a, 2b. For about 80% of stations, the correlation coefficient \((r)\) is more than 0.6 and \(R^2\) is more than 0.4. To check whether the MLR model perfor-
mance of predicting PM$_{2.5}$ improves after applying the KZ filter (the first two items on the right side of Eq. (5)), we compare the performance measure between the MLR models with and without using the KZ filter. $R^2$ and $r$ values both obviously increase after using the KZ filter, as shown in Figs. 2c-2d. $r$ values increase by more than 0.05 for 80% of stations (Fig. 2c), and $R^2$ values increase by 0.1–0.2 for about a half of stations (Fig. 2d). The above results indicate that, to better quantify the effect of meteorological factors on PM$_{2.5}$, it is suitable to separate time series of PM$_{2.5}$ and meteorological data into short-term and baseline components.

2.2. PM$_{2.5}$ variation and contributions from anthropogenic emissions and meteorology

During the COVID-19 lockdown of February-March 2020 in China, about 75% of stations show that mean PM$_{2.5}$ concentrations decrease by 30% to 60% compared to the same period in the past five years (2015–2019), as shown in Fig. 3b. The areas with the most significant reductions are mainly located in Yangtze River Delta and Hubei province (Fig. 3b). It should be noted that a few stations exhibit an increase in PM$_{2.5}$, which is mainly due to extreme pollution events such as severe dust in Hotan Prefecture in Xinjiang province, forest fire in Xishuangbanna in Yunnan province.

For almost all stations, the change of anthropogenic emissions is a leading contributor to those widespread PM$_{2.5}$ decrease. Fig. 3c shows that the anthropogenic contribution to PM$_{2.5}$ decrease is more than 50% for 95% of stations. These expected results are mainly due to a large reduction in the emission of primary pollutants in China during the lockdown (Shi and Brasseur, 2020). On the other hand, meteorological contribution is lower than 50% for 95% of stations (including 65% of stations with positive values and 30% of stations with negative values) (Fig. 3d), suggesting that the meteorological condition plays a positive but not leading role in PM$_{2.5}$ decrease for most stations. Note that meteorology is unfavorable for some stations, especially over Beijing-Tianjin-Hebei region (Fig. 3d), and more details are presented in discussion part.

We now shift our focus to regional scale. Fig. 4 shows the monthly mean PM$_{2.5}$ trends for 2015–2020 in the four regions: Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD), Pearl River Delta (PRD) and Hubei province. Note that the monthly PM$_{2.5}$ values of February and March in Fig. 4 are presented as the anomalies for individual months relative to their 2015–
2020 means. During the COVID-19 lockdown, the four regions all exhibit a sharp decrease in PM$_{2.5}$ compared to the same period in 2015–2019 (black lines in Fig. 4). These reductions are 24.1, 24.3, 13.5 and 29.5 $\mu$g/m$^3$ in BTH, YRD, PRD and Hubei, respectively. The observed variations of PM$_{2.5}$ are generally consistent with variations of PM$_{2.5}$ from anthropogenic contribution over the four regions (Fig. 4), indicating that month-to-month variability of PM$_{2.5}$ is mainly attributed to change in anthropogenic emissions. In addition, meteorological contribution changes little over the four regions except BTH (blue lines in Fig. 4).

Note that the monthly mean PM$_{2.5}$ has a large fluctuation during 2016–2017 after excluding the influence from meteorology variation (Fig. 4). At first glance, this result may seem a bit unreasonable since annual anthropogenic PM$_{2.5}$ emissions in China steadily decrease after 2013 due to Clean Air Action (Zhao et al., 2017). One possible reason for this is that monthly mean PM$_{2.5}$ emissions may not continuously decrease, which is supported by a recent study (Qu et al., 2020). They used a boosted regression tree method to model the nonlinear relationships between PM$_{2.5}$ and meteorological factors, and further removed the meteorological effects from PM$_{2.5}$ changes. They found that the monthly emissions-driven PM$_{2.5}$ fluctuations in the Beijing–Tianjin–Hebei during 2016–2017 (see their Fig. 5b), which is consistent with our results.

### 2.3. Health benefit

The avoided premature death due to PM$_{2.5}$ reduction during the COVID-19 lockdown for each province and municipality is shown in Fig. 5a. The short-term avoided premature death varies spatially, and is attributable to the combined effect of various factors such as population, baseline mortality rate, PM$_{2.5}$ reduction. For instance, Henan and Shandong both have a larger population (about 100 million ranked top 3 in China), with relatively high baseline mortality rates. These conditions, combined with PM$_{2.5}$ decrease by about 35%, lead to avoided premature death of 1161 (95% CI: 951–1367) and 1019 (95% CI: 835–1202) for Henan and Shandong, respectively. For YRD and Hubei regions with the drastic decrease of PM$_{2.5}$, the avoided premature death are 1963 (95% CI: 1604–2312) and 583 (95% CI: 478–688).

The contribution of anthropogenic or meteorological factor to PM$_{2.5}$-related health impacts during the lockdown is estimated based on the anthropogenic or meteorological contribution to PM$_{2.5}$ changes. As shown in Fig. 5, for each province
Fig. 4 – Monthly time series of mean PM$_{2.5}$ in February and March 2015–2020 for the four regions. (a) Beijing–Tianjin–Hebei, (b) Yangtze River Delta, (c) Pearl River Delta and (d) Hubei province. Daily PM$_{2.5}$ values are averaged over each region and month, and anomalies are calculated relative to 2015–2020 means for that month of the year. In each panel, the PM$_{2.5}$ trend from observations (black line) is compared to variations from meteorological (blue line) and anthropogenic contribution (red line). Detailed information about how to estimate these two contributions can be seen in the method section.

Fig. 5 – Panel (a) shows the avoided mortality due to PM$_{2.5}$ reduction during the COVID-19 lockdown (February-March 2020) for each province and municipality in China. Error bars in panel (a) represent estimates of the avoided mortality with 95% confidence intervals (CI), and is based on uncertainty of the concentration-response function coefficient $\beta$ (95% CI: $3.1 \times 10^{-4}$–$4.5 \times 10^{-4}$). Panel (b) stands for mean PM$_{2.5}$ concentrations during COVID-19 lockdown (black circles) and the same period in 2015–2019 (black squares). Meteorological and anthropogenic contributions are measured by the vertical coordinate of panel (b) on the right-hand side.

and municipality, a positive effect of anthropogenic factor on health benefit is observed and the anthropogenic contribution is more than 50%. In addition, the meteorological contributions are small positive values for most regions, indicating that meteorological factor generally also play a positive effect on health benefit. It should be note that negative values of meteorological contribution are found for some regions, such as BTH (Fig. 5b). Specifically, the total avoided premature death in BTH is 1066 (95% CI: 872–1256), and this value should increase by 352 if the meteorological condition in BTH remains unchanged between the lockdown in 2020 and the same period in 2015–2019.
3. Discussion

Some recent studies also investigated PM$_{2.5}$ variations during the COVID-19 lockdown in China (Huang et al., 2020; Shi and Brasseur, 2020; Wang et al., 2020), and their findings are consistent with our results. We further find that meteorological conditions likely have a negative influence on PM$_{2.5}$ reductions during the lockdown for some regions, leading to relatively low estimates of health benefit due to PM$_{2.5}$ reduction. For instance, in BTH region, meteorology is unfavorable during the lockdown, especially in February (see Fig. 4a). Given that PBLH and RH are both significantly correlated with PM$_{2.5}$, we compare those two meteorological parameters in BTH between two time periods: February in 2015–2019 and February in 2020. From the first to the second period, the diurnally mean RH systematically increases during the whole day and PBLH obviously decreases during the daytime, as Fig. 6 shown. Since lower PBLH likely restrain PM$_{2.5}$ dispersion and higher RH may accelerate the transformation of secondary pollutants (Li et al., 2017), these changes in meteorological conditions likely play a negative role in PM$_{2.5}$ reduction in BTH region. Adverse meteorological conditions are also found during the lockdown in northern China from recent studies (Le et al., 2020; Wang et al., 2020). Additionally, Fig. 6a shows that the pattern of diurnal variation of PM$_{2.5}$ also changes between the two time periods in BTH and this warrant further investigation in the future.

Using different references would affect the result of PM$_{2.5}$ change. In this study, we use the average value between 2015 and 2019 as the reference. Given that China has experienced an obvious decreasing trend of PM$_{2.5}$ from 2015 to 2019 (e.g., Chu et al., 2020), the magnitude of PM$_{2.5}$ change between 2020 and the reference in this study is greater than other studies used 2019 as a reference (e.g., Chu et al., 2021).

Our study has some limitations. Firstly, population and mortality rate for each city are assumed to remain static in 2015–2020, and these data for 2018 are used to assess PM$_{2.5}$-related health impact for the period (February to March) from 2015 to 2020. This limitation is due to the fact that population and mortality data are not available for the whole time period and the latest statistical yearbook can only provide data for 2018. In the past four years (2015–2018), the relative change in annual mortality is only 0.11% at the national level, and is less than 4% for 90% of provinces (not shown). Secondly, the C-R function and coefficient $\beta$ are crucial for the health impact assessment. The shape of C-R function and coefficient $\beta$ may differ across different regions in China (Chen et al., 2017). This spatial heterogeneity is not taken into account in this study since specific C-R function and coefficient $\beta$ for each city are unavailable. However, our choice of C-R function and coefficient $\beta$ is reasonable since they are assessed by a meta-analysis on 33 time-series and case-crossover studies conducted in China (Shang et al., 2013). Thirdly, our health impact assessment would be improved by using more refined data, such as city-level hazard ratio and daily mortality for specific cause and different age groups. These data sets, however, are hard to obtain. In the future, we plan to assess health impact in depth for some specific regions where the refined data are available. Fourthly, the existing C-R functions are based on epi-

Fig. 6 - Mean diurnal variation of (a) PM$_{2.5}$ concentrations, (b) planetary boundary layer height (PBLH) and (c) relative humidity in Beijing–Tianjin–Hebei on February. Red and blue colors represent mean values in 2020 and 2015–2019, respectively. The numbers in the upper left corner of panel (b) and (c) are correlation coefficients between PM$_{2.5}$ and corresponding meteorological variable based on daily values in February during 2015–2020.
demiological datasets which all represent the non-lockdown situations. The indoor exposure to PM$_{2.5}$ of outdoor origin substantially changed during the lockdown period compared to other years. Therefore, the C-R function needs to improve in the future by using new epidemiological datasets that represent the lockdown situations. Finally, this study uses a statistical method to separate meteorological and anthropogenic contribution to PM$_{2.5}$ changes. Although this similar method is widely used in previous studies (Tai et al., 2010; Wise and Comrie, 2005a; Yang et al., 2016; Zhai et al., 2019), some shortcomings still exist. For instance, the MLR model can hardly explain the nonlinear relationship between PM$_{2.5}$ and meteorology. Further studies in combination with model simulations may address this issue.

4. Conclusions

In this study, based on PM$_{2.5}$ observations from 1388 monitoring stations nationwide in China, we examined the PM$_{2.5}$ variations between the COVID-19 lockdown (February and March in 2020) and the same period in 2015–2019 for each specific site and further each province (except Hong Kong, Macao and Taiwan). Furthermore, the anthropogenic and meteorological contribution to these PM$_{2.5}$ variations is investigated by using the stepwise MLR model combined with the KZ filter. Finally, the short-term health impact due to the PM$_{2.5}$ changes is assessed during the lockdown.

During the lockdown, the obvious decrease of PM$_{2.5}$ concentrations is widely observed in China compared to the same period in 2015–2019. The national average of PM$_{2.5}$ decreases by 18 $\mu$g/m$^3$, and mean PM$_{2.5}$ for most sites (about 75%) decrease by 30%–60%. The areas with the most significant reductions are mainly located in YRD and Hubei. For BTH, YRD, PRD and Hubei, the reductions of PM$_{2.5}$ are 24.1, 24.3, 13.5 and 29.5 $\mu$g/m$^3$, respectively. Additionally, our results show that the change of anthropogenic emissions is a leading contributor to those widespread PM$_{2.5}$ reductions. Note that meteorological conditions have the negative influence on PM$_{2.5}$ reductions for some regions such as BTH, and this negative influence in BTH is likely due to low PBLH and high RH during the lockdown.

The total avoided premature death due to PM$_{2.5}$ reduction during the lockdown is 9952 (95% CI: 8141–11,730) in China, with dominant contribution (94%) from anthropogenic emission changes. The short-term health benefit varies spatially. The avoided premature death is more than 1000 for Henan and Shandong. And this value is 1963, 454 and 583 for YRD, PRD and Hubei, respectively. Additionally, the avoided premature death in BTH is 1066 (95% CI: 872–1256), and should increase by 352 if the meteorological conditions during the lockdown keep the same level as during the same period in 2015–2019.

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