Reply to Reviewer #1:

General comments: The authors simulate the decline in $PM_{2.5}$ concentration that resulted from emissions reductions during the COVID-19 pandemic using GEOS-chem. They use 1985 and 2010 emissions to simulate the 2015-20 period. They obtain reasonably good correlations between simulated and observed daily mean $PM_{2.5}$ and show that COVID-19 led to a significant decline. The study is interesting, in the sense that knowing how much $PM_{2.5}$ declined due to COVID-19 after other factors are accounted for is useful, and well-timed. The physical and chemical processes responsible for $PM_{2.5}$ concentrations during COVID are discussed to some extent. In response to my comments during the access review, the authors added two new subfigures elucidating the role of meteorology in generating $PM_{2.5}$, and they added a literature review of chemical mechanisms for the formation of the remaining pollution. **These additions are valuable, but in my opinion further major revisions are still needed before the paper can be published**, as follows:

1. Abstract and introduction.

The abstract and introduction should be refocused towards atmospheric processes. While atmospheric processes are discussed (lines 30-37 and 42-49), for Atmospheric Chemistry and Physics they should be the main topic of the introduction. The main topic of the introduction is currently Chinese air quality and COVID, but the paper is about the disentangling effects of meteorology from the effects of the COVID lockdown, and so there needs to be more detail on meteorology in China. This is done very well in the introduction to Yin and Zhang (2020); perhaps some more detail specifically on how 2020 meteorology differs from the climatology would distinguish the two studies? You say that variations in the surface wind, boundary layer height and moisture conditions affect air quality, which is not wrong, but specifically what do they typically do in China, when, and where? The literature review also lacks detail; care should be taken to point out explicitly how this paper differs from the large number of other works on the topic. I appreciate this is difficult because of the very large number of very recent publications, but it is definitely possible to do more here.

Reply:

Appreciate for your detailed and valuable suggestions, which helped us to improve the main thread of this manuscript.

(1) The main differences between our submission and other publications (with

topic about the impacts of COVID-19 on $PM_{2.5}$) are **whether disentangled effects of meteorology**. Adopting your suggestions, we enhanced related presentations in the Abstract and Introduction.

For example, in the introduction, we added a **detailed analysis of meteorological conditions about typical haze pollution events in the Beijing-Tianjin-Hebei region in December 2016**, and explained how the variations of surface wind, boundary layer height and moisture conditions influenced these severe haze events.

(2) **More specific analysis about the changes in meteorological conditions in February 2020** has also been added. Furthermore, their relationships and regressions against $PM_{2.5}$ were also discussed in lines 175-186, which were also **closely connected with comment 5.3**.

Revision:

Lines 12-14: Relative to both of February 2017 and climate mean, anomalous southerlies and moister air occurred in the east of China in February 2020, which caused considerable $PM_{2.5}$ anomalies. Thus, it is a must to disentangle the contributions of stable meteorology from the effects of the COVID-19 lockdown.

Lines 41-44: Climate variability notably influences the formation and intensity of haze pollution in China……During December 16th-21st 2016, although most aggressive control measures for anthropogenic emissions were implemented, severe haze pollution with $PM_{2.5}$ concentrations ≈ 1100μg m^{-3} still occurred and covered 710,000km^2. The continuous low surface wind speed of less than 2ms^{-1}, high humidity above 80% and strong temperature inversion lasting for 132h caused the rebound of wintertime $PM_{2.5}$ in 2016 (Yin and Wang, 2017).

Lines 48-52: From February 8 to 13 2020, North China suffered severe pollutions, with maximum daily $PM_{2.5}$ exceeding 200μg m^{-3}. During this period, weak southerly surface winds lasted for nearly 5 days, relative humidity was close to 100%, and atmospheric inversion reached more than 10°C. Although pollution emissions from basic social activities have been reduced, heavy pollution still occurred when adverse meteorological conditions characterized by stable air masses appeared (Wang et al., 2020).

2. Data description

What technology is usually used to measure PM2.5 for this dataset? When I tried the URL it didn't work. Please reference the dataset more thoroughly.

Reply:

The old URL is past-due, and we have updated the **new URL as https://quotsoft.net/air/**. We give a more detailed introduction to the cited dataset and explain the **measurement technology** of $PM_{2.5}$ in this dataset. The $PM_{2.5}$ data were monitored every 5 min using two methods: a tapered element oscillating microbalance (TEOM) and β-rays which were operated **under the China National Quality Control** (HJ/T 193-2005) and (GB3095-2012).

HJ/T 193-2005: Automated methods for ambient air quality monitoring

GB3095-2012: Ambient air quality standards

Revision:

Lines 70-73: $PM_{2.5}$ concentration data from 2015 to 2020 were acquired from the China National Environmental Monitoring Centre (https://quotsoft.net/air/). The monitoring network expanded from 1500 sites in 2015 to 1640 sites in 2020, covering approximately 370 cities nationwide. The $PM_{2.5}$ data were monitored every 5 min using two methods: a tapered element oscillating microbalance and β-rays which were operated under the China National Quality Control.

3.Model description

This section needs a description of how the model represents aerosol microphysics. The model evaluation presented at the end of this section deserves considerably more detailed study in its own section what are the biases in the model and how might they affect the subsequent analysis? Unless you can reference other studies evaluating an identical model configuration?

Reply:

The description of how the model represents **aerosol microphysics were illustrated in lines 80-85, according to the official website of GEOS-Chem**. The model configurations were **default** and **similar with many previous studies** and the evaluations of model performances were considerably improved in the following two ways and were documented in a separated paragraph (i.e., Lines 86-101).

(1) With the configuration we used, **comparisons between the observed and simulated** $PM_{2.5}$ concentrations in Feb 2017 were added as new Figure S1a and associated analysis were in lines 89-96. Obviously, mean values of simulated $PM_{2.5}$ were **consistent with the observations** (Figure S1a). The percentage of standard error / mean equals **5.8% (4.6/79.6) in NC, 7.0% (3.9/55.6) in YRD and 5.4% (3.7/70.8) in HB**, indicating the good performance of reproducing the polluted conditions. The biases possibly affected the subsequent results and brought uncertainties to some extent. We also admitted the simulated biases were larger in the south of China, which was consistent with other studies and might **explained the little positive values** in Figure 3c (closely connected with comment 7.2).

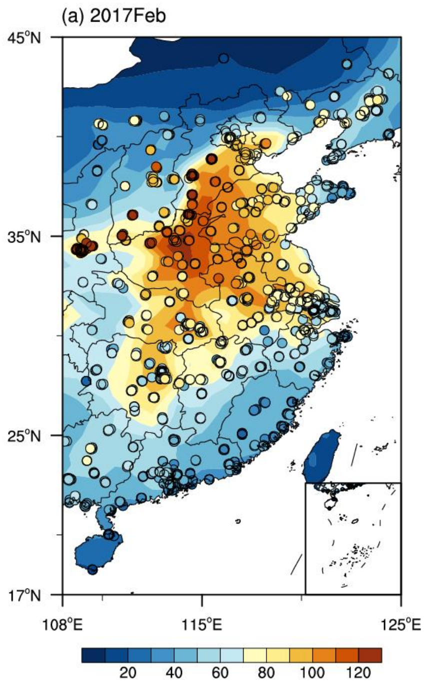
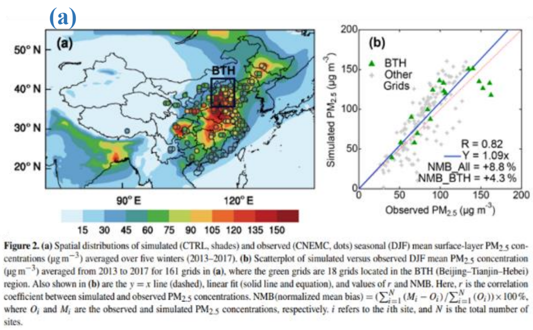


Figure S1a. Spatial distribution of observed (dots) and GEOS-Chem simulated (shading) $PM_{2.5}$ in February 2017.

Furthermore, the **simulated spatial distribution** was also similar to that of observations in Feb 2017 with **spatial correlation coefficient = 0.78**. The ability of GEOS-Chem to reproduce the daily variations of $PM_{2.5}$ in Feb 2020 was also introduced in the old version as below.

changes in February 2020 under a substantial reduction in emissions because of COVID-19 quarantines. In North China (NC), Yangtze River Delta (YRD) and Hubei Province (HB), the correlation coefficients between daily $PM_{2.5}$ observations and simulated data under 2010 (1985) emission scenario reached 0.83 (0.82), 0.67 (0.63), and 0.79 (0.73), respectively. For example, in NC, the simulation could well simulate severe haze events (e.g., from 8–14 and 18–22 February) and good air quality events (e.g., from 15–19 February), reflecting that it has ability to accurately capture the change of meteorological conditions (Fig.

(2) The default configuration of GEOS-Chem were adopted by many previous publications and we also introduced related evaluations in the revised manuscript. Dang and Liao directly evaluated the capacity of models in $PM_{2.5}$ simulations by calculating the normalized mean bias. The simulated spatial patterns of 2013-2017 winter $PM_{2.5}$ were agreed well with the measurements, which was **similar to our evaluations in Figure S1a.** The scatterplot of simulated versus observed **seasonal mean $PM_{2.5}$ concentrations** showed **overestimated** $PM_{2.5}$ concentrations with a normalized mean bias (NMB) of +8.8 % for all grids and an NMB of +4.3 % for BTH (Figure R1a). They also compared the simulated and observed **daily mean $PM_{2.5}$ concentrations** at the Beijing, Shanghai, and Chengdu grids, which represent the three most polluted regions of BTH, YRD, and the Sichuan Basin, respectively. The model has **a low bias in Beijing** with an NMB of **−9.2 %** and is unable to predict the maximum $PM_{2.5}$ concentration in some cases. For Shanghai and Chengdu, the model **has high biases with NMBs of 18.6 % and 28.7 %**, respectively (Figure R1b). This evaluation also showed a bigger simulated bias in the south of China. The model, however, can capture the spatial distributions and seasonal variations of each aerosol species despite of the biases in simulated concentrations.



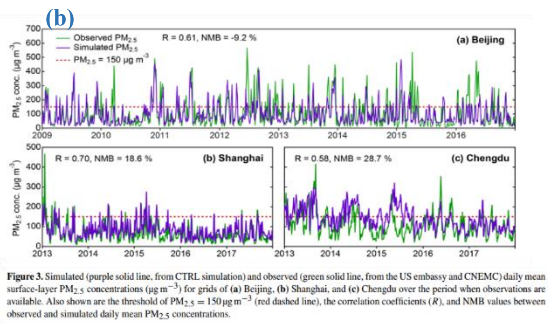


Figure R1. Key Figures in ***Dang and Liao (2019).***

Related references:

Dang, R., and Liao, H.: Severe winter haze days in the Beijing-Tianjin-Hebei region from 1985 to 2017 and the roles of anthropogenic emissions and meteorology, Atmos. Chem. Phys., 19, 10801–10816, 2019.

Revision:

Line 74: 2.2 GEOS-Chem description, evaluation and experimental design

Lines 80-85: Aerosol thermodynamic equilibrium is computed by the ISORROPIA package, which calculates the gas–aerosol partitioning of the sulfate–nitrate–ammonium system (Fountoukis and Nenes, 2007). Heterogeneous reactions of aerosols include the uptake of HO_2 by aerosols (Thornton et al., 2008), irreversible absorption of NO_2 and NO_3 on wet aerosols (Jacob, 2000), and hydrolysis of N_2O_5 (Evans and Jacob, 2005). Two alternate simulations of aerosol microphysics are implemented in GEOS-Chem: the TOMAS simulation (Kodros and Pierce, 2017) and the APM simulation (Yu and Luo, 2009).

Lines 86-96: GEOS-Chem model has been widely used to examine the historical changes in air quality in China and quantitatively separate the impacts of physical-chemical processes. Here, we simulated the $PM_{2.5}$ concentrations in February 2017 and evaluated the performance of GEOS-Chem (Figure S1a). The values of mean square error / mean equals were 5.8%, 7.0% and 5.4% in North China (NC), Yangtze River Delta (YRD) and Hubei Province (HB), respectively, indicating the good performance of reproducing the haze-polluted conditions. The absolute biases were larger in the south of China, which was consistent with Dang and Liao (2019). They also compared the simulated and observed daily mean $PM_{2.5}$ concentrations at the Beijing, Shanghai, and Chengdu grids, which had a low bias in Beijing and high biases in Shanghai and Chengdu, respectively. The simulated biases possibly affected the subsequent results and brought uncertainties to some extent. The simulated spatial distribution of $PM_{2.5}$ was also similar to that of observations with spatial correlation coefficient = 0.78. We further verified whether the simulations could capture the roles of meteorological changes in February 2020 under a substantial reduction in emissions because of COVID-19 quarantines…….

4.Method to quantify influence of quarantine

4.1 Running GEOS-chem for two different emissions scenarios seems like a good idea, and it's good to see that the changes due to meteorology are consistent between years. However, did you consider the physical justification for a linear decomposition? If we consider, crudely, the Chinese airshed as a simple chemical reactor in steady state, then the linear decomposition would not be obviously appropriate (though it may be a reasonable approximation) since the steady-state concentration is the product of the emissions and the loss lifetime.

Reply:

The linear decomposition is definitely a **reasonable and feasible approximation** and must have differences with the reality due to complex atmospheric chemical processes (also involving meteorology-emission interactions). The reasons for selecting the linear hypothesis were as follows.

(1) **From 2013 to 2019**, the impacts of emission reduction were approximatively linear, which might related to the **enhanced and reinforced control measures in China**. Because the signal of emissions reduction in China had been **particularly strong since 2013**, it could be easily detected and the assumption of a linear reduction in pollution caused by emission reduction was **applicable in China in the past few years**. This linear approximation was employed by many previous studies (Geng et al. 2017; Zheng et al. 2018) and even by **national assessments aimed to evaluate the effects of *Action Plan of Air Pollution Prevention and Control* from 2013 to 2017** (Geng et al. 2020; Wang et al. 2020). We have introduced the evaluated results in lines 137-142.

(2) After disentangling the effects of meteorology, the variations in $PM_{2.5}$ concentrations also **showed linear change** (Figure 5 in our manuscript), which laterally verified the rationality of linear approximation.

(3) Because of the significantly linear reduction of $PM_{2.5}$ due to changing emissions, the linear decomposition or approximation became reasonable ***<u>in China in recent years</u>*** to some extent.

Certainly, related presentations are lack of physical explanations. We have checked many publications, and all of them have this common problem. We also cannot show you a clear physical justification and only speculated that the obvious linear change due to emission reductions might be that the control measures in China were particularly enhanced and reinforced. In the revised versions, **we illustrated the linear decompositions were an estimated approach** and must brought some uncertainties due to ignoring the meteorology-emission interactions, the product of emissions and their loss lifetime (Lines 263-267).

Related references:

Geng, G., Zhang, Q., Tong, D., Li, M., Zheng, Y., Wang, S., and He, K.: Chemical composition of ambient $PM_{2.5}$ over China and relationship to precursor emissions during 2005–2012, Atmos. Chem. Phys., 17, 9187–9203, https://doi.org/10.5194/acp-17-9187-2017, 2017.

Geng, G., Xiao, Q., Zheng, Y., Tong, D., Zhang, Y., Zhang, X., Zhang, Q., He, H., and Liu, Y.: Impact of China's Air Pollution Prevention and Control Action Plan on PM2.5 chemical composition over eastern China, Sci. China Ser. D., 62, 1872–1884, https://doi.org/10.1007/s11430-018-9353-x, 2020.

Wang, P., Chen, K., Zhu, S., Wang, P., and Zhang, H.: Severe air pollution events not avoided by reduced anthropogenic activities during COVID-19 outbreak, Resour. Conserv. Recy., 158, http://doi:10.1016/j.resconrec.2020.104814, 2020.

Zheng, B., Tong, D., Li, M., Liu, F., Hong, C., Geng, G., Li, H., Li, X., Peng, L., Qi, J., Yan, L., Zhang, Y., Zhao, H., Zheng, Y., He, K., and Zhang, Q.: Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions, Atmos. Chem. Phys., 18, 14095-14111, 2018

Revision:

Lines 110-112: As mentioned above, we aimed to examine the impact of the COVID-19 quarantines on $PM_{2.5}$ over the February 2017 level basing on an observational-numerical hybrid method. The observed $PM_{2.5}$ difference in February 2020 (PMd_{OBS}) was linearly decomposed into three parts: the impacts of changing meteorology (PMd_M), expected routine emissions reductions (PMd_R) and COVID-19 quarantines (PMd_C), which was a reasonable approximation……

Lines 263-267: Furthermore, during the calculation process, the observed $PM_{2.5}$

difference in February 2020 was linearly decomposed into three parts. Although this linear decomposition was reasonable in china in the past few years, we must note that this approximation was lack of considering the meteorology-emission interactions, the product of the emission, the loss lifetime and particularly the sulfate-nitrate-ammonia thermodynamics (Cai et al., 2017), which brought some uncertainties.

4.2 Line 99 (minor comment) – I don't fully understand the "the PM2.5 percentage due to changing meteorology". Do you mean "the change in the percentage of PM2.5 due to changing meteorology" here and later in the paragraph?

Reply:

What we mean here is that **the percentage of changed $PM_{2.5}$ due to the differences in meteorology** is constant regardless of the emission level. This percentage is the **difference of simulated $PM_{2.5}$ between each year and 2017 under the same emission scenario divided by the simulated $PM_{2.5}$ in 2017**. We have changed the expression to be clearer.

Revision:

Line 119: Depending on the GEOS-Chem simulations, we found that the percentage of changed $PM_{2.5}$ due to the differences in meteorology remained nearly constant regardless of the emission level (Fig. S2) ……

4.3 Line 107 – "the change in emissions resulted in a linear change in air pollution". I don't think this is the message of the very nice Cai et al paper that you cite here. In fact, it is well established that emissions changes often do not lead to linear changes in air pollution, even though I do accept, from the evidence you present, that this is case in China from around 2013 to 2019. The most obvious reason is the sulfate-nitrate-ammonia thermodynamics discussed by Cai et al. Naively, reducing sulfate emissions should reduce concentrations linearly, but reducing nitrate and/or ammonium emissions may not change concentrations at all, or may result in very large decreases in concentrations, depending on the regime (whether saturated by, or limited by, ammonia, for example). Similarly, reducing primary emissions may lead to more new particle formation, as discussed by others, and more secondary aerosol formation, which would also mean the decrease in number concentration is likely sub-linear. Line197of the manuscript points this out explicitly. New particle formation wouldn't directly affect changes in mass concentration, but it could have important indirect effects through the size dependence of aerosol dry and wet deposition rates. So while decreases in

concentration may be linear with emissions in specific cases, and does seem to be true in China, this will not be true in general, and should be clarified. Also linearity in previous years, e.g. from 2013 to 2017, does not imply linearity in subsequent years. The linear extrapolation method used therefore brings with it a large uncertainty which should be studied in detail.

Reply:

Sorry for the inappropriate citation. Cai et al. paper did not show that emission reduction would lead to linear reduction of air pollution. Just as you said, **from 2013 to 2019, the impacts of emission reduction in China were approximatively linear**. This linear approximation was **employed even by national assessments** aimed to evaluate the effects of *Action Plan of Air Pollution Prevention and Control* from 2013 to 2017 (Geng et al. 2020; Wang et al. 2020).

(1) Due to the implementation of clean air action, control measures have been enhanced and reinforced in China, showing a strong emission reduction signal. Therefore, **the pollutant reduction caused by emission reduction in China from 2013 to 2019 was linear**, which might be **related to the huge emission reduction**. But we didn't check for other areas, maybe not linear reduction. The link has a lot to do with the intensity of emissions reduction. Because the signal of emissions reduction in China had been particularly strong since 2013, it could **be easily detected and showed a linear reduction**.

(2) The effect of emission reduction in February 2020 was calculated as the change of $PM_{2.5}$ caused by **expected** routine emission reduction, **which did not actually happen**, but merely **gave an assessment of the change of $PM_{2.5}$ caused by emission reduction in the case of "if no COVID-19".** Under this hypothetical assessment, the linear change was still tenable.

(3) Furthermore, what we emphasize more was **the effect of total emission reduction (**$PMd_R + PMd_C$**)**, that was, the common utility of expected routine emissions reductions and COVID-19 quarantines. This quantity was obtained after excluding the effect of meteorological conditions, **which was completely unaffected by linear extrapolation of emission reduction.**

(4) The information revealed by Cai et al. (2017) was valuable and we discussed

the possible impacts of sulfate-nitrate-ammonia thermodynamics on our approach in line 267.

Revision:

Lines 130-137: According to many previous studies, the change in emissions resulted in a linear change in air pollution in China from 2013-2019 (Wang et al., 2020; Geng et al., 2020) which might be related to the huge emission reduction due to the implementation of clean air action. Because the signal of emissions reduction in China had been particularly strong since 2013, it could be easily detected and the assumption of a linear reduction in pollution caused by emission reduction was applicable in China in the past few years. Based on this approximation, we used the method of extrapolation to speculate the impact of routine emission reduction on $PM_{2.5}$. We performed linear extrapolation based on known PMd_R values from 2015 to 2019 to obtain PMd_R in 2020 (STEP 2, Fig. S3). This PMd_R in 2020 was calculated as the change of $PM_{2.5}$ caused by expected routine emission reduction, which did not actually happen, but merely gave an assessment in the case of "if no COVID-19".

Lines 265-267: Although this linear decomposition was reasonable in china in the past few years, we must note that this approximation was lack of considering the meteorology-emission interactions, the product of the emission, the loss lifetime and particularly the sulfate-nitrate-ammonia thermodynamics (Cai et al., 2017), which brought some uncertainties.

5.Results

5.1 Line 146: the description is good but some more introductory detail and referencing would be useful. For example, what is the East Asia deep trough? Please supply reference, e.g. Song et al, J. Climate 2016.

Reply:

We have **added the description of the East Asia deep trough** and relevant references.

Revision:

Line 170: ……the East Asia deep trough, one of the most significant time-mean zonally asymmetric circulation features in the wintertime Northern Hemisphere (Song et al., 2016), shifted eastwards and northwards than climate mean……

5.2 Line 149: This is potentially a useful result, but what is the importance of the hygroscopic growth? Its importance surely depends on whether the PM2.5 measurements are of dry or of hydrated particles. If dry particles are measured, hydration might still be important if it affects deposition rates. So what is the difference in humidity and what difference to the size of typical particles would that lead to?

Reply:

Fine aerosols, such as $PM_{2.5}$ particles, will be hygroscopic growth under the environment where the relative humidity is more than 60%, so the measured value without the monitoring instrument to control the relative humidity will be virtual high. When the air is relatively dry, gaseous precursor pollutants could not obviously affect visibility. But in the presence of water molecules, polyphase chemical reactions occurs, and gaseous precursors are oxidized in water droplets or in water carried by particulate matters, accelerating the formation of particulate matter. The conversion rate of SO_2 and NO_2 into sulfate, nitrate and other particles **increases exponentially with the increase of relative humidity**. Therefore, higher humidity provides a favorable environment for the hygroscopic growth of aerosol particles, which is conducive to the formation of haze pollution and decreasing of visibility.

What we simply mean to say is the hygroscopic growth of aerosol particles highly reduced the visibility and enhanced the intensity of haze pollution, rather than impacting the concentration of $PM_{2.5}$. In the revised version, we corrected the sentence to avoid confusions.

Revision:

Lines 173-175: Physically, the weakening surface winds and strong thermal inversion corresponded to weaker dispersion conditions, and the higher humidity indicated a favorable environment for the hygroscopic growth of aerosol particles to evidently decrease the visibility.

5.3 Can you calculate approximate ventilation rates for the boundary layer in the different meteorological conditions, or otherwise increase the level of quantitative detail in lines 140-150, which are currently very qualitative? Can this be used to back up the conclusions about PM2.5? For example, the regression of PM2.5 against "BLH, wind speed, SAT and humidity" done in Yin and Zhang (2020) looks like a nice technique to understand the relationship of air pollution and meteorology, could you do the same thing here for 2020 data? Or at least provide similar numerical detail for what is the BL height and how it varies in the years studied? Is there a role for sea surface temperature here also?

Reply:

Thank you for this nice comment. Following it, we not only show more quantitative results, but also **statistically (with observations and regressions) verified** the percentage of changed $PM_{2.5}$ due to the difference in meteorology between 2017 and 2020. We have **added more quantitative analysis** in the revised presentations.

(1) In February 2020, the correlation coefficients of daily $PM_{2.5}$ and BLH, relative humidity, wind speed and SAT in North China were **-0.63, 0.44, -0.45 and 0.46** respectively, all of which **passed the 95% significance test**. Compared with the climate mean status (February 2017), in February 2020 BLH **decreased by 19.5m (34.5m)**, relative humidity **increased by 5% (10.6%)**, and SAT **rose by 1.6°C (0.9°C)** after detrending, which are conductive to the increase of $PM_{2.5}$ concentration.

(2) We used the meteorological data of boundary layer height, relative humidity, surface temperature and wind speed in February 2017 to establish a multiple linear regression equation to fit $PM_{2.5}$. The correlation coefficients between the fitting results and the actual $PM_{2.5}$ concentration in North China, Yangtze River Delta and Hubei reached 0.84, 0.64 and 0.65, all of which **passed the 99% significance test**. Then, we put the **observed meteorological data in February 2020** into the established multiple regression equation to get the predicted $PM_{2.5}$ concentration. Using the regress-predicted value, the percentage of changed $PM_{2.5}$ due to the difference between in meteorology between 2017 and 2020 were re calculated and is 20.7%, -3.2% and 9.5% in NC, YRD and HB, respectively (the hollow column in Figure S2), **which is consistent with and enhanced the robustness of the results obtained by our previous model simulation**.

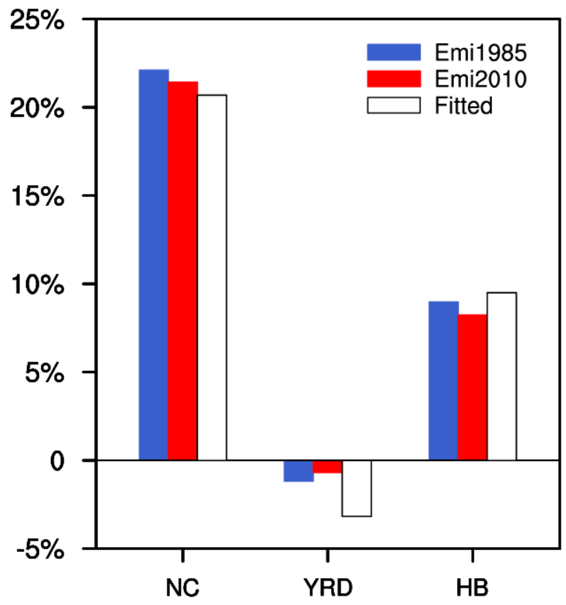


Figure S2. The percentage of changed $PM_{2.5}$ due to the difference in meteorology between 2020 and 2017 by simulated $PM_{2.5}$ with 2010 (red) and 1985 (blue) emission, and regress-fitted $PM_{2.5}$ (hollow). The GEOS-Chem simulations were driven by meteorological conditions in 2017 and 2020 under fixed emissions in 1985 and 2010. The regress-fitted $PM_{2.5}$ was calculated by putting the observed meteorological data in February 2020 into the multiple regression equation fitting $PM_{2.5}$ established by meteorological data in February 2017.

Revision:

Lines 175-186: Compared with the climate (February 2017) monthly mean, boundary layer height (BLH) decreased by 19.5m (34.5m), surface relative humidity (rhum) increased by 5% (10.6%) and surface air temperature (SAT) rose by 1.6°C (0.9°C) after detrending, which were conductive to the increase of $PM_{2.5}$ concentration in February 2020. Furthermore, the correlation coefficients of daily $PM_{2.5}$ and BLH, rhum, wind speed and SAT in North China were -0.63, 0.44, -0.45 and 0.46, respectively, all of which passed the 95% significance test and indicated importance of meteorology. We used the meteorological data in February 2017 to establish a multiple linear regression equation to fit $PM_{2.5}$. The correlation coefficients between the fitting results and the observed $PM_{2.5}$ concentration in NC, YRD and HB reached 0.84, 0.64 and 0.65, exceeding the 99% significance test. Then, we put the observed meteorological data in February 2020 into this established multiple regression equation to get the predicted

$PM_{2.5}$ concentration. Using the regress-predicted value, the percentage of changed $PM_{2.5}$ due to the differences in Meteorology between 2017 and 2020 were re-calculated and is 20.7%, -3.2% and 9.5% in NC, YRD and HB, respectively (Figure S2), which is consistent with and enhanced the robustness of the results obtained by our previous model simulation.

5.4 Line 160-165 can you estimate, with quantitative justification, uncertainty ranges for these numbers?

Reply:

We analyzed and discussed the **source of uncertainties**, and also **give the range of bias of GEOS-Chem model simulation**, but the specific range of final uncertainties of is difficult to estimate. Instead, **we can take a step back to give a more comprehensive source of uncertainty in the discussion section** (Lines 258-274).

(1) There is **a certain bias in the simulation by GEOS-Chem model**, and the biases also showed regional differences, which requires further numerical experiments when the emission inventory is updated.

(2) During the calculation process, the observed $PM_{2.5}$ difference in February 2020 was linearly decomposed into three parts. Although this **linear decomposition was reasonable in China in the past few years**, but this approximation was lack of considering the meteorology-emission interactions, the product of the emission, the loss lifetime and particularly the sulfate-nitrate-ammonia thermodynamics (Cai et al., 2017), which brought some uncertainties

(3) The calculation result of the impact of meteorology is **obtained by numerical simulations**, with certain uncertainty. When calculating the expected routine emission reduction in 2020, we use the method of extrapolation. Although the result is consistent with others observational and numerical studies, it is still conjectures rather than true values.

To restrict the possible uncertainties, we **set up some constraints**: 1. The pivotal contribution ratio of changing meteorology were calculated **under two emission levels** and **recalculated by statistical regressed model**; 2. The values of PMd_M and PMd_R were widely **compared to previous studies**.

Revision:

Lines 258-274: Because of the common update delay of the emission inventory, we employed a combined analysis consisting of observational and numerical methods. We strictly demonstrated the rationality of this method and the results, mainly based on the relatively constant contribution ratio of changing meteorology from GEOS-Chem simulations under the different emissions (Yin and Zhang, 2020). However, there was a certain bias in the simulations by GEOS-Chem model, and the biases also showed regional differences (Dang and Liao, 2019). Therefore, gaps between the assessed results and reality still exist, which requires further numerical experiments when the emission inventory is updated. Furthermore, during the calculation process, the observed $PM_{2.5}$ difference in February 2020 was linearly decomposed into three parts. Although this linear decomposition was reasonable in China in the past few years, we must note that this approximation was lack of considering the meteorology-emission interactions, the product of the emission, the loss lifetime and particularly the sulfate-nitrate-ammonia thermodynamics (Cai et al., 2017), which brought some uncertainties. The actual emission reduction effect is considerable (Fig. 3d), in line with the increasingly strengthened emission reduction policies in recent years. When calculating the PMd_R in 2020, we use the method of extrapolation. Although the result is consistent with others observational and numerical studies (Geng et al., 2019; Zhang et al., 2020; Zhou et al., 2019), it is still conjectures rather than true values. These issues need to be examined in the future studies to unlock respective effects of emissions and meteorological conditions on $PM_{2.5}$ over eastern China. To restrict the possible uncertainties, we set up some constraints: 1. The pivotal contribution ratio of changing meteorology were calculated under two emission levels and recalculated by statistical regressed model; 2. The values of PMd_M and PMd_R were widely compared to previous studies.

5.5 Line 169 – the impacts of COVID-19 quarantines on air quality was weaker south of 30N. This is an interesting conclusion. Could it be related to meteorological differences? Is this consistent with the later statement that in north China, secondary aerosol concentrations increase when primary aerosols decrease?

Is that true in south China?

5.6 Line 176 what are the reasons for the regional differences?

Reply:

The south of 30N is less polluted than the north region, therefore the **background of basic $PM_{2.5}$ concentration is relatively low (Figure S4a)**. In addition, meteorological conditions in the south in February 2020 **had no positive contribution** relative to that in February 2017, which would not lead to the increase of $PM_{2.5}$ concentration. Both of the above two reasons resulted in **a smaller space for $PM_{2.5}$ decrease**. So the $PM_{2.5}$ concentration that can be reduced by COVID-19 in the south is **not as large as** that in North China, and had regional differences.

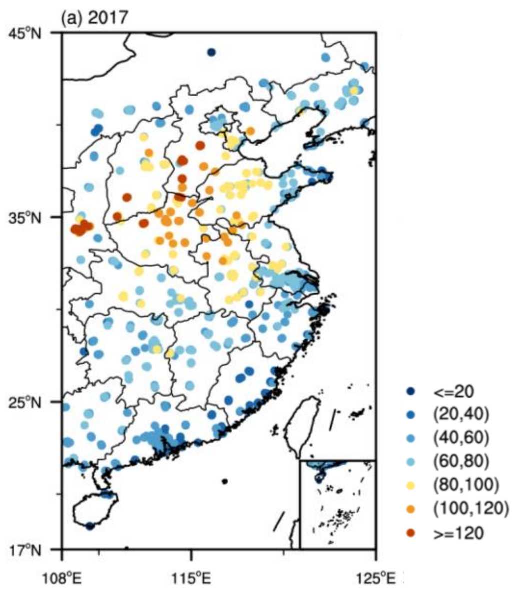


Figure S4a. Observed $PM_{2.5}$ concentrations (unit: μg/m^3) in February 2017.

Revision:

Lines 209-212: Generally, the south region was less polluted than the north, therefore the baseline of $PM_{2.5}$ concentration was relatively lower (Fig. S4a). In addition, meteorological conditions in the south in February 2020 had no positive contribution (Fig. 3a), which would not lead to the increase of $PM_{2.5}$ concentration. These two possible reasons resulted in a smaller space for $PM_{2.5}$ decrease due to COVID-19 quarantines in the south and accompanying regional differences.

6.Conclusions

6.1 Line 227-240 It is valuable to point out these shortcomings and qualifications for your study. Can you take this further by estimating uncertainties as I suggest above, and speculate what the effect of the interactions between emissions and meteorology would be?

Reply:

We can discuss and **make a comprehensive summary of the source of uncertainty** in lines 258-274, but the specific range of uncertainty is difficult to calculate (closely connected with comment 5.4).

About the interaction between emissions and meteorology, it is far away from the topic of this manuscript and we clearly pointed out **this is a new question** in the Section Discussion. Possibly, we solve this question in the near future.

Revisions:

Lines 278-280: Although the $PM_{2.5}$ dropped much, marked air pollutions also occurred during this unique experiments that the human emissions were sharply closed. This raised new scientific questions, such as changes of atmospheric heterogeneous reactions and oxidability under extreme emission control, quantitative meteorology-emission interactions, and so on.

6.2 What are the implications of the study for the practice of atmospheric chemistry and physics, beyond those of Yin and Zhang (2020)? Please spell these out in the conclusion.

Reply:

(1) If the COVID-19 epidemic did not occur, the concentrations of $PM_{2.5}$ would **increase up to 1.3–1.7 times** the observations in February 2020. Therefore, the **pollution abatement must continue**. Because of the huge population base in the east of China, the anthropogenic emissions exceeded the atmospheric environmental capacity even during COVID-19 quarantines.

(2) Although the $PM_{2.5}$ dropped much, marked air pollutions **also occurred** during this unique experiments that the human emissions were sharply closed. This raised new scientific questions, such as changes of atmospheric heterogeneous reactions and

oxidability under extreme emission control, quantitative meteorology-emission interactions, and so on. We have added these implications in the Section Conclusion.

Revision:

Lines 275-280: If the COVID-19 epidemic did not occurred, the concentrations of $PM_{2.5}$ would increase up to 1.3–1.7 times the observations in February 2020 (Figure 6). Therefore, the pollution abatement must continue. Because of the huge population base in the east of China, the anthropogenic emissions exceeded the atmospheric environmental capacity even during COVID-19 quarantines. Although the $PM_{2.5}$ dropped much, marked air pollutions also occurred during this unique experiments that the human emissions were sharply closed. This raised new scientific questions, such as changes of atmospheric heterogeneous reactions and oxidability under extreme emission control, quantitative meteorology-emission interactions, and so on.

7.1 Figure 1: what is the significance of the red color on the left side of subfigure a)?

Reply:

The **red bars** indicate an **increase** in existing confirmed cases, and the **blue bars** indicate a **decrease**. We make this significance clear in the caption of Figure 1 (a).

Revision:

Line 414: Figure 1. (a) Variation in existing confirmed cases (bar; red: increase, blue: decrease) and the ratio of accumulated confirmed cases to total confirmed cases (black line) in China…….

7.2 Figure 3: state that these figures show simulated data. What is responsible for the increases on the far left of Figure 3c?

Reply:

These figures are calculated from **observation data combined with model simulated data**, which mainly depends on the observation data. To avoid confusions, some revisions were included: (1) we have also changed these figures to **be represented as sites**, which are closer to the meaning of the calculation method; (2) In Sec. 2.3, we clearly illustrated the calculations were **based on an observational-**

numerical hybrid method.

In the Method and Discussion, we discussed some possible uncertainties. These increases on the far left were **a sort of uncertainties**. These increases were tiny and insignificant, and definitely do **not affected the main results** of our study.

Revision:

Lines 109-110: As mentioned above, we aimed to examine the impact of the COVID-19 quarantines on $PM_{2.5}$ over the February 2017 level basing on an observational-numerical hybrid method.

Figure 3.

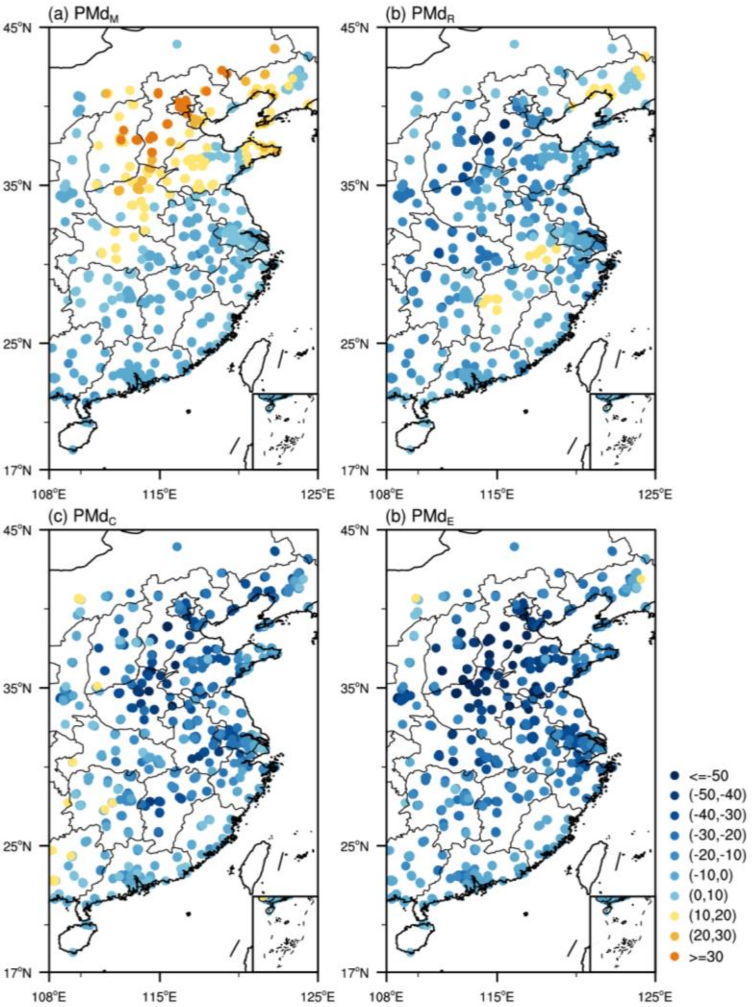


Figure 3. $PM_{2.5}$ difference (unit: μg/m^3) in February between 2020 and 2017 due to (a) changing meteorology (PMd_M), (b) expected routine emission reductions (PMd_R), (c) the COVID-19 quarantines (PMd_C), and (d) due to the total emission reduction ($PMd_E = PMd_R + PMd_C$).

7.3 Figure 4 please label color bars with units

Reply:

We have added the units to the color bar.

Revision:

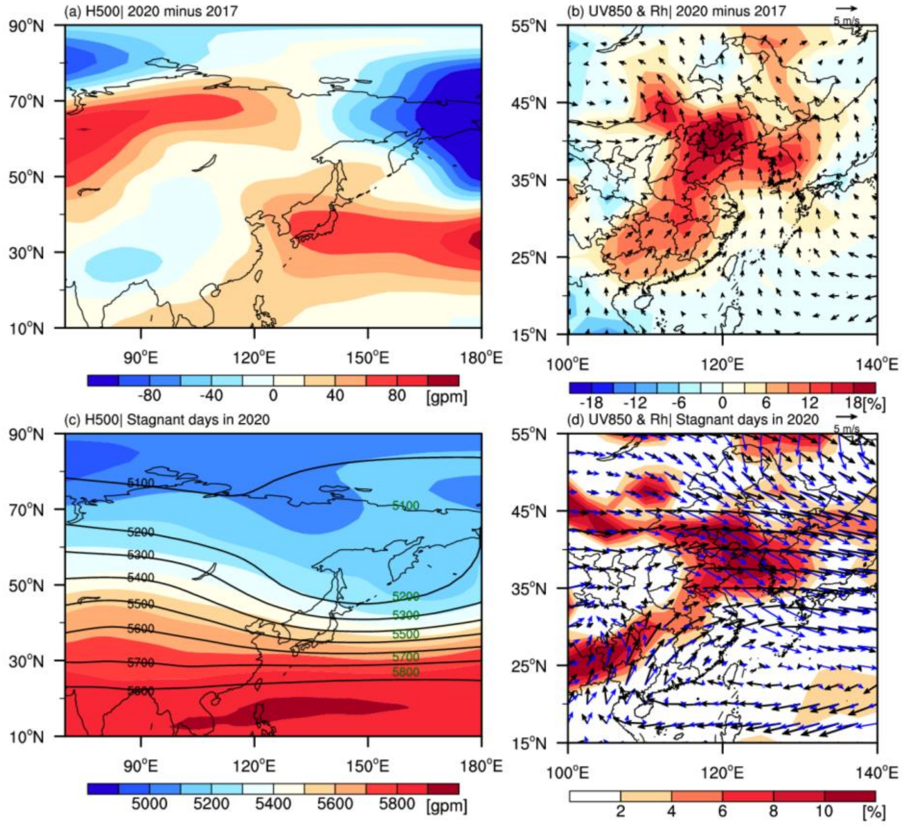


Figure 4. Differences in the observed atmospheric circulation in February between 2020 and 2017, including (a) geopotential potential height at 500 hPa (unit: gpm), (b) wind at 850 hPa (arrows; unit: m/s), surface relative humidity (shading; unit: %). The atmospheric circulations in the stagnant days (e.g., from 8–13 and 19–25 February 2020) were also showed, including (c) geopotential potential height at 500 hPa (shading) and its climate mean in February (contour), and (d) wind at 850 hPa (black arrows), its climate mean (blue arrows) and the increased surface relative humidity (shading, stagnant days minus climate mean).

Reply to Reviewer #2:

General comments: This paper attempted to quantify the effect COVID-19 on the evident PM2.5 decline after removing the influences of climate anomalies and expected routine emissions reductions. Combined with GEOS-Chem model experiments, they used both high and low emission scenarios to simulated the percentages of PM2.5 changes due to meteorological conditions which tended to increase PM2.5 in February 2020, particular in North China. And they further extrapolated the PM2.5 change due to expected routine emission reductions to isolate the decline in PM2.5 concentration due to COVID-19 quarantines in the East of China quantitatively. This study presents some interesting results and could help us better understand the response of air quality to the COVID-19. However, I think the author needs to **add some more detailed and rigorous exposition** to present their results. **Before it can be publishable, I would like the authors to address my following comments.**

Major comments

Line 65-75 This section requires a more detailed description of the model evaluation. At the end of this section, the author just showed the model could capture the change of meteorological conditions, with high similarly between simulated and observed PM2.5 data. But it is essential that the performance of this model could reproduced the observed true value of PM2.5 concentration. Please evaluate against observation.

Reply:

The evaluations of model performances were considerably improved in the following two ways and were documented in a separated paragraph (i.e., Lines 86-101).

(1) With the configuration we used, **evaluations between the observed and simulated** $PM_{2.5}$ concentrations in Feb 2017 were added as new Figure S1a and associated analysis were in lines 89-96. Obviously, **mean values of simulated** $PM_{2.5}$ were **consistent with the observations** (Figure S1a). The percentage of standard error / mean equals **5.8% (4.6/79.6) in NC, 7.0% (3.9/55.6) in YRD and 5.4% (3.7/70.8) in HB**, indicating good performance of reproducing the polluted conditions. The absolute biases were larger in the south of China. The **simulated spatial distribution** was also similar to that of observations in Feb 2017 with **spatial correlation coefficient = 0.78.**

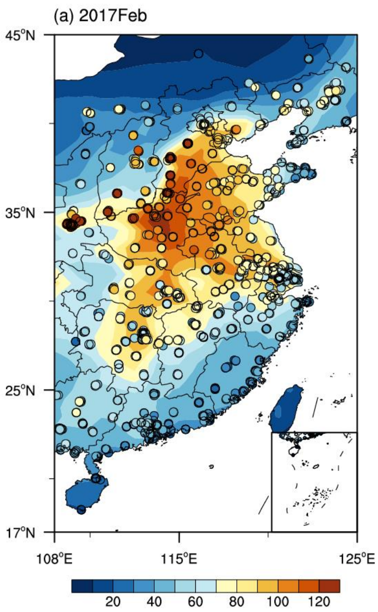


Figure S1a. Spatial distribution of observed (dots) and GEOS-Chem simulated (shading) $PM_{2.5}$ in February 2017.

Furthermore, the ability of GEOS-Chem to reproduce the daily variations of $PM_{2.5}$ in Feb 2020 was also introduced in the old version as below.

changes in February 2020 under a substantial reduction in emissions because of COVID-19 quarantines. In North China (NC), Yangtze River Delta (YRD) and Hubei Province (HB), the correlation coefficients between daily $PM_{2.5}$ observations and simulated data under 2010 (1985) emission scenario reached 0.83 (0.82), 0.67 (0.63), and 0.79 (0.73), respectively. For example, in NC, the simulation could well simulate severe haze events (e.g., from 8–14 and 18–22 February) and good air quality events (e.g., from 15–19 February), reflecting that it has ability to accurately capture the change of meteorological conditions (Fig.

(2) The model configurations were default and **similar with many previous studies**, which were adopted by many previous publications and we also introduced related evaluations in the revised manuscript. Dang and Liao directly evaluated the capacity of models in $PM_{2.5}$ simulations by calculating the normalized mean bias. The simulated spatial patterns of 2013-2017 winter $PM_{2.5}$ were agreed well with the measurements, which was **similar to our evaluations in Figure S1a.** The scatterplot of simulated versus observed **seasonal mean $PM_{2.5}$ concentrations** showed **overestimated** $PM_{2.5}$ concentrations with a normalized mean bias (NMB) of +8.8 % for all grids and an NMB of +4.3 % for BTH (Figure R1a). They also compared the simulated and observed **daily mean $PM_{2.5}$ concentrations** at the Beijing, Shanghai, and Chengdu grids, which represent the three most polluted regions of BTH, YRD, and the Sichuan Basin, respectively. The model has **a low bias in Beijing** with an NMB of

−9.2 % and is unable to predict the maximum $PM_{2.5}$ concentration in some cases. For Shanghai and Chengdu, the model **has high biases with NMBs of 18.6 % and 28.7 %**, respectively (Figure R1b). This evaluation also showed a bigger simulated bias in the south of China. The model, however, can capture the spatial distributions and seasonal variations of each aerosol species despite of the biases in simulated concentrations.

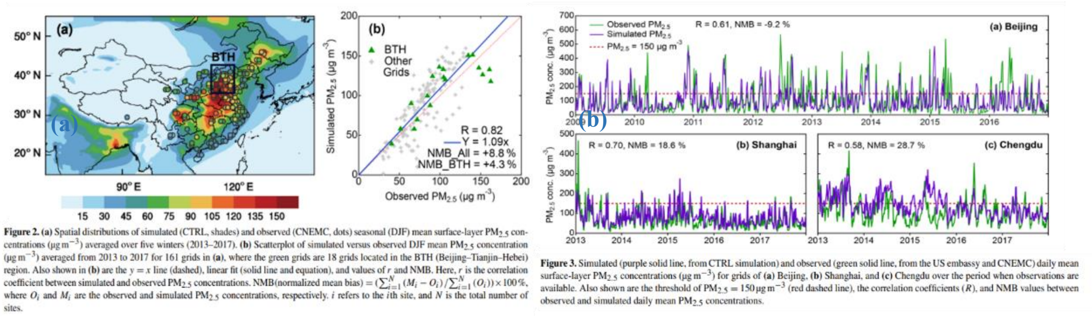


Figure R1. Key Figures in ***Dang and Liao (2019).***

Related references:

Dang, R., and Liao, H.: Severe winter haze days in the Beijing-Tianjin-Hebei region from 1985 to 2017 and the roles of anthropogenic emissions and meteorology, Atmos. Chem. Phys., 19, 10801–10816, 2019.

Revision:

Lines 86-96: GEOS-Chem model has been widely used to examine the historical changes in air quality in China and quantitatively separate the impacts of physical-chemical processes. Here, we simulated the $PM_{2.5}$ concentrations in February 2017 and evaluated the performance of GEOS-Chem (Figure S1a). The values of mean square error / mean equals were 5.8%, 7.0% and 5.4% in North China (NC), Yangtze River Delta (YRD) and Hubei Province (HB), respectively, indicating the good performance of reproducing the haze-polluted conditions. The absolute biases were larger in the south of China, which was consistent with Dang and Liao (2019). They also compared the simulated and observed daily mean $PM_{2.5}$ concentrations at the Beijing, Shanghai, and Chengdu grids, which had a low bias in Beijing and high biases in Shanghai and Chengdu, respectively. The simulated biases possibly affected the subsequent results and brought uncertainties to some extent. The simulated spatial distribution of $PM_{2.5}$ was also similar to that of observations with spatial correlation coefficient = 0.78. We further verified whether the simulations could capture the roles of meteorological changes in February 2020 under a substantial reduction in emissions because of COVID-19 quarantines…….

Line 93 The difference of PM2.5 was linearly decomposed into three parts. I think this is a reasonable approximation, but the author should give more explanation on the rationality of such decomposition.

Reply:

The linear decomposition is definitely a **reasonable and feasible approximation** and must have differences with the reality due to complex atmospheric chemical processes. The reasons for selecting the linear hypothesis were as follows.

(1) **From 2013 to 2019**, the impacts of emission reduction were approximatively linear, which might related to the **enhanced and reinforced control measures in China**. Because the signal of emissions reduction in China had been **particularly strong since 2013**, it could be easily detected and the assumption of a linear reduction in pollution caused by emission reduction was **applicable in China in the past few years**. This linear approximation was employed by many previous studies (Geng et al. 2017; Zheng et al. 2018) and even by **national assessments aimed to evaluate the effects of *Action Plan of Air Pollution Prevention and Control* from 2013 to 2017** (Geng et al. 2020; Wang et al. 2020). We have introduced the evaluated results in lines 137-142.

(2) After disentangling the effects of meteorology, the variations in $PM_{2.5}$ concentrations also **showed linear change** (Figure 5 in our manuscript), which laterally verified the rationality of linear approximation.

(3) Because of the significantly linear reduction of $PM_{2.5}$ due to changing emissions, the linear decomposition or approximation **became reasonable *in China in recent years*** to some extent.

In the revised versions, **we illustrated the linear decompositions were an reasonable estimated approach** and must brought some uncertainties due to ignoring the meteorology-emission interactions, the product of emissions and their loss lifetime (Lines 263-267).

Related references:

Geng, G., Zhang, Q., Tong, D., Li, M., Zheng, Y., Wang, S., and He, K.: Chemical composition of ambient $PM_{2.5}$ over China and relationship to precursor emissions during 2005–2012, Atmos. Chem. Phys., 17, 9187–9203, https://doi.org/10.5194/acp-17-9187-2017, 2017.

Geng, G., Xiao, Q., Zheng, Y., Tong, D., Zhang, Y., Zhang, X., Zhang, Q., He, H., and Liu, Y.: Impact of China's Air Pollution Prevention and Control Action Plan on PM2.5 chemical composition over eastern China, Sci. China Ser. D., 62, 1872–1884, https://doi.org/10.1007/s11430-018-9353-x, 2020.

Wang, P., Chen, K., Zhu, S., Wang, P., and Zhang, H.: Severe air pollution events not avoided by reduced anthropogenic activities during COVID-19 outbreak, Resour. Conserv. Recy., 158, http://doi:10.1016/j.resconrec.2020.104814, 2020.

Zheng, B., Tong, D., Li, M., Liu, F., Hong, C., Geng, G., Li, H., Li, X., Peng, L., Qi, J., Yan, L., Zhang, Y., Zhao, H., Zheng, Y., He, K., and Zhang, Q.: Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions, Atmos. Chem. Phys., 18, 14095-14111, 2018

Revision:

Lines 110-112: As mentioned above, we aimed to examine the impact of the COVID-19 quarantines on $PM_{2.5}$ over the February 2017 level basing on an observational-numerical hybrid method. The observed $PM_{2.5}$ difference in February 2020 (PMd_{OBS}) was linearly decomposed into three parts: the impacts of changing meteorology (PMd_M), expected routine emissions reductions (PMd_R) and COVID-19 quarantines (PMd_C), which was a reasonable approximation……

Lines 263-267: Furthermore, during the calculation process, the observed $PM_{2.5}$ difference in February 2020 was linearly decomposed into three parts. Although this linear decomposition was reasonable in china in the past few years, we must note that this approximation was lack of considering the meteorology-emission interactions, the product of the emission, the loss lifetime and particularly the sulfate-nitrate-ammonia thermodynamics (Cai et al., 2017), which brought some uncertainties.

Line 98-99 Please give a detailed calculation method of calculating the percentages of PM2.5 changes due to meteorological conditions.

Reply:

We use the **simulated $PM_{2.5}$ data** driven by changing meteorology with two fixed-emissions (1985 and 2010). This percentage is the **difference of simulated $PM_{2.5}$ between each year and 2017** under the same emission scenario **divided by the simulated $PM_{2.5}$ in 2017**. We have added this detailed description in the text.

Revision:

Lines 120-121: This percentage was the difference of simulated $PM_{2.5}$ between each year and 2017 under the same emission scenario divided by the simulated $PM_{2.5}$ in 2017.

Line 110 The author performed linear extrapolation to obtain PMdR in 2020. The reason to use linear extrapolation here is that the emission reduction caused by the policy is linear, or that the PM2.5 decline caused by emission reduction is approximate linear based on the calculated value of PMdR from 2015 to 2019? The calculated extrapolation results in 2020 are compared with others studies in the latter part of the paper, but please analyze the uncertainty of using this method itself.

Reply:

From 2013 to 2019, **the impacts of emission reduction on $PM_{2.5}$** in China were **approximatively linear**, which might due to the control measures in China were particularly enhanced and reinforced. This linear approximation was **employed even by national assessments** aimed to evaluate the effects of *Action Plan of Air Pollution Prevention and Control* from 2013 to 2017 (Geng et al. 2020; Wang et al. 2020).

(1) Due to the implementation of clean air action, control measures have been enhanced and reinforced in China, showing a strong emission reduction signal. Therefore, **the pollutant reduction caused by emission reduction** in China from 2013 to 2019 **was linear**, which might be related to the huge emission reduction. The link has a lot to do with the intensity of emissions reduction. Because the signal of emissions reduction in China had been particularly strong since 2013, it could **be easily detected and showed a linear reduction**.

(2) **The effect of emission reduction on $PM_{2.5}$** in February 2020 was calculated as the change of $PM_{2.5}$ caused by **expected** routine emission reduction, which did not

actually happen, but merely gave an assessment of the change of $PM_{2.5}$ caused by emission reduction in the case of "if no COVID-19"**.** Under this hypothetical assessment, **the linear change was still tenable**.

(3) Furthermore, what we emphasize more was **the effect of total emission reduction (**$PMd_R + PMd_C$**)**, that was, the common utility of expected routine emissions reductions and COVID-19 quarantines. This quantity was obtained after excluding the effect of meteorological conditions, **which was completely unaffected by linear extrapolation of emission reduction.**

(4) The calculated extrapolation results in 2020 is consistent with others observational and numerical studies, but we must note that it is still **conjectures rather than true values**, which was lack of considering the meteorology-emission interactions and the sulfate-nitrate-ammonia thermodynamics, which brought some uncertainties. We have added **the analyze of this uncertainty** in line 267.

Revision:

Lines 130-137: According to many previous studies, the change in emissions resulted in a linear change in air pollution in China from 2013-2019 (Wang et al., 2020; Geng et al., 2020) which might be related to the huge emission reduction due to the implementation of clean air action. Because the signal of emissions reduction in China had been particularly strong since 2013, it could be easily detected and the assumption of a linear reduction in pollution caused by emission reduction was applicable in China in the past few years. Based on this approximation, we used the method of extrapolation to speculate the impact of routine emission reduction on $PM_{2.5}$. We performed linear extrapolation based on known PMd_R values from 2015 to 2019 to obtain PMd_R in 2020 (STEP 2, Fig. S3). This PMd_R in 2020 was calculated as the change of $PM_{2.5}$ caused by expected routine emission reduction, which did not actually happen, but merely gave an assessment in the case of "if no COVID-19". Under this hypothetical assessment, the linear change was still tenable.

Lines 265-267: ……we must note that this approximation was lack of considering the meteorology-emission interactions, the product of the emission, the loss lifetime and particularly the sulfate-nitrate-ammonia thermodynamics (Cai et al., 2017), which brought some uncertainties.

Line 145 The changes of circulation field, humidity and wind under stagnant weather are analyzed here. Could you give more details about the specific changes in the weather conditions under these stagnant days? Such as boundary layer height and wind speed?

Reply:

Appreciate for your valuable suggestion. We not only show more **quantitative results**, but also **statistically (with observations and regressions) verified** the percentage of changed $PM_{2.5}$ due to the difference in meteorology between 2017 and 2020. We have **added more quantitative analysis** in the revised presentations.

(1) In February 2020, the correlation coefficients of daily $PM_{2.5}$ and BLH, relative humidity, wind speed and SAT in North China were **-0.63, 0.44, -0.45 and 0.46** respectively, all of which **passed the 95% significance test**. Compared with the climate mean status (February 2017), in February 2020 BLH **decreased by 19.5m (34.5m)**, relative humidity **increased by 5% (10.6%)**, and SAT **rose by 1.6°C (0.9°C)** after detrending, which are conductive to the increase of $PM_{2.5}$ concentration.

(2) We used the meteorological data of boundary layer height, relative humidity, surface temperature and wind speed in February 2017 to establish a multiple linear regression equation to fit $PM_{2.5}$. The correlation coefficients between the fitting results and the actual $PM_{2.5}$ concentration in North China, Yangtze River Delta and Hubei reached 0.84, 0.64 and 0.65, all of which **passed the 99% significance test**. Then, we put the **observed meteorological data in February 2020** into the established multiple regression equation to get the predicted $PM_{2.5}$ concentration. Using the regress-predicted value, the percentage of changed $PM_{2.5}$ due to the difference between in meteorology between 2017 and 2020 were re calculated and is 20.7%, -3.2% and 9.5% in NC, YRD and HB, respectively (the hollow column in Figure S2), **which is consistent with and enhanced the robustness of the results obtained by our previous model simulation**.

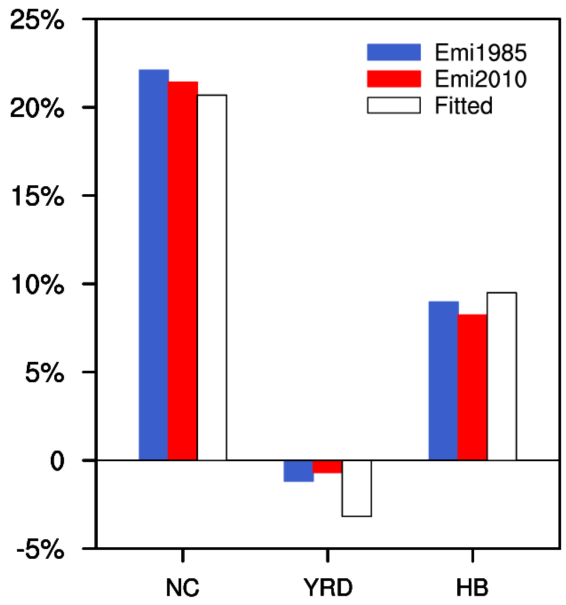


Figure S2. The percentage of changed $PM_{2.5}$ due to the difference in meteorology between 2020 and 2017 by simulated $PM_{2.5}$ with 2010 (red) and 1985 (blue) emission, and regress-fitted $PM_{2.5}$ (hollow). The GEOS-Chem simulations were driven by meteorological conditions in 2017 and 2020 under fixed emissions in 1985 and 2010. The regress-fitted $PM_{2.5}$ was calculated by putting the observed meteorological data in February 2020 into the multiple regression equation fitting $PM_{2.5}$ established by meteorological data in February 2017.

Revision:

Lines 175-186: Compared with the climate (February 2017) monthly mean, boundary layer height (BLH) decreased by 19.5m (34.5m), surface relative humidity (rhum) increased by 5% (10.6%) and surface air temperature (SAT) rose by 1.6°C (0.9°C) after detrending, which were conductive to the increase of $PM_{2.5}$ concentration in February 2020. Furthermore, the correlation coefficients of daily $PM_{2.5}$ and BLH, rhum, wind speed and SAT in North China were -0.63, 0.44, -0.45 and 0.46, respectively, all of which passed the 95% significance test and indicated importance of meteorology. We used the meteorological data in February 2017 to establish a multiple linear regression equation to fit $PM_{2.5}$. The correlation coefficients between the fitting results and the observed $PM_{2.5}$ concentration in NC, YRD and HB reached 0.84, 0.64 and 0.65, exceeding the 99% significance test. Then, we put the observed meteorological data in February 2020 into this established multiple regression equation to get the predicted

$PM_{2.5}$ concentration. Using the regress-predicted value, the percentage of changed $PM_{2.5}$ due to the differences in Meteorology between 2017 and 2020 were re-calculated and is 20.7%, -3.2% and 9.5% in NC, YRD and HB, respectively (Figure S2), which is consistent with and enhanced the robustness of the results obtained by our previous model simulation.

Line 167-170 The results of PMdC showed great differences in the north and south regions. What do you think is the cause of this regional difference? Can you give some explanation?

Reply:

The south of 30N is less polluted than the north region, therefore the **background of basic $PM_{2.5}$ concentration is relatively low (Figure S4a)**. In addition, meteorological conditions in the south in February 2020 **had no positive contribution** relative to that in February 2017, which would not lead to the increase of $PM_{2.5}$ concentration. Both of the above two reasons resulted in **a smaller space for $PM_{2.5}$ decrease**. So the $PM_{2.5}$ concentration that can be reduced by COVID-19 in the south is **not as large as** that in North China, and had regional differences.

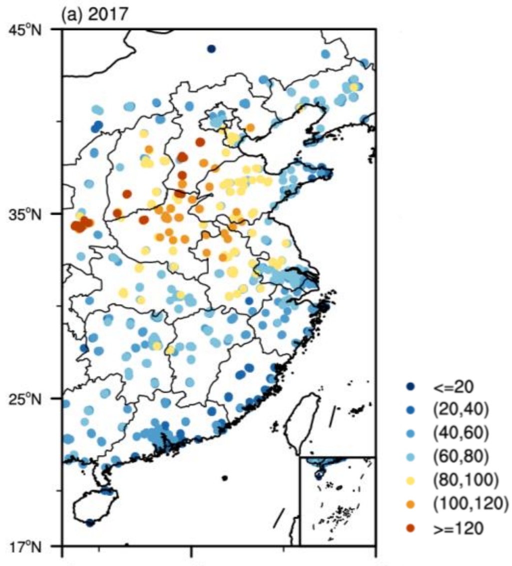


Figure S4a. Observed $PM_{2.5}$ concentrations (unit: μg/m^3) in February 2017.

Revision:

Lines 209-212: Generally, the south region was less polluted than the north, therefore the baseline of $PM_{2.5}$ concentration was relatively lower (Fig. S4a). In addition, meteorological conditions in the south in February 2020 had no positive contribution (Fig. 3a), which would not lead to the increase of $PM_{2.5}$ concentration. These two possible reasons resulted in a smaller space for $PM_{2.5}$ decrease due to COVID-19 quarantines in the south and accompanying regional differences.

Specific comments

Line 98 Please explain "the ratio of PMdM of each year/PMdOBS in 2017" more clearly. Are you sure this is divided by "PMdOBS in 2017" here? Or by observed PM2.5 in 2017?

Reply:

Sorry for this expression error. What we mean here is that to determine the ratio of PMdM of each year/ **observed $PM_{2.5}$ in 2017**, which mean the percentage of changed $PM_{2.5}$ due to the differences in meteorology compared with 2017. This percentage is the difference of simulated $PM_{2.5}$ between each year and 2017 under the same emission scenario divided by the simulated $PM_{2.5}$ in 2017. We have changed the expression to be clearer.

Revision:

Lines 117-120: Simulated $PM_{2.5}$ data driven by changing meteorology with two fixed-emissions (1985 and 2010) were employed to determine the ratio of PMd_M of each year/ observed $PM_{2.5}$ in 2017. Depending on the GEOS-Chem simulations, we found that the percentage of changed $PM_{2.5}$ due to the differences in meteorology remained nearly constant regardless of the emission level (Fig. S2)

Line 101 Keep the same one decimal place.

Reply:

We have made the **corresponding modifications** and have retained a decimal place.

Revision:

Line 122: For example, the percentages due to different meteorology between 2020 and 2017 were 22.1% (21.4%), –1.2% (–0.7%) and 9.0% (8.2%) in NC, YRD and HB under the low (high) emissions (Fig. S2).

Line 103 Please specify which value is multiplied by this percentage.

Reply:

Here we multiply the **2017 observation** by this percentage, and we have changed the expression to be clearer.

Revision:

Lines 125-126: Then, through multiplying the 2017 observation by this percentage, PMd_M can be quantified in each simulation grid with respect to 2017

Line 112 The citation format of this reference is incorrect.

Reply:

We have corrected the citation format of this reference.

Revision:

Line 139: Zhang et al. (2020) also showed that……

Line113 I think it makes more reasonable to write the abbreviation for Beijing-Tian-Hebei here instead of on line 132.

Reply:

We have marked here the abbreviation BTH of Beijing-Tianan-Hebei and have quoted the abbreviation directly later in the paper.

Revision:

Line 139: Zhang et al. (2020) also showed that the emission controls in Beijing-Tianjin-Hebei (BTH) region……

Line 158: Furthermore, Zhang et al. (2020) reported that meteorology contributes 50% and 78% of the wintertime $PM_{2.5}$ reduction between 2017 and 2013 in the BTH and YRD, respectively.

Line 124 The abbreviations for North China here and line 122 are repeated.

Reply:

We have deleted the second repeated abbreviation and referred to the abbreviation directly.

Revision:

Line 151: Relative to the observations in February 2017, negative $PM_{2.5}$ anomalies were centered in NC……

Line 195 Please write NOx here and line 68 in the same way.

Reply:

We have changed NOx into the same way as before.

Revision:

Line 226: Because of break-off transportations, reduced nitrogen oxide (NO_x) increased the concentrations of ozone and nighttime nitrate (NO_3) radical formations.

Figure 1a Clarify what the red and blue bars mean so that the reader can understand this information.

Reply:

The **red bars** indicate an **increase** in existing confirmed cases, and the **blue bars** indicate a **decrease**. We make this significance clear in the caption of Figure 1 (a).

Revision:

Line 414: Figure 1. (a) Variation in existing confirmed cases (bar; red: increase, blue: decrease) and the ratio of accumulated confirmed cases to total confirmed cases (black line) in China…….

Figure 2 Please give the latitude and longitude range of NC, YRD and HB in the figure caption.

Reply:

We select the latitude and longitude range of NC is 32.5-42°N,110-120°E, the range of YRD is 28-32.5°N,118-122°E, and the range of HB is 30-32.5°N,109.5-116°E. We have added the information in the figure caption.

Revision:

Lines 418-419: Figure 2. Differences in the observed $PM_{2.5}$ (unit: μg/m^3) in February between 2020 and 2017. The black boxes indicate the locations of North China (NC, 32.5-42°N,110-120°E), the Yangtze River Delta (YRD, 28-32.5°N,118-122°E) and Hubei Province (HB, 30-32.5°N,109.5-116°E).

Figure 3 The “due to” after each subheading is repeated, leaving out the last three.

Reply:

We have deleted the repeated “due to”.

Revision:

Lines 420-421: Figure 3. $PM_{2.5}$ difference (unit: μg/m^3) in February between 2020 and 2017 due to (a) changing meteorology (PMd_M), (b) expected routine emission reductions (PMd_R), (c) the COVID-19 quarantines (PMd_C), and (d) due to the total emission reduction ($PMd_E = PMd_R + PMd_C$).

Figure 4 Add the units of climate elements in the caption (c) and (d).

Reply:

We have added the units of geopotential potential height at 500 hPa, wind and surface relative humidity in the caption.

Revision:

Lines 426-427: ……including (c) geopotential potential height at 500 hPa (shading; unit: gpm) and its climate mean in February (contour), and (d) wind at 850 hPa (black arrows; unit: m/s), its climate mean (blue arrows) and the increased surface relative humidity (shading; unit: %, stagnant days minus climate mean).

Figure 5 The y-coordinate name is inconsistent with the figure caption.

Reply:

We have corrected the y-coordinate name.

Revision:

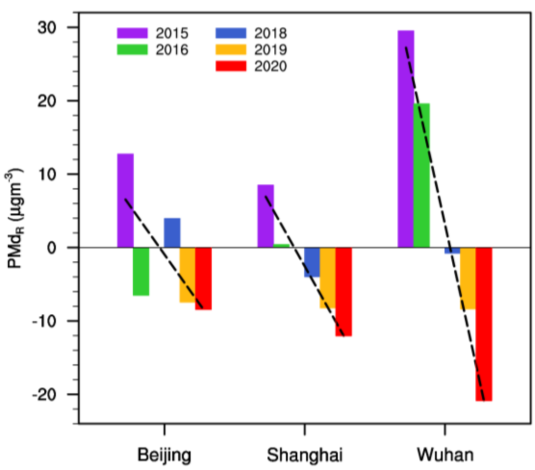


Figure 5. Variation in PMd_R (unit: μg/m^3) with respect to the February 2017 level in Beijing, Shanghai and Wuhan from 2015 to 2019. PMd_R in 2020 was linearly extrapolated from that in the 2015–2019 period. The dotted line is the linear trend.

Figure 6 Add the y-coordinate variable name and unit, just like Figure 5.

Reply:

We have added the y-coordinate variable name and unit in the figure.

Revision:

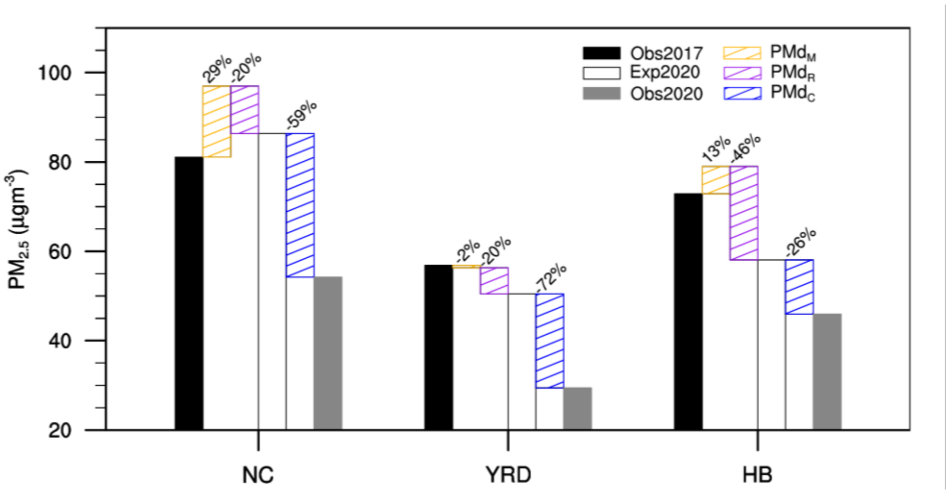


Figure 6. Contributions of PMd_M (orange bars with hatching), PMd_R (purple bars with hatching) and PMd_C (blue bars with hatching) to the change in $PM_{2.5}$ concentration (unit: μg/m^3) between 2020 and 2017 in the three regions. The observed $PM_{2.5}$ concentration in February 2017 (black) and 2020 (gray) was also plotted, and the expected $PM_{2.5}$ concentration without the COVID-19 quarantine is indicated by black hollow bars. The contribution ratios of the three factors (relative to the $PM_{2.5}$ observations in 2020) are also indicated on the corresponding bars.

Figure 7a Change the subtitle "PMd" to "PMdOBS" to maintain consistency of expression.

Reply:

We have changed in the figure.

Revision:

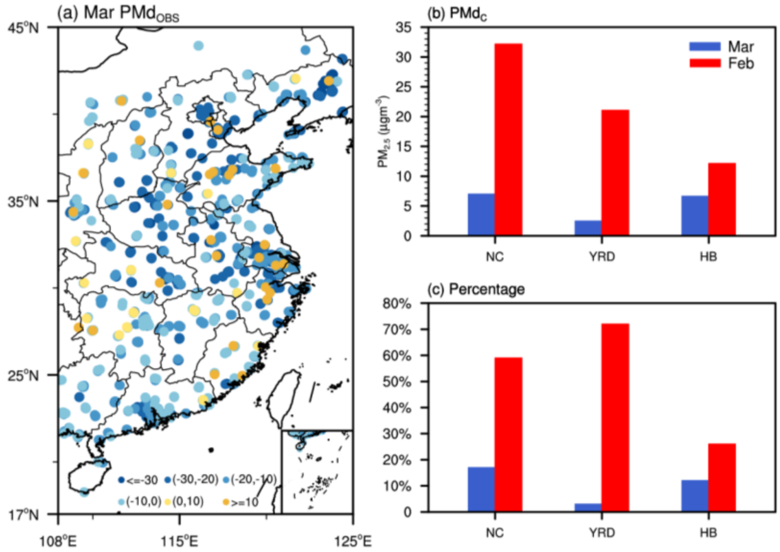


Figure 7. (a) Differences in the observed $PM_{2.5}$ (unit: μg/m^3) in March between 2020 and 2017. (b) Contributions of PMd_C to the change in $PM_{2.5}$ concentration (unit: μg/m^3) between 2020 and 2017 and (c) the contribution ratios of PMd_C (relative to the $PM_{2.5}$ observations in 2020) in March (blue) and February (red) in the three regions.

Evident $PM_{2.5}$ Drops in the East of China due to the COVID-19 Quarantines in February

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Abstract. The top-level emergency response to the COVID-19 pandemic involved an exhaustive quarantine in China. The impacts of COVID-19 quarantine on the decline in fine particulate matter ($PM_{2.5}$) were quantitatively assessed based on numerical simulations and observations in February. Relative to both of February 2017 and climate mean, anomalous southerlies and moister air occurred in the east of China in February 2020, which caused considerable $PM_{2.5}$ anomalies. Thus, it is a must to disentangle the contributions of stable meteorology from the effects of the COVID-19 lockdown. ~~The stable meteorological conditions in February 2020 caused considerable PM2.5 anomalies that were eliminated in advance.~~ The contributions of routine emission reductions were also quantitatively extrapolated. The top-level emergency response substantially alleviated the level of haze pollution in the east of China. Although climate variability elevated the $PM_{2.5}$ by 29% (relative to 2020 observations), 59% decline related to COVID-19 pandemic and 20% decline from the expected pollution regulation dramatically exceeded the former in North China. The COVID-19 quarantine measures decreased the $PM_{2.5}$ in Yangtze River Delta by 72%. In Hubei Province where most pneumonia cases were confirmed, the impact of total emission reduction (72%) evidently exceeded the rising percentage of $PM_{2.5}$ driven by meteorology (13%).

Keywords: COVID-19, $PM_{2.5}$, Emission Reduction, Climate Variability, Haze

1 Introduction

The COVID-19 pandemic devastatingly blew China in the beginning of 2020 (Luo, 2020; Xia et al., 2020; Cao et al., 2020). By April 2020, more than 84 thousand confirmed cases were reported by the National Health Commission of China, approximately 75% of which were confirmed in February (Fig. 1a). To effectively control the large spread of COVID-19 pneumonia, stringent quarantine measures were implemented by the Chinese government and people themselves, including prohibiting social activities, shuttering industries, stopping transportation, etc. (Chen S. et al., 2020). The abovementioned emergency response measures were first carried out in Wuhan on 23 January, which resulted in the delayed arrival of COVID-19 in other cities by 2.91 days, and these response measures were in effect in all cities across China, thus limiting the spread of the COVID-19 epidemic in China (Tian et al., 2020). Since March 7, the number of newly confirmed cases in China has been nearly below 100. On the other hand, the COVID-19 quarantine measures greatly reduced anthropogenic emissions, and therefore, the air quality in China was considerably improved (Wang et al., 2020). Chen K. et al. (2020) simply compared observations of atmospheric components before and during the quarantine and found that the concentration of fine particulate matter ($PM_{2.5}$) in Wuhan decreased 1.4 μg/m^3, but it decreased 18.9 μg/m^3 in 367 cities across China. Shi et al. (2020) quantified a 35% reduction of $PM_{2.5}$ on average during the COVID-19 outbreak compared to the pre-COVID-19 period. Huang et al. (2020) used comprehensive measurements and modeling to show that the haze during COVID-19 lockdown was driven by enhancements of secondary pollution, which offset reduction of primary emissions during this period in China. However, the impacts of meteorology on the air quality were neglected in many previous studies.

~~After the severe haze events of 2013, routine emission reductions resulted in an approximately 42% decrease in the annual mean $PM_{2.5}$ concentration between 2013 and 2018 in China (Cleaner air for China, 2019). In November 2019, the Ministry of Environmental Protection of China issued a series of Autumn-Winter Air Pollution Prevention and Management Plans indicating that the routine emission reductions would be conventionally implemented in the following winter (Ministry of Environmental Protection of China, 2019).~~ Climate variability notably influences the formation and intensity of haze pollution in China (Yin and Wang 2016; Xiao et al., 2015; Zou et al., 2017), and the impacts are embodied by variations in surface wind, boundary layer height and moisture conditions (Shi et al., 2019; Niu et al., 2010; Ding et al., 2014). During December 16th-21st 2016, although most aggressive control measures for anthropogenic emissions were implemented, severe haze pollution with $PM_{2.5}$ concentrations ≈ 1100μg m^{-3} still occurred and covered 710,000km^2. The continuous low surface wind speed of less than 2ms^{-1}, high humidity above 80% and strong temperature inversion lasting for 132h caused the rebound of wintertime $PM_{2.5}$ in 2016 (Yin and Wang, 2017). In winter 2017, the air quality in North China largely improved; however, the stagnant atmosphere in 2018 resulted in a major $PM_{2.5}$ rebound by weakening transport dispersion and enhancing the chemical production of secondary aerosols (Yin and Zhang 2020). Wang et al. (2020) applied the Community Multiscale Air Quality model to emphasize that the role of adverse meteorological conditions cannot be neglected even during the COVID-19 outbreak. ~~Thus, high $PM_{2.5}$ concentrations were also observed in February 2020, which were mainly attributive to limited ventilation conditions and a high humidity (Ministry of Ecology and Environment of China, 2020).~~ From February 8 to 13 2020, North China suffered severe pollutions, with maximum daily $PM_{2.5}$ exceeding 200μg m^{-3}. During this period, weak southerly surface winds lasted for nearly 5 days, relative humidity was close to 100%, and atmospheric inversion reached more than 10°C. Although pollution emissions from basic social activities have been reduced, heavy pollution still occurred when adverse meteorological conditions characterized by stable air masses appeared (Wang et al., 2020).

After the severe haze events of 2013, routine emission reductions resulted in an approximately 42% decrease in the annual mean $PM_{2.5}$ concentration between 2013 and 2018 in China (Cleaner air for China, 2019). In November 2019, the Ministry of Environmental Protection of China issued a series of Autumn-Winter Air Pollution Prevention and Management Plans indicating that the routine emission reductions would be conventionally implemented in the following winter (Ministry of Environmental Protection of China, 2019). As reported by the government, the mean ratio of work resumption in large industrial enterprises was approximately 90% in the east of China until the end of February (Fig. 1b). In this study, we attempted to quantify the impacts of the COVID-19 pandemic on the observed $PM_{2.5}$ concentration in February 2020 when the quarantine measures were the strictest. The official 7-day Chinese New Year holiday occurs in January and February and commonly accounts for approximately 25% of a month. From 2013–2020, there were only two years (2017 and 2020) when the official 7-day holiday occurred in January (Fig. 1c). Thus, to avoid the impacts of the Spring Festival, the observed $PM_{2.5}$ concentration in February 2017 (Fig. 1a) was adopted to calculate the $PM_{2.5}$ difference, which was decomposed into the results due to expected routine emission reductions, changing meteorology climate variability, and COVID-19 quarantines.

2 Datasets and methods

2.1 Data description

Monthly mean meteorological data from 2015 to 2020 were obtained from NCEP/NCAR reanalysis datasets, with a horizontal resolution of 2.5°×2.5°, including the geopotential height at 500 hPa (H500), zonal and meridional winds at 850 hPa, vertical wind from the surface to 150 hPa, and relative humidity at the surface (Kalnay et al., 1996). $PM_{2.5}$ concentration data from 2015 to 2020 were acquired from the China National Environmental Monitoring Centre (https://quotsoft.net/air/ ~~http://beijingair.sinaapp.com/~~). The monitoring network expanded from 1500 sites in 2015 to 1640 sites in 2020, covering approximately 370 cities nationwide. The $PM_{2.5}$ data were monitored every 5 min using two methods: a tapered element oscillating microbalance and β-rays, which were operated under the China National Quality Control.

2.2 GEOS-Chem description, evaluation and experimental design.

We used the GEOS-Chem model (http://acmg.seas.harvard.edu/geos/) to simulate the $PM_{2.5}$ concentration, driven by MERRA-2 assimilated meteorological data (Gelaro et al., 2017). The nested grid over China (15° N–55° N, 75–135° E) had a horizontal resolution of 0.5° latitude by 0.625° longitude and consisted of 47 vertical layers up to 0.01 hPa. The GEOS-Chem model included the fully coupled O_3–NO_x–hydrocarbon and aerosol chemistry module with more than 80 species and 300 reactions (Bey et al., 2001; Park et al., 2004). The $PM_{2.5}$ components simulated in the GEOS-Chem model included sulfate, nitrate, ammonium, black carbon and primary organic carbon, mineral dust, and sea salt. Aerosol thermodynamic equilibrium is computed by the ISORROPIA package, which calculates the gas–aerosol partitioning of the sulfate–nitrate—ammonium system (Fountoukis and Nenes, 2007). Heterogeneous reactions of aerosols include the uptake of HO_2 by aerosols (Thornton et al., 2008), irreversible absorption of NO_2 and NO_3 on wet aerosols (Jacob, 2000), and hydrolysis of N_2O_5 (Evans and Jacob, 2005). Two alternate simulations of aerosol microphysics are implemented in GEOS-Chem: the TOMAS simulation (Kodros and Pierce, 2017) and the APM simulation (Yu and Luo, 2009).

~~At present,~~ GEOS-Chem model has been widely used to examine~~, and~~ the historical changes in air quality in China ~~were also examined through modeling studies~~ and quantitatively separate the impacts of physical-chemical processes. Using the GEOS-Chem model, Yang et al. (2016) found an increasing trend of winter $PM_{2.5}$ concentrations during 1985–2005, 80% of which due to anthropogenic emissions and 20% due to meteorological conditions. ~~Dang et al. (2019) showed that this model could capture the spatial and temporal variations in severe winter haze in China and obtained increasing trends in the frequency and intensity of severe winter haze days in Beijing-Tianjin-Hebei from 1985-2017.~~Here, we simulated the $PM_{2.5}$ concentrations in February 2017 and evaluated the performance of GEOS-Chem (Fig. S1a). The values of mean square error / mean equals were 5.8%, 7.0% and 5.4% in North China (NC), Yangtze River Delta (YRD) and Hubei Province (HB), respectively, indicating the good performance of reproducing the haze-polluted conditions. The absolute biases were larger in the south of China, which was consistent with Dang and Liao (2019). They also compared the simulated and observed daily mean $PM_{2.5}$ concentrations at the Beijing, Shanghai, and Chengdu grids, which had a low bias in Beijing and high biases in Shanghai and Chengdu, respectively. The simulated biases possibly affected the subsequent results and brought uncertainties to some extent. The simulated spatial distribution of $PM_{2.5}$ was also similar to that of observations with spatial correlation coefficient = 0.78. ~~To further identify the reliability of the GEOS-Chem simulation, we focused on~~ We further verified whether the simulations could capture the roles of meteorological changes in February 2020 under a substantial reduction in emissions because of COVID-19 quarantines. In ~~North China~~ ~~(~~NC~~)~~, ~~Yangtze River Delta (~~YRD~~)~~ and ~~Hubei Province (~~HB~~)~~, the correlation coefficients between daily $PM_{2.5}$ observations and simulated data under 2010 (1985) emission scenario reached 0.83 (0.82), 0.67 (0.63), and 0.79 (0.73), respectively. For example, in NC, the simulation could well simulate severe haze events (e.g., from 8–134 and 19~~8–~~25~~2~~ February) and good air quality events (e.g., from 14~~5–~~18~~9~~ February), reflecting that it has ability to accurately capture the change of meteorological conditions (Fig. S1b).

The $PM_{2.5}$ concentration in February from 2015 to 2020 was simulated in this study. Due to delayed updates of the emission inventory, we used the emissions data of 2010 (http://geoschemdata.computecanada.ca/ExtData/HEMCO/AnnualScalar) and 1985 (M. Li et al., 2017) for the simulations, which represented high- and low-emission scenarios, respectively. In total, we conducted two sets of numerical experiments to drive the GEOS-Chem simulations, one combining the meteorological conditions from 2015 to 2020 with fixed emissions in 1985 and the other with fixed emissions in 2010, which could determine the stability of simulated results.

~~To further identify the reliability of the GEOS-Chem simulation, we focused on whether the simulations could capture the roles of meteorological changes in February 2020 under a substantial reduction in emissions because of COVID-19 quarantines. In North China (NC), Yangtze River Delta (YRD) and Hubei Province (HB), the correlation coefficients between daily PM2.5 observations and simulated data under 2010 (1985) emission scenario reached 0.83 (0.82), 0.67 (0.63), and 0.79~~

~~(0.73), respectively. For example, in NC, the simulation could well simulate severe haze events (e.g., from 8–14 and 18–22 February) and good air quality events (e.g., from 15–19 February), reflecting that it has ability to accurately capture the change of meteorological conditions (Fig. S1).~~

2.3 The method to quantify the influence of the COVID-19 quarantine.

As mentioned above, we aimed to examine the impact of the COVID-19 quarantines on $PM_{2.5}$ over the February 2017 level basing on~~,~~ an observational-numerical hybrid method. The observed $PM_{2.5}$ difference in February 2020 (PMd_{OBS}) was linearly decomposed into three parts: the impacts of changing meteorology (PMd_M), expected routine emissions reductions (PMd_R) and COVID-19 quarantines (PMd_C), which was a reasonable approximation, and the decomposition equation was $PMd_{OBS} = PMd_M + PMd_R + PMd_C$. That is, $PMd_C = PMd_{OBS} - PMd_M - PMd_R$. It should be noted that PMd_C is the impact of the COVID-19 quarantines over the situation whereby the pandemic did not occur and routine emission reductions conventionally were in effect. The value of PMd_E (i.e., $PMd_R + PMd_C$) was the total impact of the emission reductions in February 2020 over the 2017 level.

Simulated $PM_{2.5}$ data driven by changing meteorology with two fixed-emissions (1985 and 2010) were employed to determine the ratio of PMd_M of each year/~~PMd_{OBS}~~ observed $PM_{2.5}$ in 2017. Depending on the GEOS-Chem simulations, we found that the ~~$PM_{2.5}$~~ percentage of changed $PM_{2.5}$ due to ~~changing~~ the differences in meteorology remained nearly constant regardless of the emission level (Fig. S2), which was consistent with the results of Yin and Zhang (2020). This percentage was the difference of simulated $PM_{2.5}$ between each year and 2017 under the same emission scenario divided by the simulated $PM_{2.5}$ in 2017. For example, the percentages due to different meteorology between 2020 and 2017 were 22.1% (21.4%), –1.2% (–0.7%) and 9.0% (8.2%) in NC, YRD and HB under the low (high) emissions (Fig. S2). The percentage under 2010 emission scenario was selected as the final percentage because the emissions from each sector in 2010 were more similar to recent years, and thus was more reasonable. Then, through multiplying the 2017 observation~~ication~~ by this percentage ~~, PMd_M, with respect to the 2017 observations~~, PMd_M can be quantified in each simulation grid with respect to 2017 (STEP 1).

From 2015 to 2019, $PMd_C = 0$; thus, $PMd_R = PMd_{OBS} - PMd_M$. Here, we repeated STEP 1 to determine PMd_M in each year from 2015 to 2019 relative to 2017 (i.e., $PMd_M = 0$ in 2017). After removing the effect of meteorological conditions in $PM_{2.5}$ differences, PMd_R in all years except 2020 can also be calculated. According to many previous studies, the change in emissions resulted in a linear change in air pollution in China from 2013-2019 (Wang et al., 2020; Geng et al., 2020) which might be related to the huge emission reduction due to the implementation of clean air action. ~~(Cai et al., 2017; Wang et al., 2019),~~ Because the signal of emissions reduction in China had been particularly strong since 2013, it could be easily detected and the assumption of a linear reduction in pollution caused by emission reduction was applicable in China in the past few years. Based on this approximation,~~therefore,~~ we used the method of extrapolation to speculate the impact of routine emission reduction on $PM_{2.5}$. We performed linear extrapolation based on known PMd_R values from 2015 to 2019 to obtain PMd_R in 2020 (STEP 2,

Fig. S3). This PMd_R in 2020was calculated as the change of $PM_{2.5}$ caused by expected routine emission reduction, which did not actually happen, but merely gave an assessment in the case of “if no COVID-19”. In Beijing and Shanghai, for example, $PM_{2.5}$ fell by 23.1% and 26.6% due to routine emission reduction in 2019, respectively, compared with 2015. Zhou et al. (2020) indicated that emission reductions caused 20–26% decreases in winter in Beijing which has been translated into 5 years. Zhang et al. (2020)~~[22]~~ also showed that the emission controls in Beijing-Tianjin-Hebei (BTH) region have led to significant reductions in $PM_{2.5}$ from 2013 to 2017 of approximately 20 % after excluding the impacts of meteorology. Geng et al. (2020) found a 20% drop in the main component of $PM_{2.5}$ in the Yangtze River Delta from 2013 to 2017. These results are consistent with our extrapolated results~~ions~~. Therefore, it is reasonable to obtain PMd_R by extrapolation after disentangling ~~removing~~ the effects of meteorological conditions.

Through STEP 1 and STEP 2, PMd_C and PMd_R, respectively, in 2020 can be determined. PMd_{OBS} can be directly calculated from the observed data. After removing the influences of climate anomalies and routine emission reductions, the impact of COVID-19 quarantines on $PM_{2.5}$ (PMd_C) was extracted as $PMd_{OBS} – PMd_M – PMd_R$ (STEP 3).

3 Results

The mean $PM_{2.5}$ concentration in February 2020 was nearly below 80 μg/m^3 at the vast majority of sites in the east of China, which was much lower than before (Fig. S4). North China (NC) was still the most polluted region (>40 μg/m^3), but the $PM_{2.5}$ concentrations in the Pearl River Delta (PRD) and Yangtze River Delta (YRD) were < 20 μg/m^3 and < 40 μg/m^3, respectively. Relative to the observations in February 2017, negative $PM_{2.5}$ anomalies were centered in ~~North China (~~NC~~)~~, with values of approximately –60 to –40 μg/m^3 in southern Hebei Province and northern Henan Province (Fig. 2). In Hubei Province (HB), where the COVID-19 pneumonia cases were the most severe in February, the $PM_{2.5}$ concentration was 20~40 μg/m^3 lower than that in 2017. The $PM_{2.5}$ differences were also negative in YRD and PRD. Therefore, how much did air pollution decrease due to the COVID-19 quarantines in February in east of China?

Climate variability notably influences the interannual-decadal variations in haze pollution as verified by both observational analysis (Yin et al., 2015) and GEOS-Chem simulations (Dang and Liao, 2019). Furthermore, Zhang et al. (2020) reported that meteorology contributes 50% and 78% of the wintertime $PM_{2.5}$ reduction between 2017 and 2013 in the ~~Beijing-Tianjin-Hebei (~~BTH ~~) region~~ and YRD, respectively. Therefore, it is necessary to ~~remove~~disentangle the influences of climate anomalies before quantifying the contributions of the COVID-19 quarantines on the air quality. ~~Based on the GEOS-Chem simulations, PMd_M (i.e., the $PM_{2.5}$ difference due to changing meteorology) was calculated between February 2020 and 2017 (see Methods). To the south of 30°N, most PMd_M values were negative with small absolute values, at < 10 μg/m^3. To the north of 30°N, the PMd_M values were mostly positive, ranging from 30–60 μg/m^3 in BTH (Fig. 3a).~~ The highest observed $PM_{2.5}$ concentrations were 274, 223, and 303 μg/m^3 in Beijing, Tianjin and Shijiazhuang, respectively. Although human activities had sharply decreased, severe haze pollution (e.g., 8–13 and 19–25 February 2020) was not avoided, which was attributed to the stagnant atmosphere (Wang et al., 2020), and these severe haze events were also reproduced by the GEOS-Chem simulation (see Section 2.2 and Fig. S1b).

As shown in Figure 4a-b, the meteorological conditions in February 2020 were more favorable for the occurrence of haze pollution in NC. In the mid-troposphere, an anomalous anticyclone was located over NC and the Sea of Japan (Fig. 4a). These anticyclonic anomalies clearly stimulated anomalous southerlies over eastern China, which not only transported sufficient water vapor to NC but also overwhelmed the climatic northerlies in winter (Fig. 4b). In addition, the anomalous upward motion associated with anomalous anticyclones prevented the downward transportation of westerly momentum and preserved the thermal inversion layer over NC (Fig. S5). Particularly, in the stagnant days (i.e., 8–13 and 19–25 February), the East Asia deep trough, one of the most significant zonally asymmetric circulations in the wintertime Northern Hemisphere (Song et al., 2016), shifted eastwards and northwards than climate mean, which steered the cold air to North Pacific instead of North China (Fig. 4c). The climatic northerlies in February, related to East Asia winter monsoon, also turned to be south winds in the east of China (Fig. 4d). Physically, the weakening surface winds and strong thermal inversion corresponded to weaker dispersion conditions, and the higher humidity indicated a favorable environment for the hygroscopic growth of aerosol particles to evidently decrease the visibility. Compared with the climate (February 2017) monthly mean, boundary layer height (BLH) decreased by 19.5m (34.5m), surface relative humidity (rhum) increased by 5% (10.6%) and surface air temperature (SAT) rose by 1.6°C (0.9°C) after detrending, which were conductive to the increase of $PM_{2.5}$ concentration in February 2020. Furthermore, the correlation coefficients of daily $PM_{2.5}$ and BLH, rhum, wind speed and SAT in North China were -0.63, 0.44, -0.45 and 0.46, respectively, all of which passed the 95% significance test and indicated importance of meteorology. We used the meteorological data in February 2017 to establish a multiple linear regression equation to fit $PM_{2.5}$. The correlation coefficients between the fitting results and the observed $PM_{2.5}$ concentration in NC, YRD and HB reached 0.84, 0.64 and 0.65, exceeding the 99% significance test. Then, we put the observed meteorological data in February 2020 into this established multiple regression equation to get the predicted $PM_{2.5}$ concentration. Using the regress-predicted value, the percentage of changed $PM_{2.5}$ due to the differences in meteorology between 2017 and 2020 were re-calculated and is 20.7%, -3.2% and 9.5% in NC, YRD and HB, respectively (Fig. S2), which is consistent with and enhanced the robustness of the results obtained by our previous model simulation. Based on the GEOS-Chem simulations, PMd_M ~~(i.e., the $PM_{2.5}$ difference due to changing meteorology)~~ was calculated between February 2020 and 2017 (see Methods). To the south of 30°N, most PMd_M values were negative with small absolute values, at < 10 μg/m^3. To the north of 30°N, the PMd_M values were mostly positive, ranging from 30~60 μg/m^3 in BTH (Fig. 3a). ~~The weakening surface winds and strong thermal inversion corresponded to weaker dispersion conditions, and the higher humidity indicated a favorable environment for the hygroscopic growth of aerosol particles.~~

Since 2013, the Chinese government has legislated and implemented stringent air pollution prevention and management policies that have clearly contributed to air quality improvement (Wang et al., 2019). As mentioned above, without the COVID-

19 pandemic, these emission reduction policies would certainly remain in effect in February 2020. Thus, we extrapolated PMd_R (i.e., the $PM_{2.5}$ difference due to expected routine emission reductions) between February 2020 and 2017 to isolate the impacts of the COVID-19 quarantines (i.e., PMd_C). PMd_R was mostly negative in the east of China (Fig. 3b). Because the impacts of meteorology were proactively removed, these negative values illustrated that routine emission reductions substantially reduced the wintertime $PM_{2.5}$ concentration. The contributions of the emission reduction policies were the greatest in the south of BTH and were also remarkable in Hubei Province (Fig. 3b). Although the PMd_R of Beijing in 2016 did not strictly comply with the pattern of monotonous decrease, which might be caused by the fluctuation of policy and its implementation, the value of PMd_R in 2020 relative to 2017 was –8.4 μg/m^3 and was comparable to the 11.5 μg/m^3 reductions due to policy during 2013–2017 (Zhang et al., 2020). In Shanghai, PMd_R was –12.0 μg/m^3 (Fig. 5), whose magnitude was proportional with assessments by Zhang et al. (2020), and the trend was nearly linear. The rationality of the extrapolations of PMd_R was also proved in Section 2.3. The trend of PMd_R in Wuhan was –9.6 μg/m^3 per year from 2015–2019, which indicated high efficiency of the emission reduction policies and resulted in large PMd_R values in 2020 (i.e., –21.8 μg/m^3).

By disentangling ~~removing~~ the impacts of meteorology and routine emission reduction policies, the change in $PM_{2.5}$ due to the COVID-19 quarantines was quantitatively extracted. As expected, this severe pandemic caused dramatic slumps in the $PM_{2.5}$ concentration across China (Fig. 3c). Large PMd_C values (approximately –60 to –30 μg/m^3) were located in the high-polluted NC regions where intensive heavy industries were stopped and the traditional massive social activities and transportations around Chinese New Year were cancelled as part of the COVID-19 quarantine measures. To the south of 30°N, the impacts of the COVID-19 quarantines on the air quality were relatively weaker (–30 ~ 0 μg/m^3) than those in the north~~, which was possibly related to the background conditions of air quality improvement~~. Generally, the south region was less polluted than the north, therefore the baseline of $PM_{2.5}$ concentration was relatively lower (Fig. S4a). In addition, meteorological conditions in the south in February 2020 had no positive contribution (Fig. 3a), which would not lead to the increase of $PM_{2.5}$ concentration. These two possible reasons resulted in a smaller space for $PM_{2.5}$ decrease due to COVID-19 quarantines in the south and accompanying regional differences. To reduce the assessment uncertainties, the percentage of changed $PM_{2.5}$ due to the differences in meteorology were ~~PMd_C was also~~ recalculated based on the GEOS-Chem simulations with fixed emission in 1985~~, which represented a low emission scenario~~. As described in the Methods section, the recalculated PMd_C ~~results~~ in Figure S6 are consistent with those in Figure 3c, showing a high robustness. Furthermore, the mean $PM_{2.5}$ concentration decreases due to the COVID-19 quarantines in NC, HB and YRD were analyzed, which accounted for 59%, 26% and 72% of the observed February $PM_{2.5}$ concentration in 2020~~, revealing clear regional differences~~ (Fig. 6).

It should be noted that the sum of PMd_R and PMd_C (i.e., PMd_E) is the total contribution of the emission reduction in February 2020 with respect to 2017 (Fig. 3d). In NC, YRD and HB, the COVID-19 quarantines and routine emission reductions drove $PM_{2.5}$ in the same direction. The mean $PM_{2.5}$ decrease in NC, due to the total emission reduction, was –43.3 μg/m^3, accounting for 79% of the observed February $PM_{2.5}$ concentration in 2020 (Fig. 6). Although the absolute values of both PMd_R

and PMd_C in YRD were smaller than those in NC, the change percentage (92%) was larger because of the lower base $PM_{2.5}$ concentration. In HB, where more than 80% of the confirmed COVID-19 cases in China occurred and the cities were in emergency lockdown, the total anthropogenic emissions were clearly limited, which resulted in a 72% decline in $PM_{2.5}$ in the atmosphere (Fig. 6). In particular, if the anthropogenic emissions did not decline, the $PM_{2.5}$ concentration in NC, YRD and HB would increase to nearly twice the current observation (Fig. 6), indicating significant contributions of human activities to the air pollution in China.

The declines of $PM_{2.5}$ seemed not to be directly proportional to the almost complete shutoff of vehicle traffics and industries, that is, the reduction ratio of $PM_{2.5}$ concentrations were smaller than that of precursor emissions (Wang et al., 2020). The unexpected air pollutions during the marked emission reductions were closely related to the stagnant air flow, enhanced productions of secondary aerosols, and uninterrupted residential heating, power plants and petrochemical facilities (Le et al., 2020). The partial impacts of stagnant meteorological conditions have been explained earlier (Fig. 4). In Wuhan, the $PM_{2.5}$ remained the main pollutant during the city lockdown and the high level of sulphur dioxide (SO_2) may be related to the increased domestic heating and cooking (Lian et al., 2020). In North China, large reductions of primary aerosols were observed, but the decreases in secondary aerosols were much smaller (Sun et al., 2020; Shi et al., 2020). Because of break-off transportations, reduced nitrogen oxide (NO*x*~~NO_x~~) increased the concentrations of ozone and nighttime nitrate (NO_3) radical formations. The increased oxidizing capacity in the atmosphere enhanced the formation of secondary particulate matters (Huang et al., 2020). Thus, the non-linear relationship of emission reduction and secondary aerosols also partially contributed to the haze occurrence during the COVID-19 lockdown. ~~Although the $PM_{2.5}$ dropped much, marked air pollutions also occurred during this unique experiments that the human emissions were sharply closed. This implied reconsiderations of policy for pollution controls and necessity to cut off secondary productions of particulate matters (Le et al., 2020; Huang et al., 2020).~~

4 Conclusions and discussion

In the beginning of 2020, the Chinese government implemented top-level emergency response measures to contain the spread of COVID-19. The traditional social activities surrounding Chinese New Year, industrial and transportation activities, etc. were prohibited, which effectively reduced the number of confirmed cases in China. Concomitantly, anthropogenic emissions, which are the fundamental reason for haze pollution, were dramatically reduced by the COVID-19 quarantine measures. In this study, we employed observations and GEOS-Chem simulations to quantify the impacts of the COVID-19 quarantines on the air quality improvement in February 2020 after decomposing ~~removing~~ the contributions of expected routine emission reductions and climate variability. Although the specific influences varied by the region, the COVID-19 quarantines substantially decreased the level of haze pollution ~~level~~ in the east of China (Fig. 6). In North China, the meteorological conditions were stagnant that enhanced the $PM_{2.5}$ concentration by 30% (relative to the observations in 2020). In contrast, the expected routine emissions reductions and emergency COVID-19 quarantine measures resulted in an 80% decline. In YRD, the impacts of meteorology were negligible but the COVID-19 quarantines decreased $PM_{2.5}$ by 72%. In Hubei Province, the impact of the total emission reduction (72%) evidently exceeded the $PM_{2.5}$ increase due to meteorological conditions (13%). In March, due to the continued control of the COVID-19, the quarantines measures still contributed to the negative anomalies of the observed $PM_{2.5}$ between 2020 and 2017 (Figure 7a). Because the activities in production and life have been gradually resumed in March, the $PM_{2.5}$ drops caused by the COVID-19 quarantines became weaker compared with February (Fig. 7b, c). The contributions of PMd_C to the change of $PM_{2.5}$ concentration in NC, YRD and HB declined from 32.2, 21.0 and 12.1 µg/m^3 in February to 7.0, 2.4 and 6.7 µg/m^3 in March respectively.

Because of the common update delay of the emission inventory, we employed a combined analysis consisting of ~~statistical~~ observational and numerical methods. We strictly demonstrated the rationality of this method and the results, mainly based on the relatively constant contribution ratio of changing meteorology from GEOS-Chem simulations under the different emissions (Yin and Zhang 2020).~~, and the $PM_{2.5}$ drops due to COVID-19 quarantines which calculated based on the GEOS-Chem simulations with fixed emissions of 1985 were also relatively stable.~~ However, there was a certain bias in the simulations by GEOS-Chem model, and the biases also showed regional differences (Dang and Liao, 2019). Therefore, g~~G~~aps between the assessed results and reality still exist, which requires further numerical experiments when the emission inventory is updated. Furthermore, ~~D~~during the calculation process, the observed $PM_{2.5}$ difference in February 2020 was linearly decomposed into three parts. Although this linear decomposition was reasonable in C~~c~~hina in the past few years, we must note that this approximation was lack of considering the meteorology-emission interactions, the product of the emission, the loss lifetime and particularly the sulfate-nitrate-ammonia thermodynamics (Cai et al., 2017), which brought some uncertainties. ~~The PMd_M is based on 2010 emissions, which are more representative of the emissions of each sector in recent years. The calculated $PM_{2.5}$ percentages due to changing meteorology are relatively stable regardless of the emission level, but the result is obtained by numerical simulations, with certain uncertainty.~~ ~~In fact, t~~The actual emission reduction effect is ~~still~~ considerable (Fig. 3d), in line with the increasingly strengthened emission reduction policies in recent years. When calculating the PMd_R in 2020, we use the method of extrapolation. Although the result is consistent with others observational and numerical studies (Geng et al., 2020; Zhang et al., 2020; Zhou et al., 2019), it is still conjectures rather than true values. ~~In fact, the actual emission reduction effect is still considerable (Fig. 3d), in line with the increasingly strengthened emission reduction policies in recent years.~~ ~~Furthermore, we separated the effects of meteorology and emission reduction on $PM_{2.5}$, not taking into account the possible interaction between these two factors.~~ These issues need to be examined in the future studies to unlock ~~of the~~ respective effects of emissions and meteorological conditions on $PM_{2.5}$ over eastern China. To restrict the possible uncertainties, we set up some constraints: 1. The pivotal contribution ratio of changing meteorology were calculated under two emission levels and recalculated by statistical regressed model; 2. The values of PMd_M and PMd_R were widely compared to previous studies.

If the COVID-19 epidemic did not occurred, the concentrations of $PM_{2.5}$ would increase up to 1.3–1.7 times the observations in February 2020 (Fig. 6). Therefore, the pollution abatement must continue. Because of the huge population base in the east of China, the anthropogenic emissions exceeded the atmospheric environmental capacity even during COVID-19 quarantines. Although the $PM_{2.5}$ dropped much, marked air pollutions also occurred during this unique experiments that the human emissions were sharply closed. This raised new scientific questions, such as changes of atmospheric heterogeneous reactions and oxidability under extreme emission control, quantitative meteorology-emission interactions, and so on. ~~Although the $PM_{2.5}$ dropped much, marked air pollutions also occurred during this unique experiments that the human emissions were sharply closed.~~ This also implied reconsiderations of policy for pollution controls and necessity to cut off secondary productions of particulate matters basing on sufficient scientific research (Le et al., 2020; Huang et al., 2020). Some ~~S~~studies estimated that thousands of deaths were prevented during the quarantine because of the air pollution decrease (Chen K. et al., 2020). However, medical systems were still overstressed, and transportation to hospitals also decreased. Furthermore, the deaths related to air pollution were almost all due to respiratory diseases (Wang et al., 2001), and their corresponding medical resources were also further stressed by COVID-19. Therefore, the mortality impacted by the air pollution reduction during the COVID-19 outbreak should be comprehensively assessed in future work.

Data availability. Monthly mean meteorological data are obtained from ERA5 reanalysis data archive: https://cds.climate.copernicus.eu/cdsapp#!/search?type=dataset. $PM_{2.5}$ concentration data are acquired from the China National Environmental Monitoring Centre: http://beijingair.sinaapp.com/. The emissions data of 1985 can be downloaded from http://geoschemdata.computecanada.ca/ExtData/HEMCO/AnnualScalar/, and that of 2010 can be obtained from MIX: http://geoschemdata.computecanada.ca/ExtData/HEMCO/MIX.

Acknowledgements

The National Natural Science Foundation of China (41991283, 9174431 and 41705058), the funding of Jiangsu innovation & entrepreneurship team, and the special project “the impacts of meteorology on large-scale spread of influenza virus” from CIC-FEMD supported this research.

Authors’ contribution

Wang H. J. and Yin Z. C. designed and performed researches. Zhang Y. J. simulated the $PM_{2.5}$ by GEOS-Chem model and Li Y. Y. did the statistical analysis. Yin Z. C. prepared the manuscript with contributions from all co-authors.

Competing interests

The authors declare no conflict of interest.

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Figure Captions

Figure 1. (a) Variation in existing confirmed cases (bar; red: increase, blue: decrease) and the ratio of accumulated confirmed cases to total confirmed cases (black line) in China. (b) The ratio of work resumption in large industrial enterprises in the east of China. (c) Time of the official 7-days holiday of Chinese New Year from 2013 to 2020.

Figure 2. Differences in the observed $PM_{2.5}$ (unit: μg/m^3) in February between 2020 and 2017. The black boxes indicate the locations of North China (NC, 32.5-42°N,110-120°E), the Yangtze River Delta (YRD, 28-32.5°N,118-122°E) and Hubei Province (HB, 30-32.5°N,109.5-116°E).

Figure 3. $PM_{2.5}$ difference (unit: μg/m^3) in February between 2020 and 2017 ~~(a)~~ due to (a) changing meteorology (PMd_M), (b) ~~due to~~ expected routine emission reductions (PMd_R), (c) ~~due to~~ the COVID-19 quarantines (PMd_C), and (d) due to the total emission reduction ($PMd_E = PMd_R + PMd_C$).

Figure 4. Differences in the observed atmospheric circulation in February between 2020 and 2017, including (a) geopotential potential height at 500 hPa (unit: gpm), (b) wind at 850 hPa (arrows; unit: m/s), surface relative humidity (shading; unit: %). The atmospheric circulations in the stagnant days (e.g., from 8–13 and 19–25 February 2020) were also showed, including (c) geopotential potential height at 500 hPa (shading; unit: gpm) and its climate mean in February (contour), and (d) wind at 850

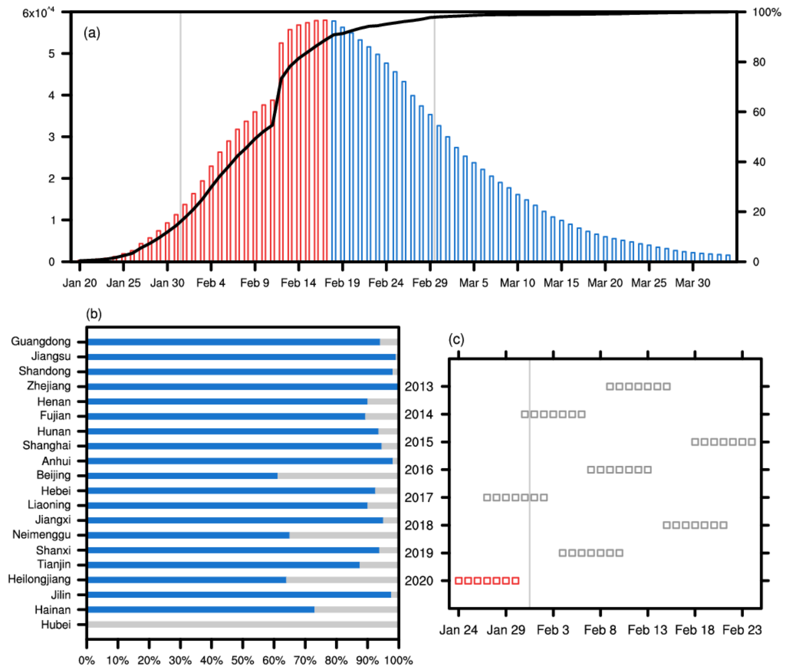
hPa (black arrows; unit: m/s), its climate mean (blue arrows) and the increased surface relative humidity (shading; unit: %, stagnant days minus climate mean).

Figure 5. Variation in PMd_R (unit: μg/m^3) with respect to the February 2017 level in Beijing, Shanghai and Wuhan from 2015 to 2019. PMd_R in 2020 was linearly extrapolated from that in the 2015–2019 period. The dotted line is the linear trend.

Figure 6. Contributions of PMd_M (orange bars with hatching), PMd_R (purple bars with hatching) and PMd_C (blue bars with hatching) to the change in $PM_{2.5}$ concentration (unit: μg/m^3) between 2020 and 2017 in the three regions. The observed $PM_{2.5}$ concentration in February 2017 (black) and 2020 (gray) was also plotted, and the expected $PM_{2.5}$ concentration without the COVID-19 quarantine is indicated by black hollow bars. The contribution ratios of the three factors (relative to the $PM_{2.5}$ observations in 2020) are also indicated on the corresponding bars.

Figure 7. (a) Differences in the observed $PM_{2.5}$ (unit: μg/m3) in March between 2020 and 2017. (b) Contributions of PMd_C to the change in $PM_{2.5}$ concentration (unit: μg/m^3) between 2020 and 2017 and (c) the contribution ratios of PMd_C (relative to the $PM_{2.5}$ observations in 2020) in March (blue) and February (red) in the three regions.

Figures



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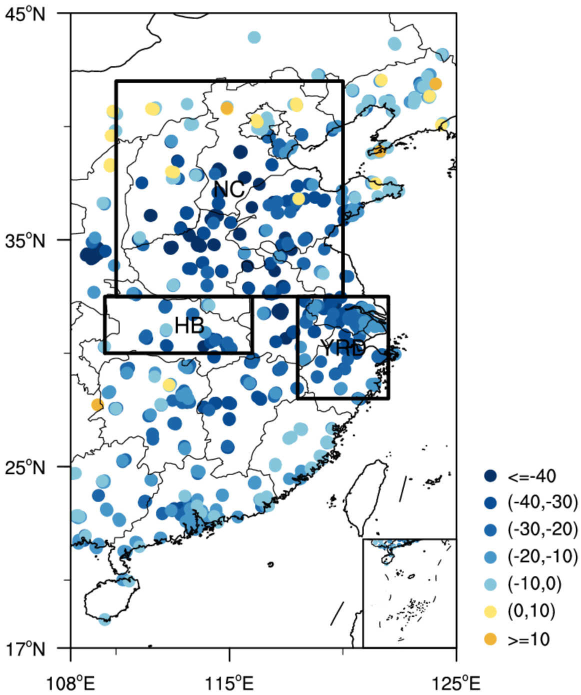

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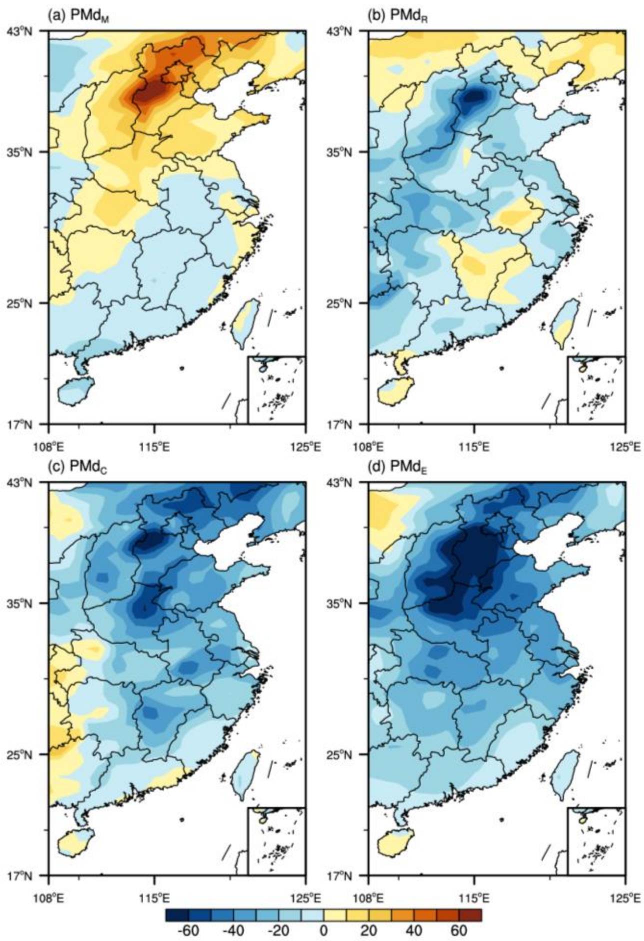

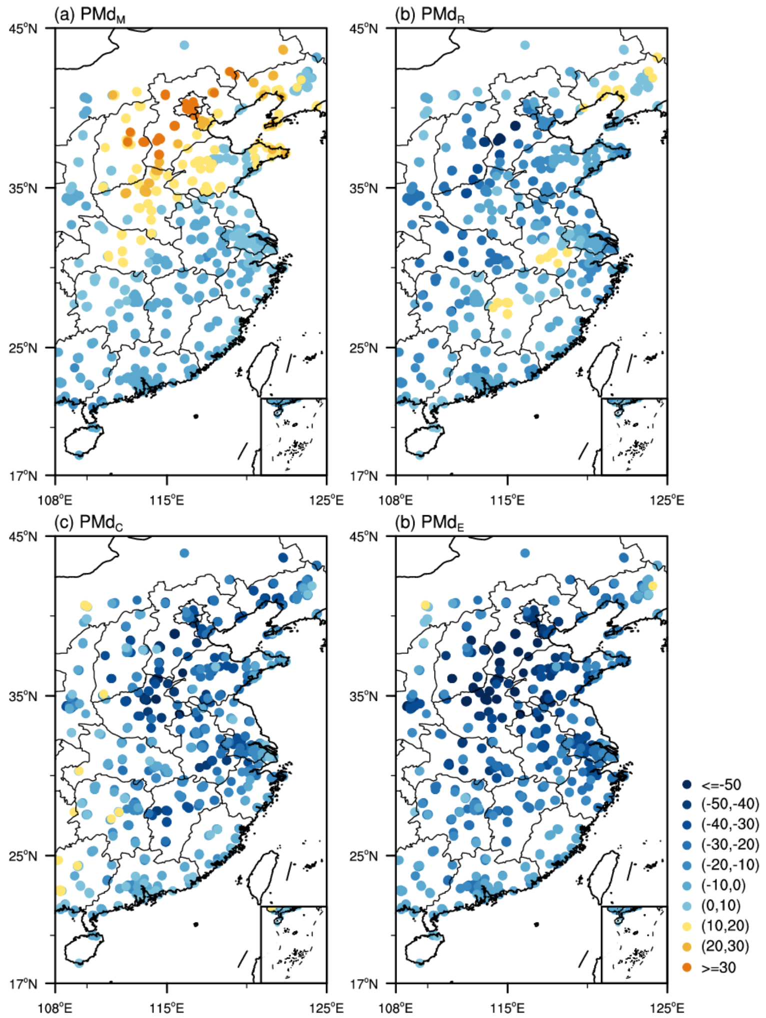

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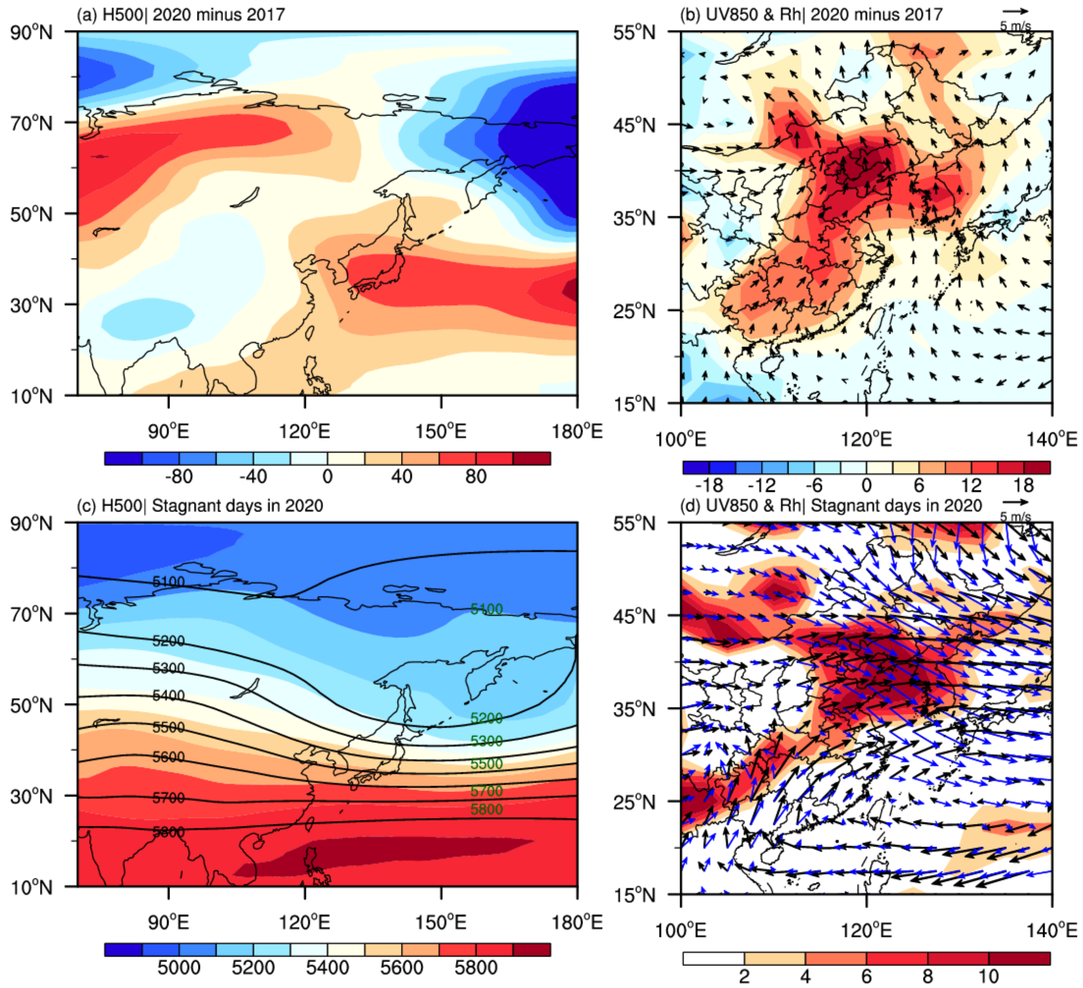
(a) H500| 2020 minus 2017
(b) UV850 & Rh| 2020 minus 2017
5 m/s
(c) H500| Stagnant days in 2020
(d) UV850 & Rh| Stagnant days in 2020
5 m/s
90°N
70°N
50°N
30°N
10°N
90°E
120°E
150°E
180°E
55°N
45°N
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25°N
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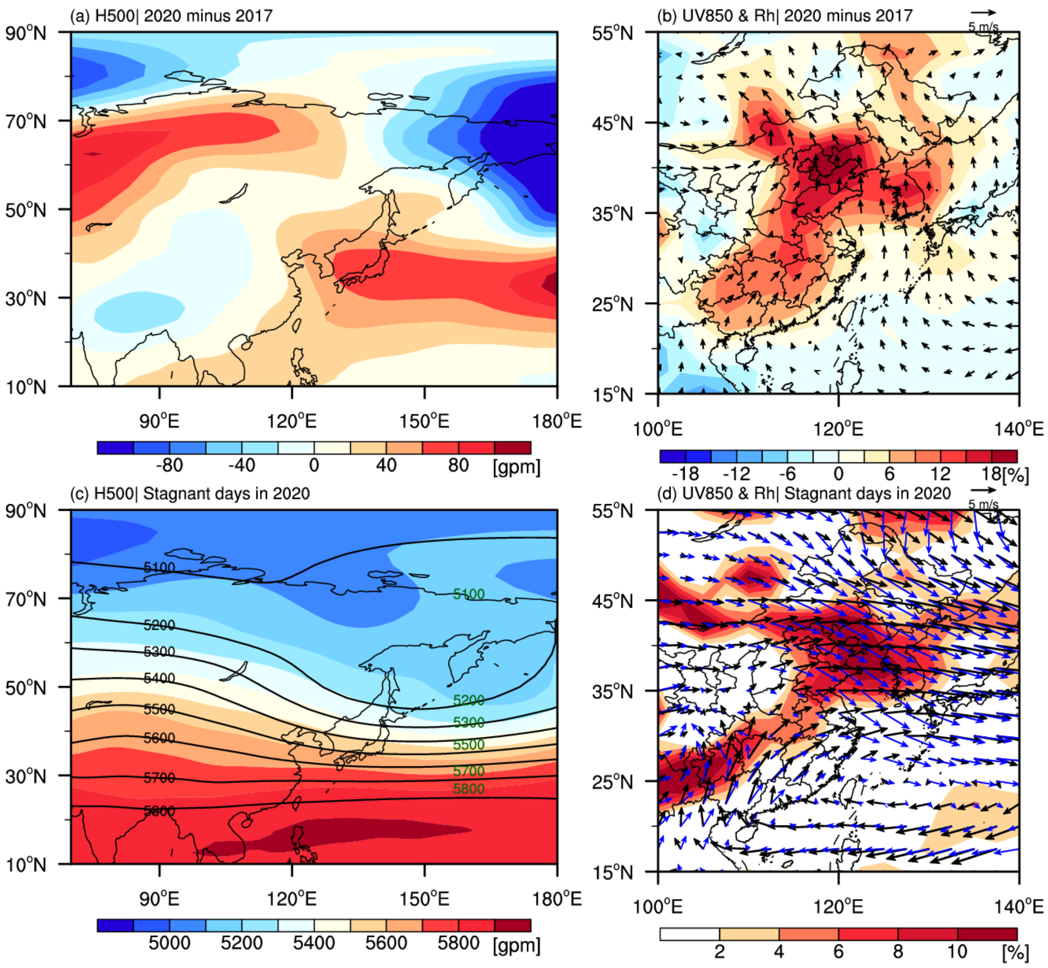
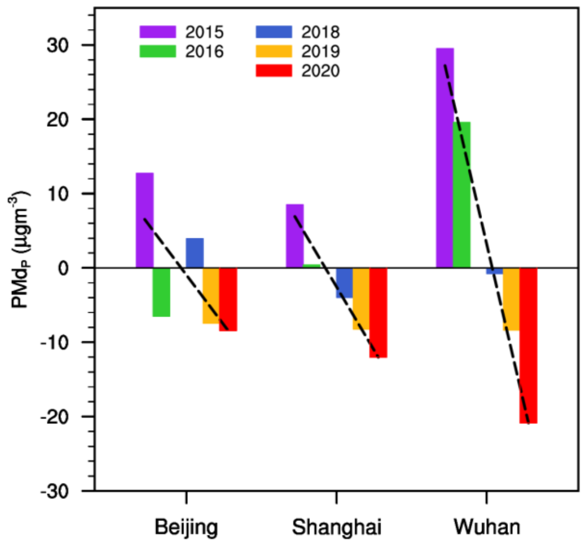


Figure 4. Differences in the observed atmospheric circulation in February between 2020 and 2017, including (a) geopotential potential height at 500 hPa (unit: gpm), (b) wind at 850 hPa (arrows; unit: m/s), surface relative humidity (shading; unit: %). The atmospheric circulations in the stagnant days (e.g., from 8–13 and 19–25 February 2020) were also showed, including (c) geopotential potential height at 500 hPa (shading; unit: gpm) and its climate mean in February (contour), and (d) wind at 850 hPa (black arrows; unit: m/s), its climate mean (blue arrows) and the increased surface relative humidity (shading; unit: %, stagnant days minus climate mean).



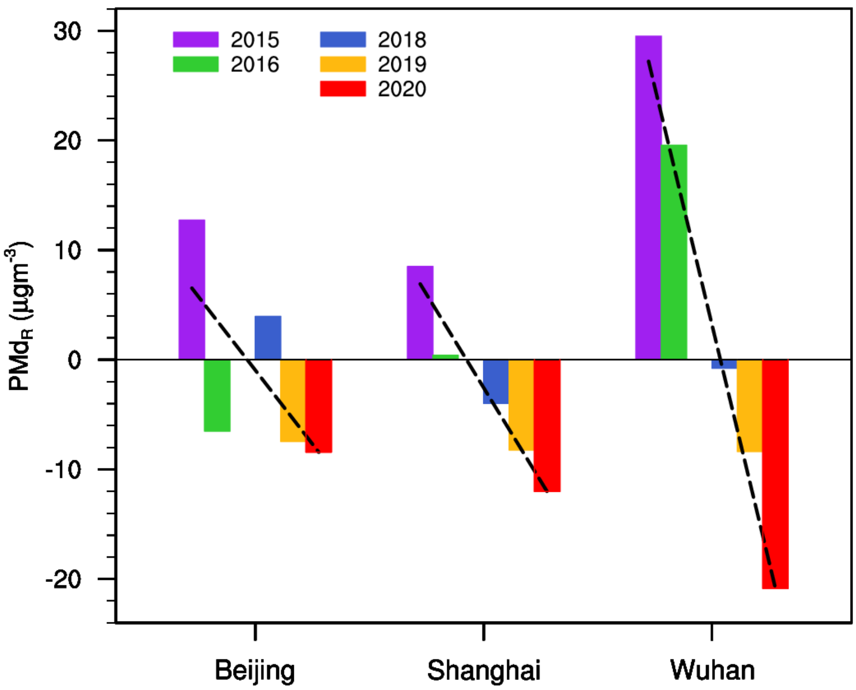
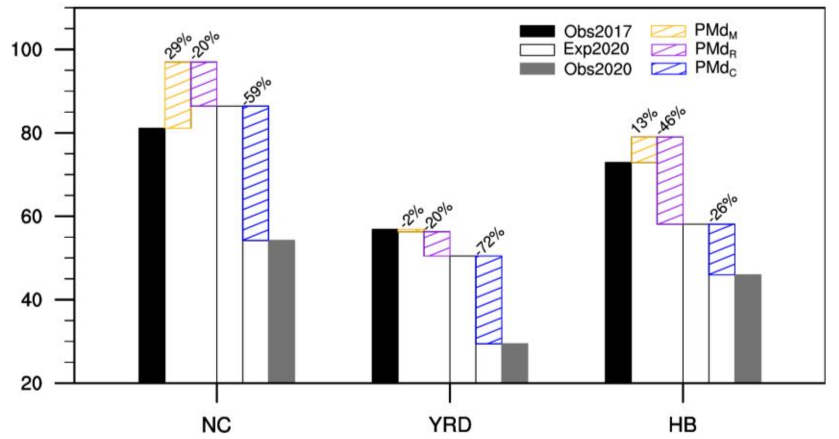


Figure 5. Variation in PMd$_R$ (unit: μg/m^3) with respect to the February 2017 level in Beijing, Shanghai and Wuhan from 2015 to 2019. PMd$_R$ in 2020 was linearly extrapolated from that in the 2015–2019 period. The dotted line is the linear trend.



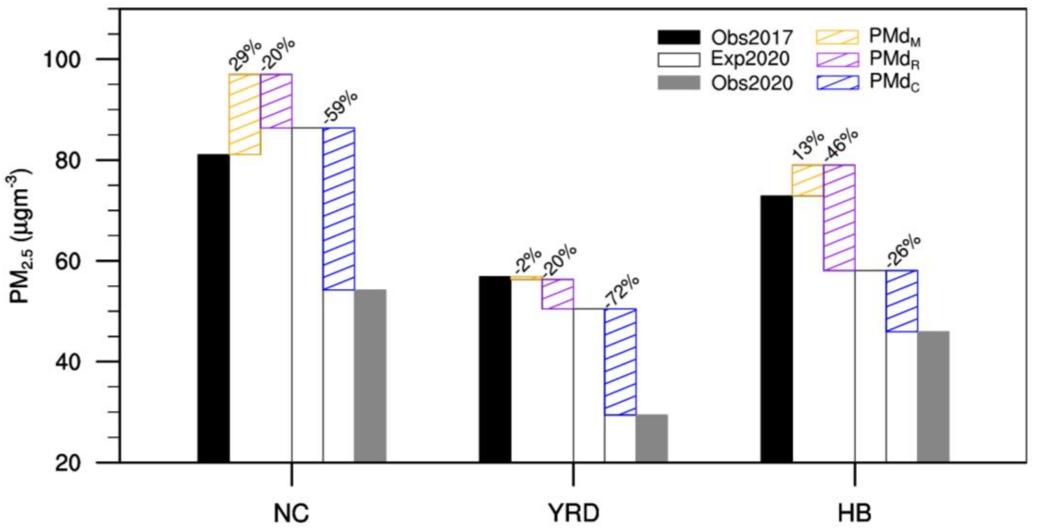
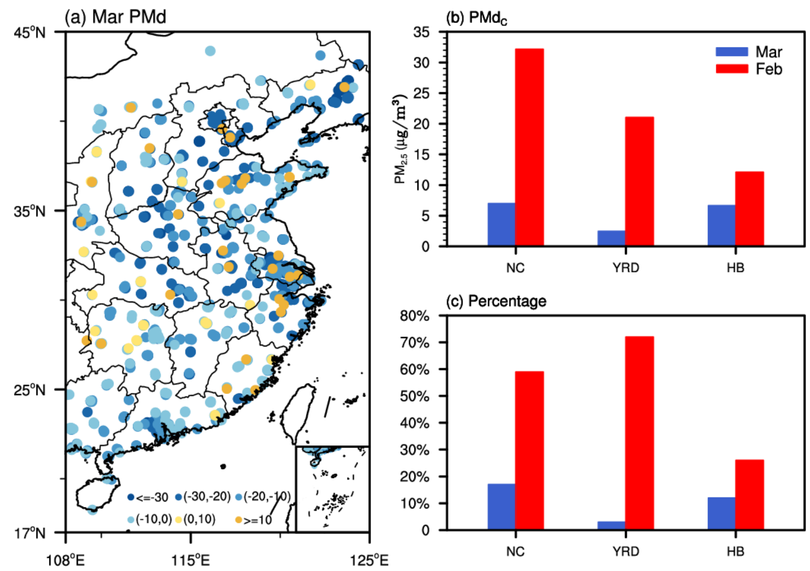


Figure 6. Contributions of PMd_M (orange bars with hatching), PMd_R (purple bars with hatching) and PMd_C (blue bars with hatching) to the change in $PM_{2.5}$ concentration (unit: μg/m^3) between 2020 and 2017 in the three regions. The observed $PM_{2.5}$ concentration in February 2017 (black) and 2020 (gray) was also plotted, and the expected $PM_{2.5}$ concentration without the COVID-19 quarantine is indicated by black hollow bars. The contribution ratios of the three factors (relative to the $PM_{2.5}$ observations in 2020) are also indicated on the corresponding bars.



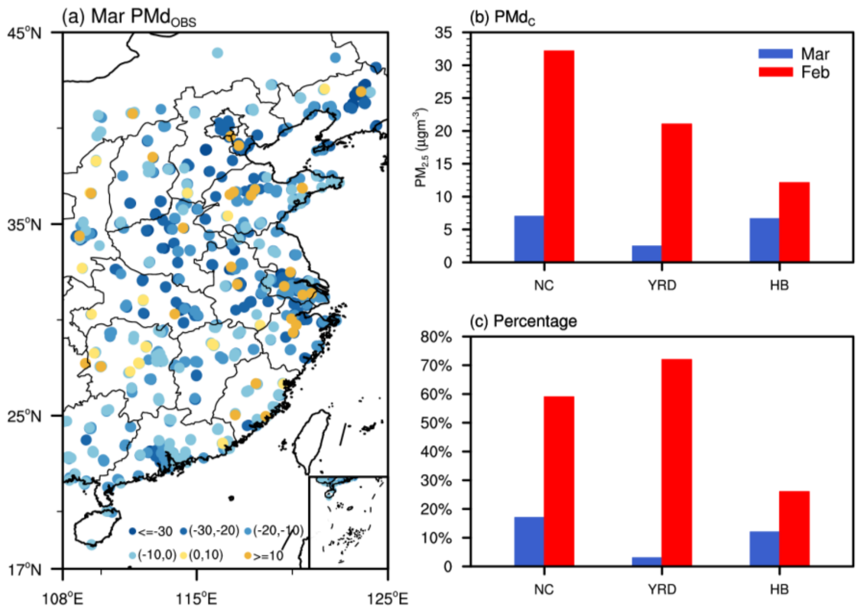


Figure 7. (a) Differences in the observed $PM_{2.5}$ (unit: μg/m^3) in March between 2020 and 2017. (b) Contributions of PMd_C to the change in $PM_{2.5}$ concentration (unit: μg/m^3) between 2020 and 2017 and (c) the contribution ratios of PMd_C (relative to the $PM_{2.5}$ observations in 2020) in March (blue) and February (red) in the three regions.