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Assessing the recent impact of COVID-19 on carbon emissions from China using domestic economic data

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Abstract

The outbreak of coronavirus disease 2019 (COVID-19) has caused tremendous loss to human life and economic decline in China and worldwide. It has significantly reduced gross domestic product (GDP), power generation, industrial activity and transport volume; thus, it has reduced fossil-related and cement-induced carbon dioxide (CO_2) emissions in China. Due to time delays in obtaining activity data, traditional emissions inventories generally involve a 2-3-year lag. However, a timely assessment of COVID-19's impact on provincial CO_2 emission reductions is crucial for accurately understanding the reduction and its implications for mitigation measures; furthermore, this information can provide constraints for modeling studies. Here, we used national and provincial GDP data and the China Emission Accounts and Datasets (CEADs) inventory to estimate the emission reductions in the first quarter (Q1) of 2020. We find a reduction of 257.7 Mt CO_2 (11.0%) over Q1 2019. The secondary industry contributed 186.8 Mt CO_2 (72.5%) to the total reduction, largely due to lower coal consumption and cement production. At the provincial level, Hubei contributed the most to the reductions (40.6 Mt) due to a notable decrease of 48.2% in the secondary industry. Moreover, transportation significantly contributed (65.1 Mt), with a change of -22.3% in freight transport and -59.1% in passenger transport compared with Q1 2019. We used a point, line and area sources (PLAS) method to test the GDP method, producing a close estimate (reduction of 10.6%). One policy implication is a change in people's working style and communication methods, realized by working from home and holding teleconferences, to reduce traffic emissions. Moreover, GDP is found to have potential merit in estimating emission changes when detailed energy activity data are unavailable. We provide provincial data that can serve as spatial disaggregation constraints for modeling studies and further support for both the carbon cycle community and policy makers.

Key words: CO_2 decrease; COVID-19; Gross domestic product; Transport; Inventory

1 Introduction

China’s fossil fuel combustion and industrial processes contribute more than 25% to total global CO_2 emissions (Friedlingstein et al., 2019). Largely due to the rapid increase in gross domestic product (GDP), China’s CO_2 emissions experienced a period of rapid increase prior to 2013, and since then, except for 2017, they have decreased (Shan et al., 2020;Guan et al., 2018). The traditional method for developing an emissions inventory generally involves a 2-3-year time lag due to the delayed availability of activity data (Friedlingstein et al., 2019;Le Quéré et al., 2020). This lag is a major obstacle in situations where near-real time emissions estimates are needed.

An alternative method is to use the GDP change rate to reflect CO_2 emissions (Jenny and Sara, 2016;Wang et al., 2019;Sarkodie and Owusu, 2017;Tucker, 1995). Compared to fuel consumption data, GDP data are more readily available as a near-real time index, especially at the subnational level, where there is a greater lag in publishing statistical data. Since CO_2 emissions mainly come from the secondary industry, which includes subsectors such as power, industry processes and cement production that emit a large proportion of CO_2, the growth rate of the secondary industry plays an important role in shaping the total changes in CO_2 emissions.

Coronavirus disease 2019 (COVID-19) has caused great loss of human life and has impacted all other socio-economic-environmental aspects of life, including global CO_2 emissions (Le Quéré et al., 2020;Epidemiology Team, 2020). Since the Wuhan lockdown on January 23, 2020, China has implemented a series of strict measures, including temporarily stopping public transport, restricting the free flow of workers, and confining residents to their homes, to combat the virus. These measures have also represented a great economic sacrifice. This shrinkage in economic activity has been accompanied by a lower consumption of fossil fuel and decreases in industrial processes that emit CO_2 (Le Quéré et al., 2020;Sarkodie and Owusu, 2017;Wang et al., 2020;Wang et al., 2019); thus, CO_2 emissions have certainly dropped compared to the same period in the previous year.

However, few studies have been conducted on the decrease in China's CO_2 emissions associated with the COVID-19, especially at the provincial level (Le Quéré et al., 2020;IEA, 2020;Liu et al., 2020). A few studies and news reports indicate that the decrease might have temporarily reached 25% (Myllyvirta, 2020;IEA, 2020). In this study, we collected national and provincial GDP and transport data and used the GDP method to calculate the emission decrease in China at both the national and provincial levels for the first quarter (Q1) of 2020. We then used a point, line, and area sources (PLAS) method to test this approach. The data can help in understanding the magnitude of the emission decrease due to the COVID-19 lockdowns and provide information to help policy makers promote the local economy and develop emission reduction policies.

2 Data and Methods

2.1 Data

Statistical GDP data at the national and provincial levels were derived from databases and news releases provided by the National Bureau of Statistics of China

(NBS) and provincial statistics bureaus (see Table S1 for details). Sectoral growth rate data were derived from the Beijing, Tianjin and Hebei statistics bureaus. Provincial transportation data (freight and passenger distance traveled and change rates) were obtained from the Ministry of Transport of the People's Republic of China (MOT) (MOT, 2020), and the Hubei data were derived from the Department of Transportation of Hubei Province. Quarterly GDP deflator data were from both the NBS (NBS, 2020b) and the World Bank; GDP (deflator) was calculated using price index deflation (NBS, 2013). This method means directly deflating value-added at the current price using the relevant price index and calculating value-added at a constant price, which is shown as follows:

Value-added at the constant price of a certain industry = value-added at the current price of the industry ÷ price index of the industry.

Data on daily coal consumption for six main power groups from 2011 to 2020 were derived from the Wind database (https://www.wind.com.cn/).

Along with the change in quarterly GDP (deflator) for the three industry categories, we also need a baseline inventory of CO_2 emissions with the same classification. We used 2017 annual provincial CO_2 emissions data from the China Emission Accounts and Datasets (CEADs) inventory because it offers local optimized emission factors for coal and timely updates (Shan et al., 2020;Shan et al., 2017). Additionally, we used the GDP deflator scaling factor (0.25, the ratio of Q1 2019 to 2017 full year) to obtain the Q1 2019 baseline emissions (Table S4, S5). The CEADs inventory provides emissions data for 51 subsectors for 2017, and its classification is presented in Table S2. We treat urban, rural and other subsectors (mainly residential and commercial emissions) as the tertiary industry due to their similarities. We further updated the results to 2020 Q2 regarding national and province-level GDP, the corresponding CO_2 emission reductions, ground transport data, daily coal consumption data and the confirmed number of cases and presented them in both the main text and supplementary materials (Figure S1-S12).

2.2 Methods

2.2.1 GDP scaling method

Previous studies have demonstrated that per capita CO_2 emissions have a positive linear relationship with per capita GDP, especially in developing countries (Wang et al., 2019;Jenny and Sara, 2016), as shown in Figure S1. In a short time span of two years or several quarters, assuming that the population does not change drastically, CO_2 emissions are well associated with GDP (Eq. 1) (Jenny and Sara, 2016). We assumed that the emission factor for each of the industry categories remains unchanged from the 2019 level in 2020. Using the "Industrial Classification for National Economic Activities" (GB/T 4754-2017) (NBS, 2017) and considering the actual situation in China, the first classification level directly adopts the Three Industries Classification Regulations enacted in 2003 by the NBS, with division into the primary industry, secondary industry and tertiary industry. The primary industry refers to farming, forestry, animal husbandry and fishery. The secondary industry refers to the mining industry; the manufacturing industry; the electricity, heat, gas and water production and supply industries; and construction. The tertiary industry refers to industries other than those belonging to the primary and secondary industries.

$$CO_2 \text{ emissions}=\Sigma[\text{Activity data}(GDP)_i \times EF_i] \qquad (\text{Eq. } 1)$$

where i equals the three major sectors: the primary industry, secondary industry, and tertiary industry. See the detailed classification in the references (NBS, 2013, 2019):

GDP refers to the gross domestic product of industry i;

EF refers to the emission factors of industry i.

Assuming that the EF_i is maintained at the same level, the CO_2 decrease can be calculated as follows:

$$\Delta CO_2 \text{ emissions} =\Sigma[\text{Change rate of } GDP_i \times CO_2 \text{ emissions}_i] \qquad (\text{Eq. } 2)$$

We further separated the tertiary industry into two subsectors, transport and nontransport, due to their different emissions features. A drastic decline in the transport sector (Le Quéré et al., 2020;MOT, 2020) and detailed distance traveled data can be obtained from the MOT. For the nontransport sector, we used the GDP method described above.

2.2.2 Transport scaling method

For the transport sector, we used the change rates in the provincial total distance traveled data obtained from the MOT as scaling factors.

$$\Delta CO_2 \text{ emissions}_{\text{Transport}} = \text{Change rate of distance traveled} \times CO_2 \text{ emissions}_{\text{Transport}} \qquad (\text{Eq. } 3)$$

The transport-reduced emissions are combined with the nontransport results to yield the final estimate.

2.2.3 Testing the GDP method using a point, line and area sources method (PLAS)

We next used the PLAS method to test the results estimated with the GDP method. The validation data for the Beijing-Tianjin-Hebei region inventory are from the Energy Research Institute of the National Development and Reform Commission. This inventory provides the emissions shares of point, line and area sources for Beijing, Tianjin and Hebei, respectively. We reclassified the sector growth rate into the PLAS from the Beijing, Tianjin and Hebei statistics based on data availability. We used industry data, the statistical traffic data obtained from the MOT and tertiary industry data as point sources, line sources and area sources, respectively.

ΔCO_2 emissions $=\Sigma$[Change rate of emissions $_{\text{type i}}$*CO_2 emissions $_{\text{type i}}$] (Eq. 4)

where type i represents the three major types: the point, line and area sources, which here refer to power and industry; traffic; and the service industry, residential activities and commercial activities, respectively.

3 Results and Discussion

3.1 National-level CO_2 emission decrease

The estimated total CO_2 emissions decreased by 257.7 million tons (Mt) (11.0%) for Q1 2020 compared with Q1 2019, which is consistent with the decreases obtained by Le Quéré et al. (2020) (242 Mt) and Liu et al. (2020) (260 Mt). Both of these studies concentrated on global and national estimates and time disaggregation into daily units using proxy data, and the differences between these studies ranged from 1% to 7%. The consistent estimates were largely due to the similar activity data from the NBS that were used. The secondary industry contributed the majority of the decrease (186.8 Mt), and the tertiary and primary industries contributed 70.0 Mt and 0.9 Mt to the decrease, respectively (Figure 1, a). Their contributions are largely determined by the characteristics of emissions and, thus, the emissions shares of each major sector. In the CEADs inventory, the secondary industry contributes 83.7% to total emissions, while the tertiary and primary industries contribute 15.2% and 1.1%, respectively. The secondary industry includes power and cement production, both of which are sectors that produce large emissions, contributing ~40% to total emissions (Liu et al., 2015b;Shan et al., 2020;Liu et al., 2015a;Lei et al., 2011;Liu et al., 2020). Power and cement production saw decreases in production of 8.4% and 23.9% in Q1 2020 (NBS, 2020b) and 13.5% and 29.5% in the first two months of Q1 2020, respectively (NBS, 2020a). These results are consistent with those of Le Quéré et al. (2020), Myllyvirta (2020) and Liu et al. (2020), who found that power and industry coal consumption decreased by 6.8% and 23.6%~30%, respectively. The GDP change rate for the secondary industry was -9.6% for Q1 2020, even though the total GDP change rate was -6.8% (Figure 1, b). This reason may be why the calculated CO_2 decrease was higher than the mean GDP change rate, indicating that COVID-19 mainly influenced industrial production through the “safer at home” orders by governments. This situation is different from the 2008 financial crisis, when GDP decreased by 1.7% in 2009 (World Bank, 2020), while CO_2 emissions fell by only 1.4% (Friedlingstein et al., 2019). The financial crisis mainly impacted finance-related sectors that do not release the same level of CO_2 as the secondary industry, and after the crisis, emissions rebounded quickly (Le Quéré et al., 2020), and the rebound was much slower during Q2 2020 (Figure S1 and S10, S2 and S11). Regarding the uncertainty, the GDP activity data obtained from the NBS have a difference from the provincial total and the national total of 0.1%-7.4% (NBS, 2020); thus, the maximum error derived from GDP can reach 7.4% or 19.1 Mt CO_2. The assumption underpinning the emission factors for the three major sectors may also introduce a slight uncertainty. Such an uncertainty is difficult to quantify but is likely to be smaller than the uncertainty derived from GDP. Moreover, as pointed out by recent studies, a rebound in economic activity caused by stimulus packages issued by governments (Sarkodie and Owusu, 2020a) may ultimately lead to more CO_2 emissions (Le Quéré et al., 2020). In general, the decreases in emissions as a result of previous economic crises were only temporary, with a fast rebound in emissions and emissions levels reaching even higher than the previous average in the postcrisis period (Peters et al., 2012). Thus, when planning and implementing economic stimulus, governments need to consider the environmental effects by more strongly prioritizing low-carbon methods.

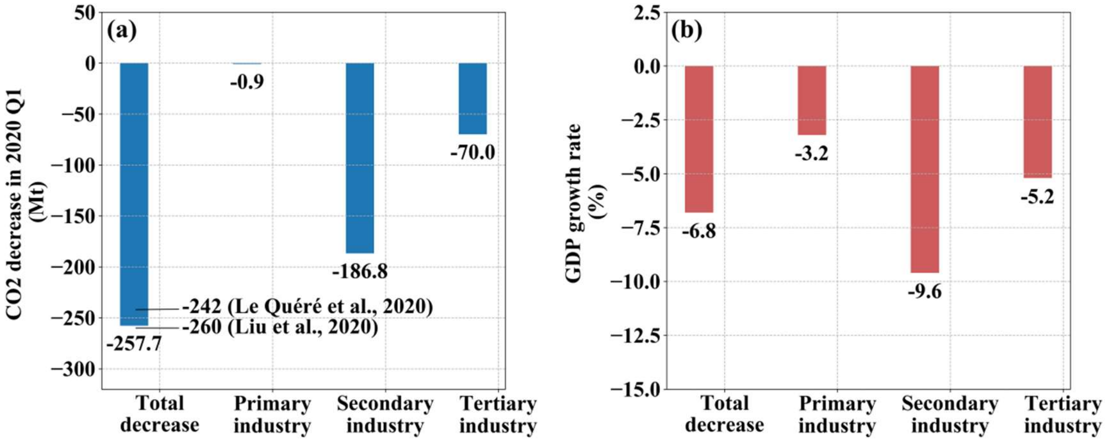
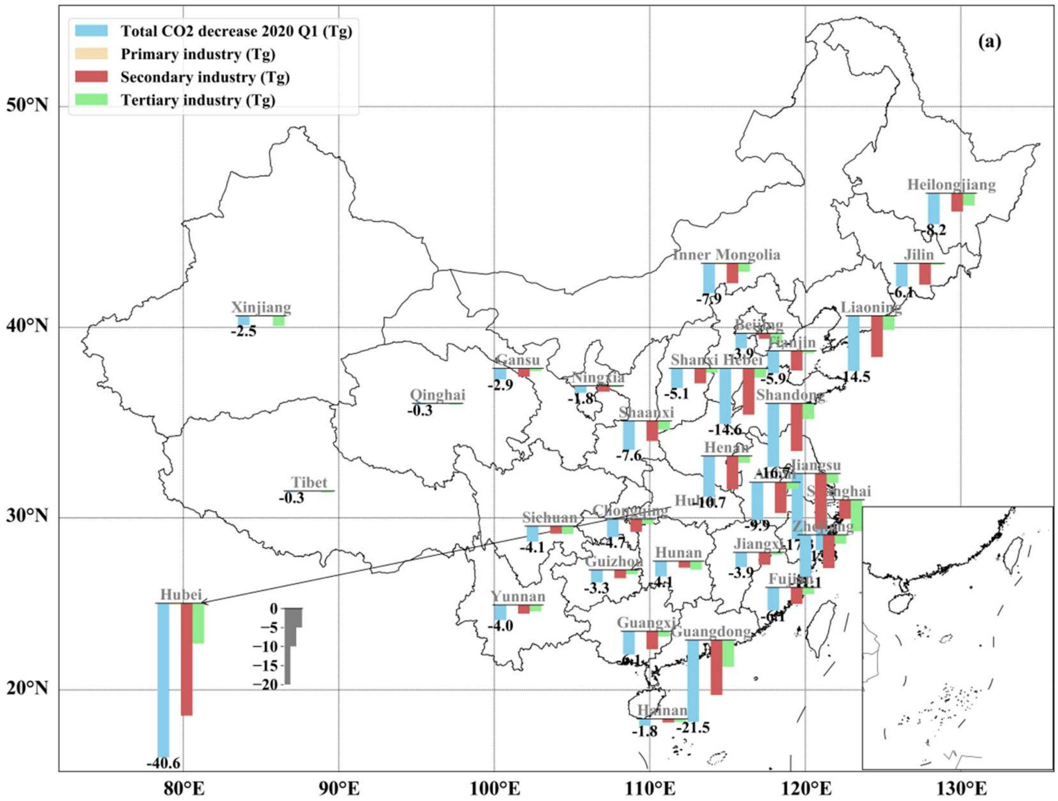


Figure 1. China's CO_2 emission decrease in Q1 2020 (a) and GDP growth rate (b) compared to Q1 2019.

3.2 Spatial pattern of the CO_2 emission decreases at the provincial level

The spatial distribution of the CO_2 emission decrease was closely related to the severity of the impacts of COVID-19 (Figure 2 and Figures S2 and S3). A linear relationship was found between the $\log_{10}$ of the total number of confirmed cases and the CO_2 emission reduction (Figure S3, R^2=0.61), while a similar linear relationship was found between COVID-19-attributable deaths and confirmed cases (Sarkodie and Owusu, 2020b), indicating the direct impact of the number of confirmed cases in regard to both human health and socio-economic activity. As expected, Hubei Province showed the largest CO_2 decrease, 40.7 Tg (or 44.4%) (Figure 2, Figure S4, Table S3), which corresponds to the 48.2% decrease in secondary industry GDP. The lockdown from January 23 to April 8 caused by COVID-19 was not limited to Wuhan, and all prefecture-level cities in Hubei Province were locked down before January 25. The CO_2 emission decreases in Guangdong, Jiangsu, and Shandong were 21.6, 17.3 and 16.8 Tg, respectively (Figure 2, a, Table 1); correspondingly, the secondary industry GDP change rates were -8.8%, -7.1% and -14.1%, respectively (Figure 2, b). These three provinces were all high emissions contributors (Shan et al., 2020). The provinces in the North China Plain and Eastern China also had noticeable declines of 10-15 Tg (Figure 2, a, Table 1), resulting from a 10%~20% decrease in secondary industry GDP (Figure 2, b). In contrast, the central and southern provinces mostly saw decreases in CO_2 emissions of 0-5 Tg at a secondary industry GDP change rate of less than -10%. In Western China, where the impact of COVID-19 was small, the influence on economic and industrial production was also slight, with CO_2 emissions in Qinghai Province dropping by only 0.3 Tg (or 1.0%). Taking the Q2 2020 into account, most provinces showed a less reduction due to the recovery of economy (Figure S4 and S5). Moreover, at the provincial level, there was a significant linear relationship (p value<0.001) between the CO_2 emission decrease and $\log_{10}$ of the total number of confirmed cases (Figure S3). Although Le Quéré et al. (2020) and Liu et al. (2020) reported national and major sector decreases, here, we present spatial decreases at the provincial level. Considering the homology of CO_2 with NO_2, our results had spatial patterns consistent with those of Bauwens et al. (2020) and Huang et al. (2020). Both of these studies showed 40%~60% reductions in NO_2 based on Tropospheric Monitoring Instrument (TROPOMI), Ozone Monitoring Instrument (OMI) and ground-based monitoring for the North China Plain and Eastern China. Moreover, Collivignarelli et al. (2020) found a significant reduction in most pollutants (PM_{10}, $PM_{2.5}$, BC, benzene, CO and NO_x) during the lockdown in Milan. This result is also consistent with that of Bashir et al. (2020) , who showed that pollutants including PM_{10}, $PM_{2.5}$, SO_2, NO_2, and CO are significantly correlated with the total number of confirmed cases and associated deaths in California. Furthermore, Fattorini and Regoli (2020) found that the total number of confirmed cases is positively correlated with chronic air pollution in Italy. Long-term air-quality data (NO_2, O_3, $PM_{2.5}$ and PM_{10}) significantly correlated with cases of COVID-19 in 71 provinces, indicating that chronic exposure to atmospheric contamination may represent a favorable context for the spread of the virus. Reductions in CO_2 emissions were also found to be significantly correlated with the total number of confirmed cases at the province level in this study (Figure S3). However, the decrease signals may be too weak to be detected by ground-based CO_2 concentration monitoring (Kutsch et al., 2020;Ott et al., 2020) and satellite-based column CO_2 observations (Schwandner et al., 2017) due to the mask of natural variability from a “noisy” global carbon cycle and meteorology (Le Quéré et al., 2020;Kutsch et al., 2020;Peters et al., 2017;Ballantyne et al., 2012).

Moreover, we tested the GDP estimation results by the PLAS method. We take the Beijing-Tianjin-Hebei regions as an example. The CO_2 emission decreases for Beijing, Tianjin and Hebei estimated by the PLAS method were 5.8, 4.9, and 11.0 Tg (totaling 21.8 Tg), respectively (Figure S6), while the GDP method obtained values of 4.0, 5.9, and 14.6 Tg (total 24.5 Tg, Table 1), respectively, for differences of 32.4%, 18.5%, and 32.6% (totaling 12.0%), respectively. Specifically, the decreases in the point, line and area sources were 2.2, 3.1, and 0.5 Tg for Beijing; 4.1, 0.4, and 0.5 Tg for Tianjin; and 8.9, 1.0, and 1.2 Tg for Hebei. Although these two methods used different assumptions and data, they produced reasonably consistent results, with a mean difference of 12.0%. Moreover, due to the lack of a detailed change rate for the PLAS sector data (e.g., power and industry data) for Q1 2020, Beijing showed a larger difference than Tianjin and Hebei.



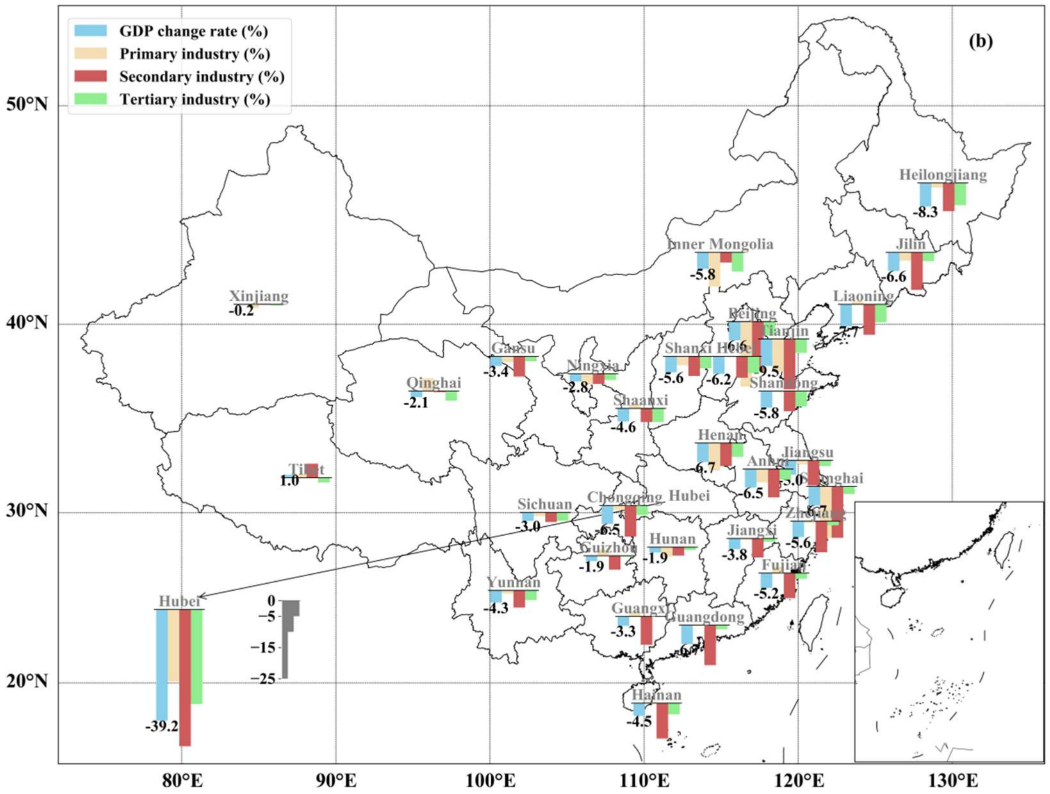


Figure 2. Provincial CO_2 emission decreases in Q1 2020 (a) and GDP change rates (b) compared to Q1 2019.

Table 1. Province-level CO_2 emission reductions (Tg) in major sectors and subsectors for 2020 Q1 compared with 2019 Q1.

Province	Total CO_2 reductions	Primary industry	Secondary industry	Tertiary industry	Subsector of the tertiary industry: Transport	Subsector of the tertiary industry: Nontransport
Beijing	4.0	0.0	1.4	2.5	2.2	0.3
Tianjin	5.9	0.0	5.2	0.7	0.5	0.2
Hebei	14.6	0.0	12.2	2.4	1.7	0.8
Shanxi	7.6	0.0	5.3	2.3	2.0	0.3
Inner Mongolia	7.9	0.4	5.3	2.2	1.8	0.4
Liaoning	14.6	0.0	10.8	3.7	3.2	0.5
Jilin	6.1	0.0	5.7	0.5	0.3	0.1
Heilongjiang	8.2	0.1	4.9	3.3	2.5	0.8

Shanghai	13.4	0.0	5.0	8.3	8.1	0.2
Jiangsu	17.3	0.0	14.7	2.6	2.5	0.1
Zhejiang	11.1	0.0	8.8	2.3	2.2	0.1
Anhui	10.0	0.1	8.1	1.8	1.6	0.2
Fujian	6.1	0.0	4.4	1.8	1.7	0.0
Jiangxi	3.9	0.0	3.3	0.6	0.6	0.0
Shandong	16.8	0.0	12.6	4.2	3.5	0.6
Henan	10.8	0.2	8.8	1.8	1.5	0.4
Hubei	40.7	0.4	29.6	10.6	7.6	3.0
Hunan	4.1	0.1	1.7	2.3	2.1	0.1
Guangdong	21.6	0.0	14.5	7.1	6.8	0.2
Guangxi	6.1	0.0	4.7	1.4	1.4	0.0
Hainan	1.8	0.0	1.0	0.8	0.8	0.0
Chongqing	4.7	0.0	3.4	1.3	1.2	0.1
Sichuan	4.1	0.0	2.0	2.1	1.8	0.3
Guizhou	3.3	0.0	2.2	1.2	1.1	0.0
Yunnan	4.0	0.0	2.3	1.7	1.6	0.1
Shaanxi	5.2	0.0	4.0	1.2	1.0	0.2
Gansu	2.9	0.0	2.2	0.7	0.6	0.1
Qinghai	0.3	0.0	0.0	0.3	0.2	0.1
Ningxia	1.8	0.0	1.5	0.3	0.3	0.0
Xinjiang	2.5	0.0	0.2	2.7	2.6	0.0
Tibet	0.3	0.0	0.1	0.4	0.3	0.0

3.3 Provincial CO_2 decreases in road transport

The transport sector contributes 7%-9% to China’s total CO_2 emissions (Shan et al., 2020;Zheng, 2018). Transport is the sector seeing the greatest influence on CO_2 emissions as a result of the lockdown. Only two days after the Wuhan lockdown on January 23, 2020, all other prefecture-level cities in Hubei Province were locked down. During the 76-day lockdown period, public transport, including urban public transport, subways, ferries, and long-distance passenger transport, was shut down, and airports and railway stations were temporarily closed (WCNCPCCC, 2020). People were ordered to stay home as much as possible except for essential needs, and all these measures suddenly and substantially decreased on-road transport. Consequently, the decrease in CO_2 emissions was 7.6 Mt (Figure 3 a, Table 1), and the corresponding distance-weighted transport turnover change rate was -83.9%. Specifically, according to the statistics of the Department of Transport of Hubei Province, in Q1, the freight and passenger turnover volume decreased by 93.4% and 70.1%, respectively, compared to the same period in 2019 (Figure S7). Shanghai, Guangdong and Shandong Provinces had emission decreases of 8.1, 6.8 and 3.5 Mt CO_2 (Figure 3 a, Table 1), with distance-weighted decreases of 63.4%, 40.2% and 32.1% in the transport turnover volume (Figure 3 b). The transport change rates for Hainan, Xinjiang and Heilongjiang were also high (nearly -50%), but the decreases were relatively small (0.8~2.6 Tg) due to the low total baseline emissions. Other provinces mostly had decreases of 1~2 Tg (or 20%~30%). In total, the ground-based transport CO_2 decrease for the 31 provinces was 65.1 Mt (or 32.7%), which is comparable to the estimate (79.8 Mt or 36.2%) by (Liu et al., 2020). The reduced passenger turnover contributed more than the freight turnover, and freight turnover recovered faster than the passenger (Figure S7 and S8). Le Quéré et al. (2020) estimated that surface transport contributed ~50% to the global decrease. Analyzing long-term measurements in Beijing from 2012 to 2020, Sun et al. (2020) showed drastic reductions (on average, 30%-50%) in primary aerosol species associated with traffic, cooking and coal burning during the pandemic. Another study showed that 28%-51% (mean 37%) of work can be done at home in the United States (Dingel and Neiman, 2020). People's commute times shrank from an average of ~30 minutes to a few steps down the hall. A survey of 2500 Americans found that 42% were teleworking full-time, and they reduced transport emissions through less driving compared to their previous commute (Cruickshank, 2020). Moreover, Collivignarelli et al. (2020) found that due to the severe constraints on people's movement during the lockdown in Milan, a significant reduction in most pollutants was attributable to vehicular traffic. As policy implications, working from home and changing communication channels by holding Internet-based virtual video conferences can reduce traffic emissions.

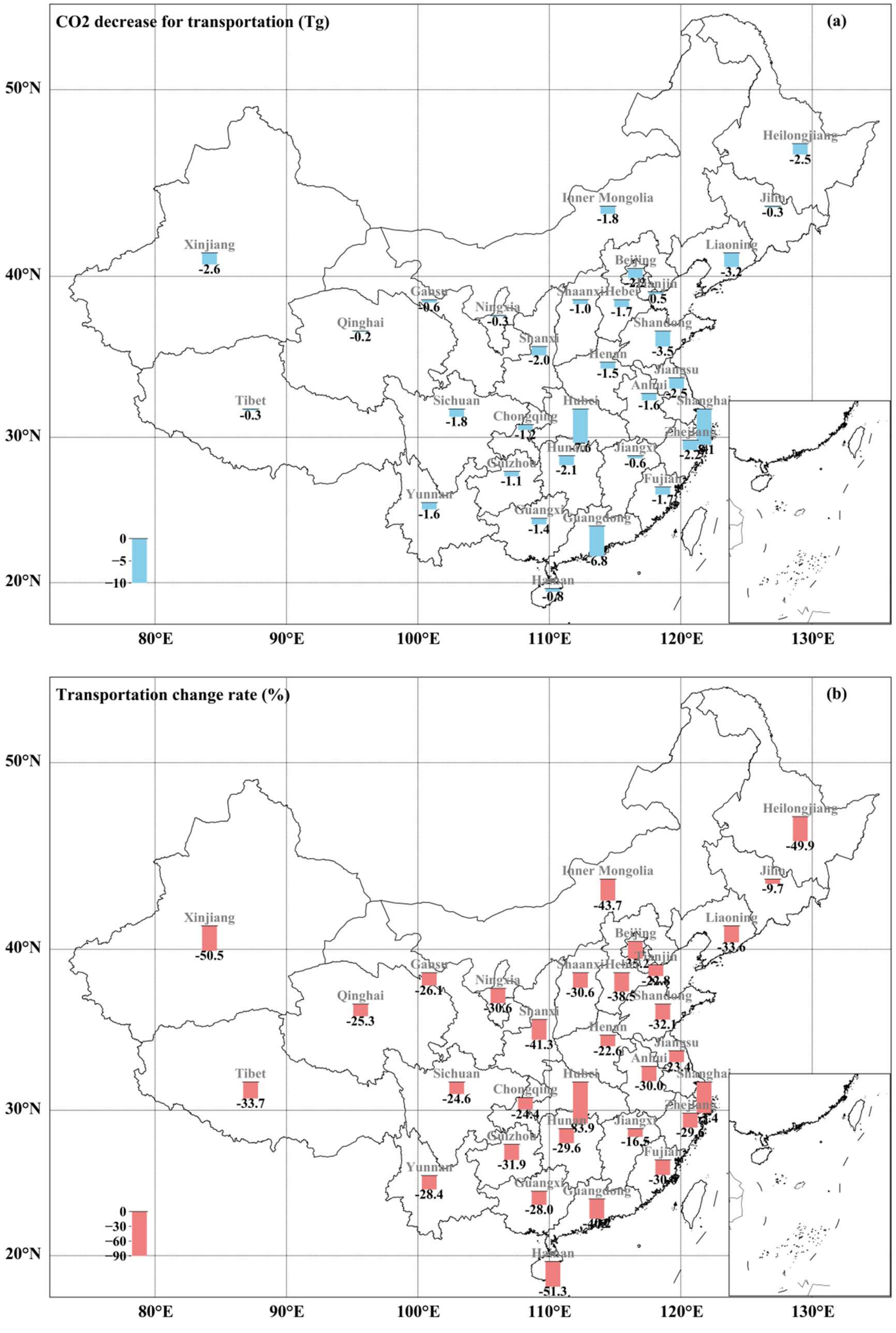


Figure 3. Transport emission decrease in Q1 2020 (a) and distance-weighted freight and passenger turnover growth rate (b) compared to Q1 2019.

3.4 Daily coal consumption at six main power groups and implications

Calculating the CO_2 emission decrease for all of 2020 depends on the duration of the lockdown and the recovery of energy and economic activity. Using the daily coal consumption at six power generation groups as an indicator, the mean decreases were estimated at 13.4% for Q1 2020 compared to Q1 2019 (Figure 4 and Figure S9), with a peak decrease of 25%. These results strongly correspond to the number of confirmed cases reported by the Chinese Center for Disease Control and Prevention; for the first four months, the decrease was 12.6%, and for April alone, it was 9.9%. With the alleviation of the impacts of COVID-19 and the economic stimulus package, CO_2 emissions are rebounding, although they have not yet returned to the prepandemic levels for Q1 2020 (~10% lower than the previous 10-year mean, Figure 5), they were above the mean for Q2 2020. By simply extrapolating the rate to the whole year, the decreases were estimated at a low bound of 3.9% if prepandemic conditions return by July and a high bound of 7.4% if impacts remain until the end of 2020. This prediction is consistent with the estimates by Le Quéré et al. (2020) (2.6%5.6%). Since the emission reductions associated with the pandemic are only temporary, GHG emissions will skyrocket again in reviving economies (Le Quéré et al., 2020;Zambrano-Monserrate et al., 2020) , and a long-term structural change in the economies of countries is needed (Guan et al., 2018). As advocated by the Chinese and UK governments, we must strengthen international solidarity to address global environmental and climate challenges by taking green and low-carbon roads for economic recovery (MEE, 2020).

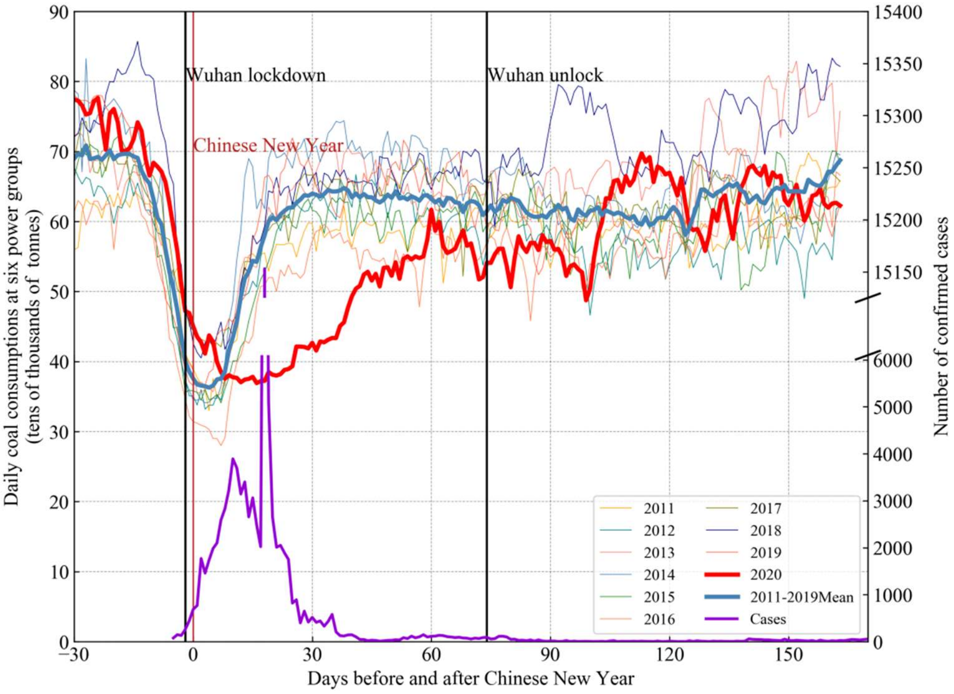


Figure 4. Daily coal consumption at six main power groups from 2011 to 2020 (left y-axis) and the number of confirmed cases (right y-axis). The coal consumption data were derived from https://www.wind.com.cn/. The daily number of confirmed cases was derived from http://www.chinacdc.cn/. Data were accessed on August 7, 2020.

4 Conclusions

Using the national and provincial GDP of three major sectors, transport statistical data and a bottom-up inventory as a baseline, we conducted an analysis of China's CO_2 emission decrease in Q1 2020 related to COVID-19 mitigation measures. The overall decrease was estimated as 257.7 Mt (11.0%), and Hubei contributed the most (15.6%) to this decrease. In terms of sectoral contribution, ground transport significantly contributed (25.0%). The estimates based on the GDP method were reasonably consistent with those based on the PLAS method. This study showed that GDP has potential merit in estimating emission changes when detailed energy activity data are unavailable, and future studies focusing on province-level emission reductions can use this method. Moreover, modeling studies that require spatial information on CO_2 reductions can use these results to constrain the input data. The estimated decrease helps to explain the impacts of COVID-19 on China's CO_2 emissions and is useful for understanding local economic recovery and for policy makers to develop emission reduction strategies, for example, policies that promote working from home and holding teleconferences to reduce traffic emissions and policies that invest in cleaner energy that emits less CO_2. It is likely that the emission reductions associated with the pandemic are only temporary and to prevent emissions from skyrocketing again due to economic stimulus, a long-term structural change in the economies of countries is needed, green and low-carbon roads must be taken for economic recovery.

Data availability. The inventory data are available from Shan et al. (2020). The GDP data are available from http://data.stats.gov.cn/english/easyquery.htm?cn=B01.

Author contributions. PFH and YLS conceived and designed the study. PFH and QXC collected and analyzed the data sets. PFH, TO and NZ led the paper writing, with contributions from all coauthors.

Competing interests. The authors declare that they have no conflicts of interest.

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Tianjin-Hebei inventory. We thank Ms. Xiaoli Zhou and Mr. Zhe Hu for their help in data collection and processing.

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