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Aggravated air pollution and health burden due to traffic congestion in urban China

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Abstract. Vehicle emissions are regarded as a primary contributor to air pollution and related adverse health impacts. Heavy traffic congestion increases traffic flow and thus produces more O_3 precursor emissions, leading to more adverse air quality issues. Although the development of a vehicle emission inventory has received great concern and continuous efforts, limitations still exist. For example, real-time diurnal variations and increases in emission rates due to traffic congestion are not well understood. In this study, we developed a new temporal allocation approach in transportation emissions to investigate the impact on air quality and health burden due to traffic congestion in China in 2020. Both real-time congestion-level data and emission correction factors were considered in the approach. Results show that traffic congestion aggravates air pollution and health burden across China, especially in the urban clusters such as the North China Plain and Sichuan Basin. In these regions, the average annual increases in fine particulate matter ($PM_{2.5}$) and ozone (O_3) could be up to $3.5\,\mu g\,m^{-3}$ and 1.1 ppb, respectively. The excess $PM_{2.5}$ and O_3 attributed to the traffic congestion also induce an additional 20 000 and 5000 premature deaths in China, respectively. In major cities, the increased rate of premature mortality caused by traffic congestion may reach 17.5 %. Therefore, more effective and comprehensive vehicle emission control policies or better planning of the road network should be established to reduce traffic congestion and improve air quality in China.

1 Introduction

With the rapid development of the economy and automobile industry, the number of vehicles has increased significantly in China in the most recent decade. In June 2021, according to the Chinese government, China's number of vehicles reached 384 million with the highest historical growth rate of 32.33 % (compared to the year 2020). However, the increasing number of vehicles has deteriorated the air quality in China (Hao et al., 2007; Zhang et al., 2016; Miao et al., 2019). Xu et al. (2019) reported that vehicle volume was the most significant contributor to air pollution compared to other factors such as population density during 2005–2016 in China. The vehicle emissions, including nitrogen oxides ($NO_x = NO_2 + NO$) and volatile organic compounds (VOCs), are the essential precursors of fine particulate matter ($PM_{2.5}$) and ozone (O_3) (Wang et al., 2019; Jeong et al., 2019; Li et al., 2016; B. Liu et al., 2017; Yao et al., 2015). Although the Ministry of Ecology and Environment of the People's Republic of China (MEE) has implemented a series of strategies (such as updating vehicular emission standards) to reduce vehicle emissions in recent years, it was still the dominant contributor to $PM_{2.5}$ concentration in key regions such as Beijing–Tianjin–Hebei (BTH) in China (Gao et al., 2018). Thus, it is vital to have a comprehensive understanding of vehicle emissions, with the aim being to effectively alleviate the air pollution in China.

Vehicle emissions also cause adverse health impacts since they are a major source of $PM_{2.5}$ and O_3 (Levy et al., 2010; Zhang and Batterman, 2013; Zhang et al., 2017; Shindell et al., 2011; Y. Huang et al., 2020). Although $PM_{2.5}$ has decreased substantially in China (Zhang et al., 2019), it continues to receive substantial attention due to the strong correlation between adverse health impacts and climate change (De Kok et al., 2006; Chen et al., 2018; Xu et al., 2017; Bond et al., 2013). According to the MEE, the annual $PM_{2.5}$ concentration in China was $33 \, \mu g \, m^{-3}$ in 2020, which is still ~ 7 times the latest World Health Organization (WHO) standard (World Health Organization, 2021). Tong et al. (2020b) stated that vehicle emissions have the highest impact on public health during morning rush hour with annual premature deaths up to 4435 (95 % confidence interval (CI): 3655, 4904) in Beijing, China. Considering O_3, Cohen et al. (2017) reported that O_3 concentrations in all major Chinese metropolitan regions were at least 10 % higher than the Chinese Ambient Air Quality Standard (CAAQS) level ($160 \, \mu g \, m^{-3}$). In 2015, 47 000 (CI 95 %: 32 000 to 70 000) fewer deaths attributable to O_3 exposure were projected by the implementation of vehicle emission controls (Wang et al., 2020). In China, the transportation-attributed deaths related to $PM_{2.5}$ and O_3 in 2015 are 11 % of all sources of emissions (Anenberg et al., 2019). Therefore, it is significant to figure out the related health impacts of vehicle emissions to reduce the number of premature deaths in China.

Chemical transport models (CTMs) have been widely used to study vehicle emissions and their impacts on air quality (Liu et al., 2010; Che et al., 2011; Q. Zhang et al., 2020). Zhang et al. (2012) found that the transportation sector was an important contributor to nitrate (a major component of $PM_{2.5}$) in China by using the source-oriented version of the Community Multiscale Air Quality (CMAQ) model. However, the CTM performance highly depends on the emission inventories (Hu et al., 2016a), which may lead to uncertainties in understanding vehicle emissions. In China, the vehicle emission inventory has been developed on national, regional (Deng et al., 2020; Jiang et al., 2020), provincial (Liu et al., 2022; Y. H. Liu et al., 2017) and city levels in China (Sun et al., 2020b; Yang et al., 2019), which is essential for determining air pollution sources and making environmental control policies. The accurate temporal allocation of the vehicle emission inventory is beneficial for air quality simulation. Zheng et al. (2014) first calculated the monthly vehicle emissions in China by estimating the monthly emission factors at the county level. Sun et al. (2020a) introduced the speed correction curves to improve the simulation of vehicle emission factors. However, there are still shortcomings with temporal allocation in the development of vehicle emission inventories. First, most of the emission inventories are distributed at a monthly level (Jiang et al., 2020), without providing a robust diurnal distribution profile. Second, the emission inventory could not be updated in time and is usually available after several years of latency, offering limited help to understand the current air pollution (Zheng et al., 2021a). Third, the changes in emission rates due to traffic congestion are not considered (Liu et al., 2022), since they could not accurately reflect the temporal emission distribution in the inventory. In China, more than 80 % of cities have suffered from heavy traffic congestion that leads to substantial changes in air pollutants such as $PM_{2.5}$ and O_3 (Tong et al., 2020a; Zhang et al., 2018). Consequently, a more comprehensive temporal distribution approach of vehicle emissions is urgently required.

In this study, we used real-time traffic congestion data and the updated CMAQ model (Ying et al., 2015) to investigate the characteristics of vehicle emissions in China in 2020. The air-pollution-related premature mortality rate (from O_3 and $PM_{2.5}$) was also evaluated to determine health impacts attributed to the changes in vehicle emissions. The purposes of this study are (1) to provide a diurnal profile for vehicle emission, (2) to improve the hourly vehicle emission rates based on the real-time traffic congestion data, and (3) to determine the response of air quality and the associated health impacts from the updated emissions. This study aims to give an in-depth investigation of traffic congestion and its related air quality and health impacts, which has important implications for establishing effective control strategies in China.

2 Methods

2.1 Temporal allocation approach of vehicle emissions

The hourly temporal coefficient in the diurnal profile was estimated considering both the traffic flow and the emission rate. First, the traffic flow at the city level was calculated based on TomTom congestion-level data (collected from https://www.tomtom.com/en_gb/traffic-index/ranking/, last access: 15 September 2021). The TomTom data used GPS devices to estimate traffic congestion in a total of 404 cities across 58 countries, aiming to show how people were moving on the local and global level in real-time and over time. The TomTom congestion level (CL) describes the extra travel time as a percentage compared to the non-congestion situation, which was obtained in 22 major cities in China (Fig. S1 in the Supplement). When CL is zero, the traffic is smooth without congestion but with cars and emissions. In these 22 cities, traffic flows asymptotically to the maximum value as CL increases due to the sigmoid relationship. In this study, daily and hourly congestion-level data were collected to achieve high temporal resolution. Then, CL was converted to traffic flow using a sigmoid function – Eq. (1) from Liu et al. (2020):

$$Q = a + \frac{b \cdot CL^c}{d^c + CL^c},$$ (1)

where Q is the daily mean car counts, while a, b, c and d are empirical parameters to fit the sigmoid function without physical meanings, and their values are 100.87, 671.06, 1.98 and 6.49, respectively, according to Liu et al. (2021). In general, the vehicle emissions were proportional to the traffic flow based on TomTom data as described by Gong et al. (2017), and the temporal coefficient was calculated as Eq. (2):

$$HTC_{w,h} = \frac{Q_{w,h}}{\sum_h Q_{w,h}},$$ (2)

where $HTC_{w,h}$ is the hourly temporal coefficient (unit: %), and w means weekday or weekend, for which different traffic flows are considered separately.

Vehicle emissions were influenced by both traffic flow and emission rate (Zhang et al., 2018). During off-peak traffic hours, the emission rates were significantly lower than peak hours because vehicles were more polluting under congested conditions due to the frequent low and idle speed (Y. Zhang et al., 2020). To reflect the impact of congestion, this study used the temporal coefficient with the emission correction factor to reflect the emission changes in the peak hours as shown in Eq. (3):

$$E'_{w,ph} = E_m \times HTC_{w,ph} \times ECF_h,$$ (3)

where $E'_{w,ph}$ stands for the emission rate at peak hours (ph ranges from 00:00 to 23:00 GMT+8), E_m is the original emissions in month m, and ECF_h is the emission correction factor, determined by the driving speed from the national technical guidelines on emission inventory (Mee, 2014) (Table S1 in the Supplement). ECF values were from gasoline-type vehicles since they were the most dominant vehicle type in China (Wu et al., 2017). Our method may slightly underestimate the transportation emissions since diesel vehicles were an important contributor to NO_x emissions (Sun et al., 2018), which should be improved in the future.

2.2 CMAQ model application and validation

The CMAQ model version 5.0.1 with the updated secondary organic aerosol (SOA) formation mechanism was applied in this study (Ying et al., 2015). The mechanism incorporated a more explicit description of isoprene oxidation chemistry and isoprene SOA formation pathways. The surface uptake of dicarbonyls and isoprene epoxides, glyoxal, and methylglyoxal SOA formation pathways were all considered in the model. The simulation period was the whole year of 2020. The Weather Research and Forecasting (WRF) model version 4.2.1 was used to generate the meteorological inputs, using the high-resolution final reanalysis data from the National Centers for Environmental Prediction (NCEP; https://rda.ucar.edu/datasets/ds083.3/, last access: 2 October 2021). The WRF model setup is listed in the Table S2 in the Supplement. The anthropogenic emissions were from the Multi-resolution Emission Inventory for China (MEIC; http://www.meicmodel.org/, last access: 2 October 2021) based on the year 2020 (Zheng et al., 2021b, 2018). Due to the lack of explicit vehicle emissions in the MEIC inventory, the vehicle emissions in this study were estimated based on the on-road emission ratios of the Emissions Database for Global Atmospheric Research (EDGAR; https://edgar.jrc.ec.europa.eu/, last access: October 2021) (Crippa et al., 2020). The open burning and biogenic emissions were from the Fire INventory from NCAR (FINN) (Wiedinmyer et al., 2011) and the Model of Emissions of Gases and Aerosols from Nature version 2.1 (MEGAN2.1) (Guenther et al., 2012), respectively.

We set up three CMAQ simulation cases using different transportation emissions as summarized below: (1) the diurnal profile was determined using TomTom data, without considering the changes in emission rates due to congestion (BASE); (2) the diurnal profile was the same as the BASE case, and emission rates were adjusted using the actual speed correction coefficient from Table S1 (CASE 1); and (3) the diurnal profile was the same as the BASE case, and emission rates were adjusted under the extreme congestion condition (emission correction factors from $< 20\,km\,h^{-1}$ in Table S1; CASE 2). For CASE 1, the average speeds were 26.0 and $27.3\,km\,h^{-1}$ for workdays and weekends, respectively. As a result, the emission correction factors from the $20–30\,km\,h^{-1}$ range were used in CASE 1.

The WRF model performance is shown in Table S3 in the Supplement with observation data from the National Climate Data Center (NCDC; https://www.ncdc.noaa.gov/, last

access: 20 March 2021). Four key parameters including temperature at 2 m (T2), wind speed and wind direction at 10 m (WS and WD), and relative humidity (RH) were selected in the validation. The WRF model simulated the higher T2 in the winter but lowered T2 in other seasons, indicating the mean bias (MB) value variations. WS was slightly overpredicted for the whole year, and its gross error (GE) values all met the benchmark (Emery et al., 2001). For WD, its MB values have met the benchmark, while the GE values were 30 % larger than the benchmark. RH was slightly overpredicted in all months. Our WRF model performance was comparable to previous studies in China (Hu et al., 2016a), which could provide reasonable meteorological inputs for the CMAQ model.

The CMAQ model performance of the BASE case is shown in Table S4 in the Supplement. The observation data are from China National Environmental Monitoring Centre (CNEMC; http://www.cnemc.cn/, last access: 15 August 2021), and a total of 1600 sites are included in the validation. The CMAQ model predictions agrees well with the observations (except the O_3 in February being slightly over the criteria), which is comparable to and even better than previous studies (Hu et al., 2016b; Liu et al., 2020). Consequently, the CMAQ model provides robust results to investigate the impacts on air quality and public health from traffic congestion.

2.3   Estimation of premature mortality from air pollution

The premature mortality rate for $PM_{2.5}$-related and O_3-related diseases was estimated according to the methods as follows.

2.3.1   Estimation of $PM_{2.5}$-related premature mortality

The annual premature mortality rate due to long-term exposure to $PM_{2.5}$ from chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD), lung cancer (LC) and cerebrovascular disease (CEVD) was estimated in this study. The relative risk (RR) from Burnett et al. (2014) was used to estimate premature mortality, as shown in Eqs. (4) and (5):

$$RR = 1, \text{ for } c < c_{cf}, \tag{4}$$

$$RR = 1 + \alpha\left\{1 - \exp\left[-\gamma(c - c_{cf})^\delta\right]\right\}, \text{ for } c \geq c_{cf}, \tag{5}$$

where c is the predicted average annual $PM_{2.5}$ concentration from the CMAQ model, and c_{cf} represents the threshold concentration, below which there is no additional health risk; α, β, and γ are relevant parameters, calculated using the Monte Carlo method (including 1000 simulations) from the Global Health Data Exchange (http://ghdx.healthdata.org/, last access: 15 August 2021) as described in Guo et al. (2018). In this study, RR was calculated for people above the age of 30, and the premature mortality (ΔMort) was determined using Eq. (6):

$$\Delta\text{Mort} = y_0\left[\frac{RR - 1}{RR}\right]\text{Pop}, \tag{6}$$

where y_0 is the baseline mortality rate, obtained from the China Health Statistical Yearbook 2020 (https://www.yearbookchina.com/navibooklist-n3020013080-1.html, last access: 15 August 2021), and Pop is the population data that are from China's seventh census (http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/, last access: 15 August 2021) as shown in Fig. S1.

2.3.2   Estimation of O_3-related premature mortality

In this study, China-specific concentration–response functions (CRFs) were adapted to estimate the health impacts due to O_3 exposure (Gu and Yim, 2016; Gu et al., 2018). The relative risk of mortality with corresponding annual maximum daily 8 h average ozone (MDA8 O_3) concentrations is calculated using Eq. (7):

$$RR = \exp[\theta(c - c_{cf})], \tag{7}$$

where θ is fitted by meta-regression based on the previous epidemiological studies in China (Gu et al., 2018), and c and c_{cf} denote the average annual MDA8 O_3 concentration from the CMAQ model and the threshold value, below which there is no additional risk, respectively. The threshold concentration of MDA8 O_3 was $70\,\mu\text{g m}^{-3}$ in this study (Xie et al., 2017). The same as $PM_{2.5}$, the premature mortality rate caused by O_3 is calculated by Eq. (6), including cardiovascular diseases (CDMs), COPD, IHD and LC.

3   Results and discussion

3.1   Diurnal temporal allocation in the vehicle emissions

The congestion levels in urban China have clearly shown the workday and weekend patterns (Fig. S2 in the Supplement), which is consistent with previous studies (Wen et al., 2020; Y.-H. Liu et al., 2018). In general, the congestion levels are alleviated during the weekends. On workdays, the average congestion level is 1.4 times that on weekends. Among the 22 cities, the peak congestion level (54 %) is found at 08:00 GMT+8 on Mondays. In terms of temporal variations, the congestion levels on workdays and weekends all present the bimodal patterns with different peak hours. As a result, rush hour times are selected as 07:00–10:00 and 16:00–19:00 for workdays and 10:00–11:00 and 14:00–19:00 for weekends. Figure S3 shows the 22-city average traffic flow (Q) calculated from Eq. (1) using the TomTom congestion data. Compared with the level of congestion, the traffic flow on workdays shows a more similar result to weekends, which may underestimate the peak traffic flow on workdays. Equation (1) was derived merely based on data in Paris due to the real-time traffic data limitation (Liu et al., 2020). Particularly, congestion level and traffic flow in Beijing, Shanghai, Guangzhou and Chengdu are shown in Figs. S4 and S5. The changes in Beijing and Shanghai are roughly the same. In these two cities, traffic flows and congestion levels are higher
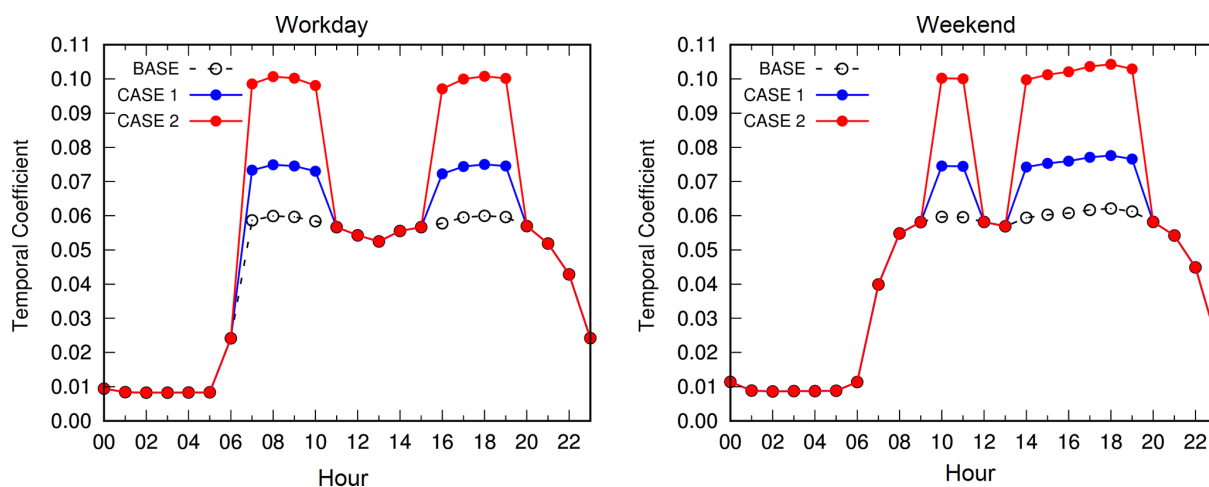
Figure 1. The VOC temporal coefficient in the hourly diurnal profile of all simulation cases on workdays and weekends.

in the morning than in the evening, which is in contrast to Chengdu and Guangzhou. In addition, the traffic flow is largest in Beijing in the morning and Chengdu in the evening. Using this equation in China may introduce additional uncertainties since each city has a specific relationship between congestion level and traffic flow. Thus, more localized traffic flow data are required to improve the accuracy of the vehicle emission inventory development.

Figure 1 shows the hourly temporal coefficient in the diurnal profile of all cases (take VOC emissions as an example, other pollutants are similar). In the BASE case on workdays, the temporal coefficient in rush hour is much lower than the congestion level, indicating the BASE case may underestimate the emission rates. The cases considering changes in emissions (CASE 1 and 2) have comparable trends to the congestion level, with the temporal coefficient larger than 0.07 in rush hour. Considering the emission changes, CASE 2 has the highest emission rate (Figs. S6 and S7). Notable increases in NO_x, VOCs and CO emissions are found in CASE 2 compared with the BASE case, especially in the areas that have a higher number of vehicles and population density, such as the North China Plain (NCP), Yangtze River Delta (YRD) and Sichuan Basin (SCB), and these increases could lead to significant impacts on air quality and public health.

3.2 Response of air quality due to traffic congestion

The air quality index (AQI) in China is determined by the concentrations of six major pollutants: $PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO. Since $PM_{2.5}$ is a major component of PM_{10} and there is no obvious change in the SO_2 emissions (Fig. S7), the changes in the other four pollutants ($PM_{2.5}$, O_3, NO_2 and CO) are discussed in this section. Figure 2 shows the concentration and changes in these four pollutants due to urban traffic congestion. According to the CMAQ re-

sults, the annual average concentrations of $PM_{2.5}$, MDA8 O_3, NO_x and CO are $\sim 35\,\mu g\,m^{-3}$, 55 ppb, 10 ppb and 0.36 ppm, respectively, in 2020. The concentrations of the $PM_{2.5}$ and MDA8 O_3 are approximately 7.0 and 1.2 times those of the WHO 2021 standard (World Health Organization, 2021), which may lead to severe health impacts. Ubiquitously, the peak values of these pollutants are predicted in the NCP and SCB regions, with the annual average $PM_{2.5}$ higher than $60\,\mu g\,m^{-3}$. In addition, traffic congestion has aggravated air pollution across China, which is consistent with the previous study (Xu et al., 2019). Among all simulated cases, CASE 2 (extreme congestion conditions) has the highest pollutant level. The significant enhancements in these pollutants (compared to the BASE case) are simulated in NCP and SCB. The maximum increases in $PM_{2.5}$ and O_3 are $3.5\,\mu g\,m^{-3}$ and 1.1 ppb, respectively. Our simulation was conducted in 2020, covering the COVID-19 lockdown period. During the lockdown, a drastic decrease was reported in traffic flow ($\sim 70\%$), which may even eliminate the traffic congestion and its impacts on air quality (X. Huang et al., 2020; Zheng et al., 2021b). More remarkable changes in air quality associated with the traffic congestion are expected during the normal year.

$PM_{2.5}$, NO_2 and CO have lower concentrations on weekends than on workdays (Fig. S8 in the Supplement), similar to previous studies (Y.-H. Liu et al., 2018; Wen et al., 2020; Bao et al., 2016), which is partially attributed to the lower anthropogenic emissions on weekends. Significant decreases on weekends are predicted in the NCP and the SCB regions. In the NCP region, the reduction in $PM_{2.5}$ is up to $6.0\,\mu g\,m^{-3}$. In contrast, the rising trend of O_3 occurred on weekends, which is consistent with previous studies (Wang et al., 2021b; Zhao et al., 2019; Wang et al., 2021a). The elevated O_3 is attributed to the reduced NO_x emissions on weekends, which promoted the formation of O_3 under a VOC-limited regime
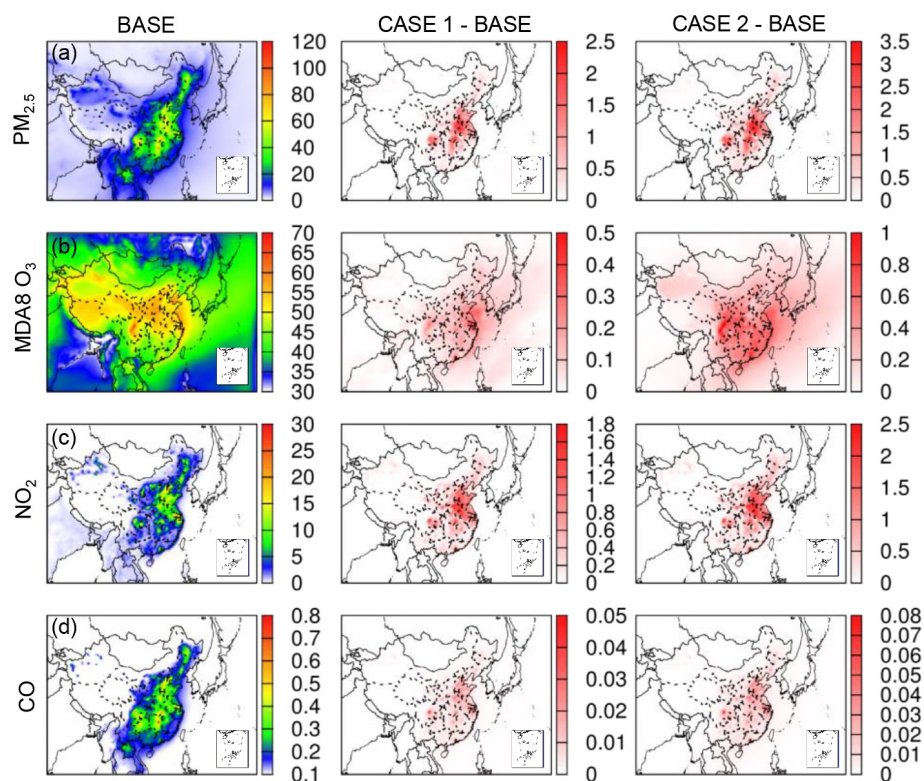
Figure 2. The annual average concentrations of **(a)** $PM_{2.5}$, **(b)** MDA8 O_3, **(c)** NO_2 and **(d)** CO of BASE case, as well as their differences from CASE 1 and CASE 2 in 2020. The unit for $PM_{2.5}$ is micrograms per cubic meter ($\mu g\,m^{-3}$), for MDA8 O_3 and NO_2 parts per billion (ppb), and for CO parts per million (ppm).

and reduced the titration impacts (Li et al., 2019; Blanchard and Tanenbaum, 2003).

To further investigate the traffic congestion impacts on air quality in urban areas, four representative megacities are selected (Fig. S1): Beijing (NCP), Shanghai (YRD), Guangzhou (PRD) and Chengdu (SCB). Except for Shanghai, the traffic congestion (CASE 2) enhances the $PM_{2.5}$ concentration during the morning and evening rush hour times (Fig. 3). The peak of $PM_{2.5}$ always occurred in the morning or evening rush hour, indicating the important role of the traffic congestion in the $PM_{2.5}$ formation (Tong et al., 2020a). Different workday–weekend patterns are also found in these megacities. The most obvious weekend impact is in Guangzhou with more than 30 % of $PM_{2.5}$ reduced in the morning peak hours (compared to workdays). Interestingly, in Shanghai a slightly rising $PM_{2.5}$ concentration is predicted on weekends, resulting from the changes in emissions and regional transport during weekends and weekdays (Atkinson-Palombo et al., 2006; Mönkkönen et al., 2004). A similar phenomenon was also reported in Nanjing (Shen et al., 2014), another megacity in the YRD region. For all these megacities, the lower NO_2 concentrations on weekends lead to slightly higher O_3 (Figs. S9–S12).

3.3 The aggravated health burden due to traffic congestion

The traffic congestion leads to more severe health impacts throughout China. As shown in Table 1, the total estimated $PM_{2.5}$-related annual premature deaths are 0.90, 0.91 and 0.92 million for BASE, CASE 1 and CASE 2, respectively. The extreme congestion (CASE 2) has induced an average 1.7 % increase in the total premature mortality rate in China. The CEVD is the most important contributor to total premature mortality, followed by IHD. When considering the extreme congestion situation (CASE 2), the CEVD and IHD cause 0.51 and 0.24 million deaths, respectively, amounting to 81 % of the total premature mortality. In China, the high annual premature mortality rate due to excess $PM_{2.5}$ is estimated in regions with the higher $PM_{2.5}$ concentrations or population density, such as the NCP and PRD regions (Figs. 4 and S13). This result is comparable with previous studies (Guan et al., 2019; Xie et al., 2016; Maji et al., 2018). More severe health impacts due to traffic congestion are also predicted in these regions. It is noted that in the PRD, the annual average $PM_{2.5}$ concentration is $\sim 20\,\mu g\,m^{-3}$ (57 % of the national average value), but the region still experiences serious health risks, mainly attributed to the surge in population density. The population in Guangdong province (where
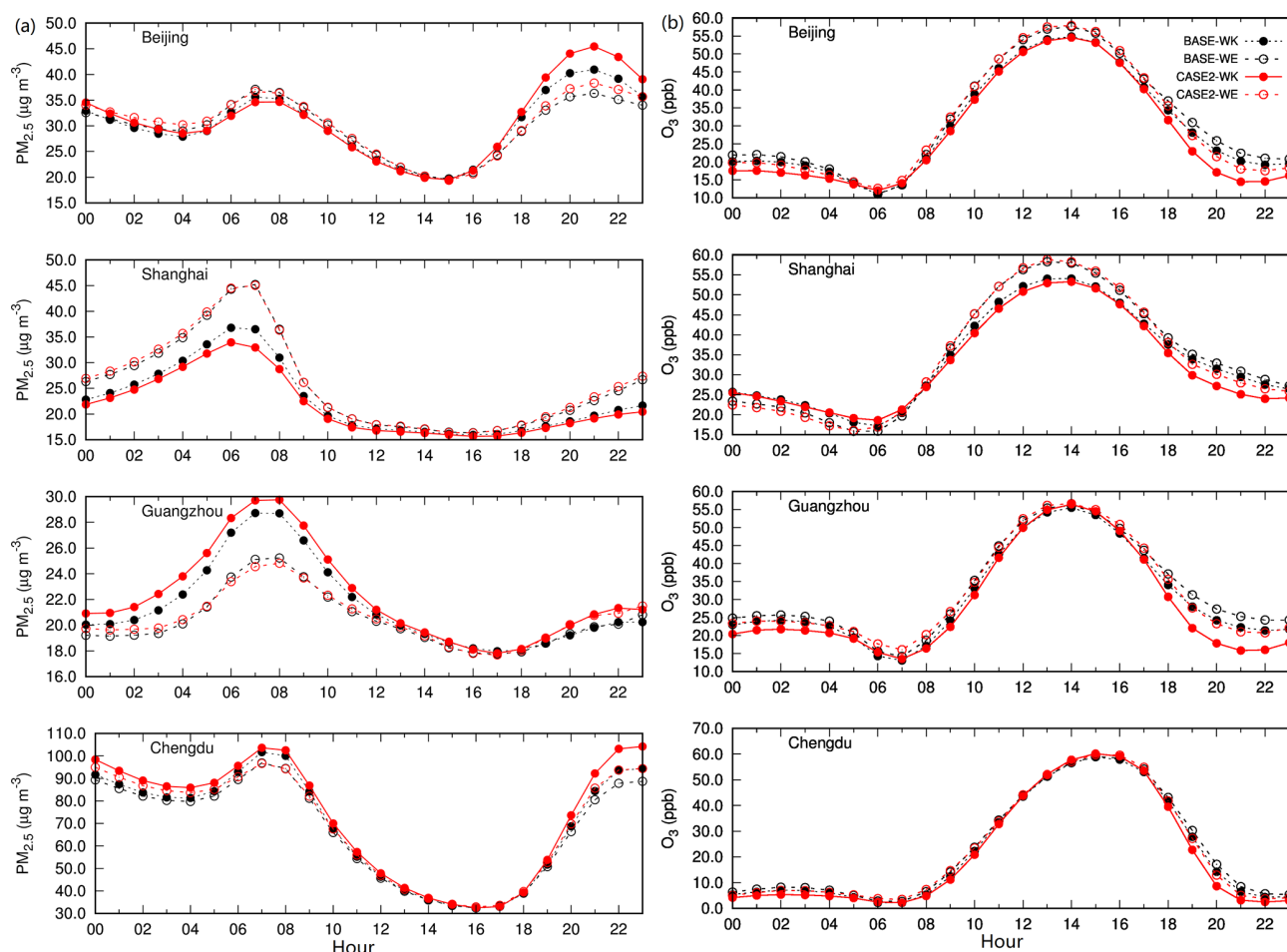
Figure 3. The diurnal profile of PM$_{2.5}$ and O$_3$ concentrations of BASE (without considering congestion) and CASE 2 (considering congestion) in Beijing, Shanghai, Guangzhou and Chengdu. WK: workday; WE: weekend.

Table 1. Annual premature deaths ($\times 10^4$ deaths) in China due to COPD, LC, IHD, CDM and CEVD for all simulations.

PM$_{2.5}$-related	COPD	LC	IHD	CEVD	Total
BASE	8.93	8.43	24.15	49.17	90.68
CASE 1	9.03	8.54	24.28	49.74	91.60
CASE 2	9.10	8.61	24.44	50.09	92.24
O$_3$-related	COPD	LC	IHD	CDM	Total
BASE	4.53	3.30	8.18	25.34	41.35
CASE 1	4.55	3.31	8.21	25.47	41.54
CASE 2	4.58	3.34	8.27	25.72	41.91

the PRD region is located) increased by 21.7 million from 2010 to 2020, ranking first in China (http://www.stats.gov.cn/tjsj/tjgb/rkpcgb/, last access: 2 October 2021). Thus, the establishment of emission control policies in the future should also refer to the socioeconomic development level in addition to the pollution level.

As cities are mostly affected by traffic congestion, representative cities from each province in mainland China except Lasa in Tibet were selected to compare the differences among regions. The most significant response to PM$_{2.5}$-related health impacts due to the traffic congestion is in Beijing, with an additional 120 annual deaths (Fig. 4). In Chengdu and the major cities in the YRD (Shanghai, Suzhou and Nanjing), traffic congestion also negatively impacts public health. Surprisingly, in Sanya the increase in PM$_{2.5}$-related premature mortality is estimated as high as 17.5 % (Fig. S1), which is much higher than that of most megacities. On workdays and weekends, the CEVD is the most significant contributor to the PM$_{2.5}$-related health burden in megacities (Fig. 6). Except for Shanghai, all megacities (Beijing, Guangzhou and Chengdu) have lower mortality on weekends, coinciding with a previous study (Tong et al., 2020a). However, in Shanghai, a 14 % increase in PM$_{2.5}$-related daily mortality on weekends is estimated due to the higher PM$_{2.5}$ concentration.
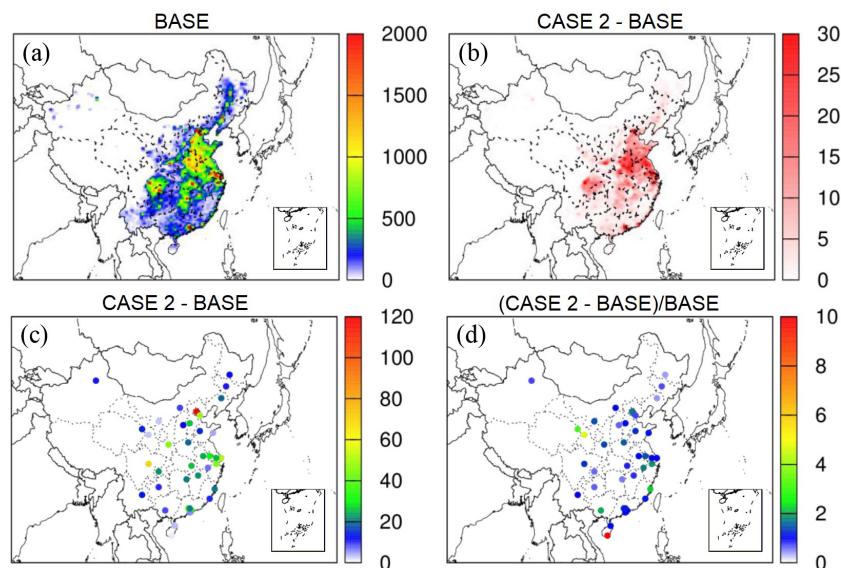
Figure 4. The total $PM_{2.5}$-related premature mortality rate of **(a)** BASE case and its difference from CASE 2 across China **(b)** and in major cities **(c, d)**.
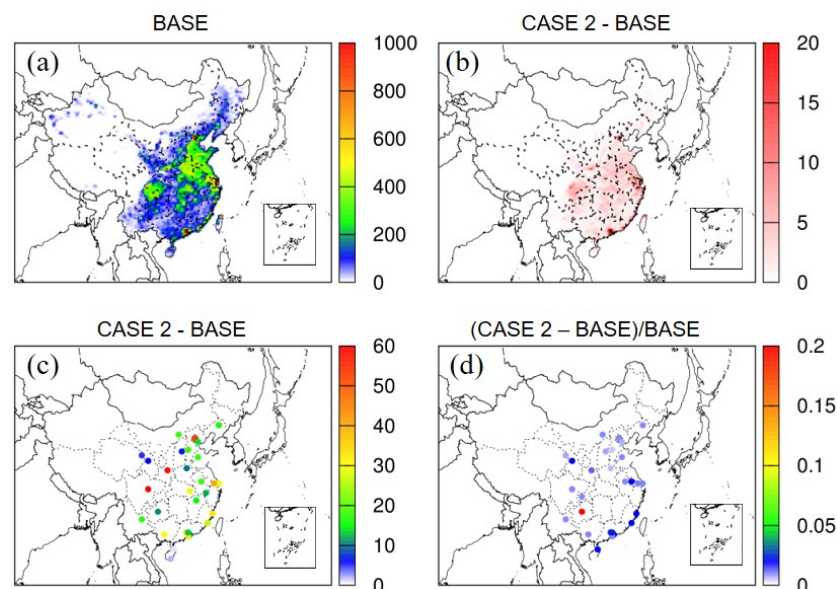

Figure 5. The total O_3-related premature mortality rate of **(a)** BASE case and its difference from CASE 2 across China **(b)** and in major cities **(c, d)**.

As for O_3, the total estimated O_3-associated annual premature deaths are 0.414, 0.415 and 0.419 million for BASE, CASE 1 and CASE 2, respectively. The extreme congestion leads to an average 1.4 % increase in the total premature mortality rate in China. CMD became the major disease rather than IHD. In CASE 2, with the extreme congestion situation considered, the CEVD and IHD cause 0.26 and 0.08 million deaths, respectively, amounting to 81 % of the total premature mortality. In China, the high annual premature mortality rate due to excess O_3 is estimated in the YRD and PRD re-

gions (Figs. 5 and S14). This result is consistent with previous studies (H. Liu et al., 2018; Chen et al., 2021).

Unlike $PM_{2.5}$, in the city level, the most significant O_3-related health impacts due to traffic congestion are in Chongqing, where 139 deaths are added each year (Fig. 5). In Chengdu, Beijing, and the major cities in the YRD (Suzhou, Shanghai) and PRD (Foshan), negative public health impacts of excess O_3 are also associated with traffic congestion. An average of 46 deaths are added in these regions as estimated in this study. In Beijing, the O_3-related premature mortality
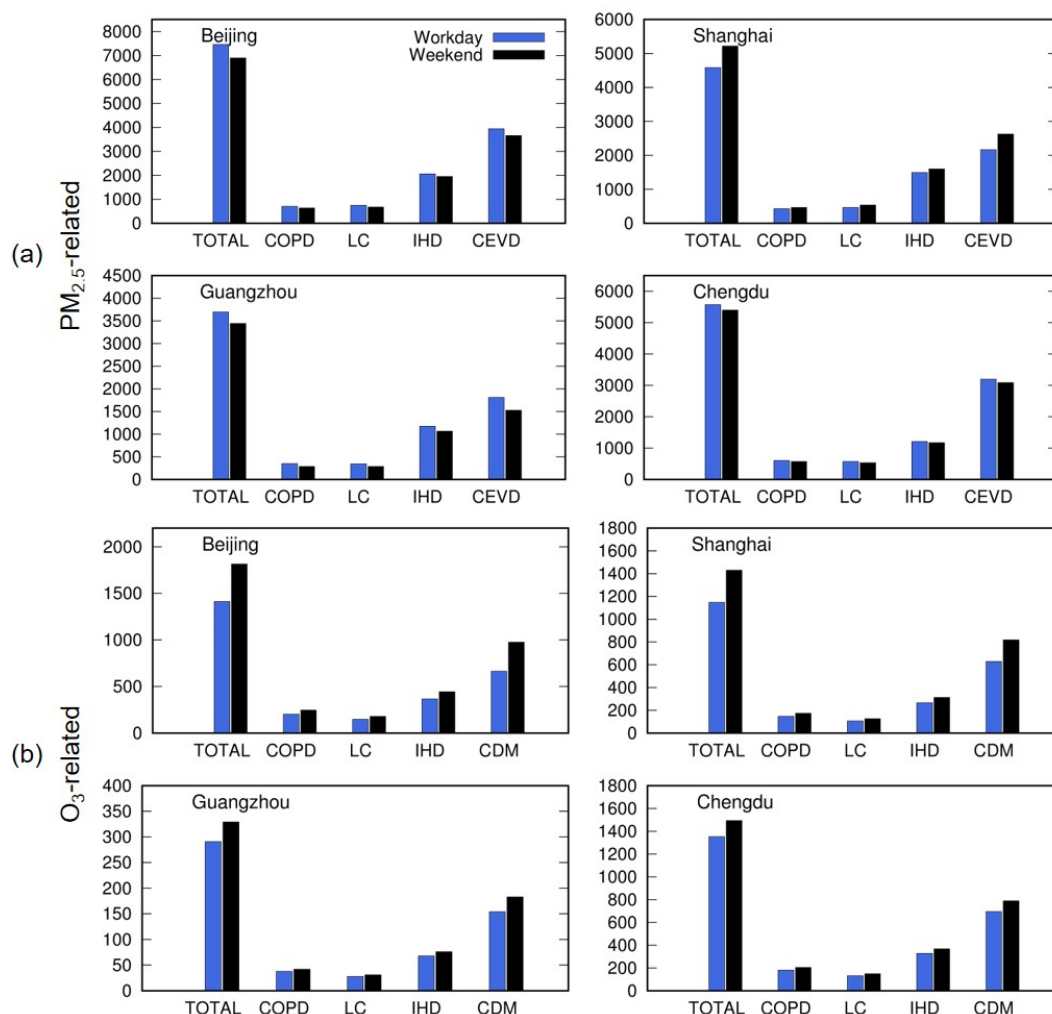
Figure 6. The annual premature mortality rate from COPD, LC, IHD, CDM and CEVD of CASE 2 in Beijing, Shanghai, Guangzhou and Chengdu. Panel **(a)** is $PM_{2.5}$-related and **(b)** is O_3-related.

rate increases by 1.1 %. This result is comparable to Zhong et al. (2017), in which emergency ambulance call rates related to heart disease were higher by 2.9 % in Beijing, when the traffic congestion index increased by 20 %. Traffic congestion causes more O_3 precursor emissions to be produced, which raises O_3 concentration and aggravates health risks, in agreement with previous studies (Bigazzi et al., 2015; Ahmad and Aziz, 2013; Wang et al., 2021a). Thus, more effective vehicle control regulation in urban areas should be considered to avoid premature death from air pollution. In addition, CDM is the major contributor to the O_3-related health burden on workdays and weekends. On weekends, mortality is higher for all diseases (CDM, COPD, LC and IHD) in these cities (Beijing, Shanghai, Guangzhou and Chengdu), resulting from the O_3 weekend effect (Zeldin et al., 1989; Tang et al., 2008) (Fig. 6). In Beijing, the mortality rate on weekends is 33.6 % higher than on weekdays and 47.0 % for CDM in particular.

3.4   Uncertainty discussion

In this study, there are some uncertainties in the temporal allocation approach, involving two variables: traffic flow and emission rate. The traffic flow is calculated by using Eq. (1), which is derived based on the observation data in Paris due to data limitations (Liu et al., 2020). Thus, it may not entirely reflect the actual traffic flow in China, and it introduces uncertainties in the following CMAQ simulations. Besides, the emission rate changes only depend on the driving speed in this study, which could cause deviation. The emission rate is influenced by various factors, such as meteorological conditions, geographical conditions, fuel quality, deterioration level, load rating and driving conditions (Sun et al., 2021). However, it is challenging to incorporate all these factors into the emission rate correction on such a national scale. Therefore, further efforts should be made to reduce the uncertainties in the vehicle emission inventory.

4 Conclusions

In this study, we develop a new temporal allocation approach to transportation emissions to investigate traffic congestion responses to air quality and health impacts in urban China. The real-time congestion data from TomTom are used to generate the hourly diurnal temporal profile of the vehicle emissions, and emission correction factors are applied to qualify the emission rate changes corresponding to the traffic congestion. Our results show that traffic congestion increases pollutant concentrations, especially in the highly developed urban clusters such as the NCP and SCB. The annual average increases in $PM_{2.5}$, MDA8 O_3, NO_2 and CO are up to $3.5\,\mu g\,m^{-3}$, 1.1 ppb, 2.5 ppb and 0.1 ppm, respectively. In addition, the rising $PM_{2.5}$ and O_3 concentrations attributed to traffic congestion also enhance the health burden across China. Compared to the BASE case, the extreme congestion condition (CASE 2) results in an additional 20 000 ($PM_{2.5}$-related) and 5000 (O_3-related) premature deaths in China. Similar to the phenomenon in air quality, the remarkable increases are estimated in the urban clusters with a higher population density. Therefore, more effective and comprehensive vehicle control policies that consider socioeconomic factors should be implemented to alleviate China's air pollution and health burden in the future.

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