Unprecedented decline in summertime surface ozone over eastern China in 2020 comparably attributable to anthropogenic emission reductions and meteorology

Hao Yin, Xiao Lu, Youwen Sun, Ke Li, Meng Gao, Bo Zheng and Cheng Liu

1 Key Laboratory of Environmental Optics and Technology, Anhui Institute of Optics and Fine Mechanics, HFIPS, Chinese Academy of Sciences, Hefei 230031, People’s Republic of China
2 University of Science and Technology of China, Hefei 230026, People’s Republic of China
3 School of Atmospheric Sciences, Sun Yat-sen University, Zhuhai 519082, People’s Republic of China
4 Jiangsu Key Laboratory of Atmospheric Environment Monitoring and Pollution Control, Jiangsu Collaborative Innovation Center of Atmospheric Environment and Equipment Technology, School of Environmental Science and Engineering, Nanjing University of Information Science and Technology, Nanjing 210044, People’s Republic of China
5 Department of Geography, Hong Kong Baptist University, Hong Kong 999077, People’s Republic of China
6 Institute of Environment and Ecology, Tsinghua Shenzhen International Graduate School, Tsinghua University, Shenzhen 518055, People’s Republic of China
7 Department of Precision Machinery and Precision Instrumentation, University of Science and Technology of China, Hefei 230026, People’s Republic of China
8 Key Laboratory of Precision Scientific Instrumentation of Anhui Higher Education Institutes, University of Science and Technology of China, Hefei 230026, People’s Republic of China
9 Anhui Province Key Laboratory of Polar Environment and Global Change, University of Science and Technology of China, Hefei 230026, People’s Republic of China
10 Center for Excellence in Regional Atmospheric Environment, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen 361021, People’s Republic of China

* Authors to whom any correspondence should be addressed.

E-mail: luxiao25@mail.sysu.edu.cn and ywsun@aiofm.ac.cn

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Abstract

China’s nationwide monitoring network initiated in 2013 has witnessed continuous increases of urban summertime surface ozone to 2019 by about 5% year−1, among the fastest ozone trends in the recent decade reported in the Tropospheric ozone assessment report. Here we report that surface ozone levels averaged over cities in eastern China cities decrease by 5.5 ppbv in May–August 2020 compared to the 2019 levels, representing an unprecedented ozone reduction since 2013. We combine the high-resolution GEOS-Chem chemical model and the eXtreme Gradient Boosting (XGBoost) machine learning model to quantify the drivers of this reduction. We estimate that changes in anthropogenic emissions alone decrease ozone by 3.2 (2.9–3.6) ppbv (57% of the total 5.5 ppbv reduction) averaged over cities in eastern China and by 2.5 ~ 3.2 ppbv in the three key city clusters for ozone mitigation. These reductions appear to be driven by decreases in anthropogenic emissions of both nitrogen oxides (NOx) and volatile organic compounds, likely reflecting the stringent emission control measures implemented by The Chinese Ministry of Environmental and Ecology in summer 2020, as supported by observed decline in tropospheric formaldehyde (HCHO) and nitrogen dioxides (NO2) from satellite and by bottom-up emission estimates. Comparable to the emission-driven ozone reduction, the wetter and cooler weather conditions in 2020 decrease ozone by 2.3 (1.9–2.6) ppbv (43%). Our analyses indicate that the current emission control strategies can be effective for ozone mitigation in China yet tracking future ozone changes is essential for further evaluation. Our study also reveals important potential to combine the mechanism-based, state-of-art atmospheric chemical models with machine learning model to improve the attribution of ozone drivers.
1. Introduction

Surface ozone significantly damages human health and ecosystem (Jerrett et al 2009, Anenberg Susan et al 2012, Tai et al 2014). It is mainly generated from nitrogen oxides (NO\textsubscript{x}) and volatile organic compounds (VOCs) through sunlight driven photochemical reactions (Monks et al 2015, Sun et al 2020, 2021). China is the present-day global hot spot of urban ozone pollution, with significantly higher daily maximum 8 h average (MDA8) ozone levels and faster increasing trends over 2013–2019 compared to other industrialized regions worldwide reported in the Tropospheric ozone assessment report (Fleming et al 2018, Lu et al 2018, 2020), even though the domestic anthropogenic NO\textsubscript{x} emissions has been reduced by 20% since 2012 (Zheng et al 2018). Recent studies have reported that the observed ozone increases over China extended to spring 2020 in the coronavirus disease 2019 (COVID-19) lockdown period, highlighting the complexity of ozone mitigation (Le et al 2020, Huang et al 2021, Li et al 2021, Yin et al 2021). China’s energy consumptions and travel demands resumed in May and returned to comparable levels of 2019 (Zheng et al 2020). In June 2020, the Chinese Ministry of Environmental and Ecology (MEE) implemented The 2020 action plan on VOCs mitigations (the Chinese MEE) (table SI (available online at stacks.iop.org/ERL/16/124069/mmedia)), an action following the 2018–2020 action plan on defending the blue sky (Chinese State Council 2018) aiming at a 10% and 15% reduction of anthropogenic VOCs and NO\textsubscript{x} emissions relative to the 2015 level. Here, we examine whether these measures can be effective to mitigate summertime (May–August) ozone pollution in 2020.

We first present an unprecedented widespread decrease in observed summertime ozone levels in Chinese cities in 2020 after a continuous increase from 2013 to 2019 since the nationwide monitoring network was launched. A critical underlying question is that to what extent the reduction of summertime ozone is driven by anthropogenic emission control measures rather than meteorology. A standard approach is to apply state-of-art chemical transport models (CTMs) with sensitivity simulations (e.g. fixed anthropogenic levels but with varied meteorology) to quantify ozone change drivers (Lu et al 2019a). However, uncertainties in emission estimates and model deficiencies can lead to systematic bias in CTMs that affect the accuracy of their sensitivity to changes in either emissions or meteorology (Fu et al 2015, Young et al 2018, Lu et al 2019b).

In this study, we introduce the eXtreme Gradient Boosting (XGBoost) machine learning model to correct the bias of ozone predictions from the GEOS-Chem CTM. We use the novel GEOS-Chem-XGBoost modeling approach to separate the role of emission and meteorology in ozone variability and estimate the uncertainties with the ensemble of sensitivity tests. Our analyses reveal for the first time that changes in domestic anthropogenic emissions contribute substantially to the summertime ozone reduction in 2020 relative to 2019 levels, thus delivers important policy implications for ozone mitigation over China.

2. Materials and methods

2.1. Ozone observation

We obtain hourly surface ozone observations in 2013–2020 from the China National Environmental Monitoring Center network (http://106.37.208.233:20035/). This nationwide network began operating in 74 major cities in 2013, and extended to 367 cities by 2020. We apply data quality control method to remove unreliable outliers following our previous studies (Lu et al 2018). Observations at monitoring sites within a city are averaged hourly to represent ozone air quality at city level. We report the MDA8 ozone values as the ozone metric.

2.2. Tropospheric nitrogen dioxide (NO\textsubscript{2}) and formaldehyde (HCHO) observation

We use the daily tropospheric NO\textsubscript{2} and HCHO columns retrieved from TROPOMI (Veefkind et al 2012) to examine the changes of ozone precursors in 2020 vs 2019. TROPOMI is a nadir-viewing spectrometer instrument with a ground pixel size of 7 km × 7 km and local passing time at approximately 13:30. TROPOMI retrievals of NO\textsubscript{2} and HCHO columns (de Smedt et al 2018, van Geffen et al 2020) have been applied in recent ozone studies over China (Li et al 2020, 2021). We use the Level 3 data with a spatial resolution of 25 km × 25 km. Pixels with quality assurance values less than 50% for HCHO and 75% for NO\textsubscript{2} have been removed.

2.3. GEOS-Chem CTM simulation

We use the nested-grid version of GEOS-Chem CTM 12.2.1 to simulate ozone and other atmospheric chemical components over China (http://wiki.seas.harvard.edu/geos-chem/index.php/GEOS-Chem_12#New_data_directories_in_12.2.1). The model is conducted at a horizontal resolution of 0.25° × 0.3125° with the boundary conditions from a global simulation at 2° × 2.5° resolution, driven by GEOS-FP assimilated meteorological data. GEOS-Chem includes a detailed HO\textsubscript{x}–NO\textsubscript{x}–VOC–ozone–halogen–aerosol tropospheric chemistry mechanism (Wang et al 1998, Bey et al 2001, Park et al 2004, Mao et al 2013, Yin et al 2019, 2020) and has been widely used in ozone modeling studies over China (Ni et al...
We use the community emissions data system inventory for global anthropogenic emissions at the latest 2017 level (McDuffie et al. 2020), with the Chinese anthropogenic emissions from the multi-resolution emission inventory (Zheng et al. 2018). We scale the Chinese anthropogenic emissions to 2019 levels based on observations of primary air pollutants and emission trends reported by the MEE following (Li et al. 2021), resulting in a scaling factor of 87.3% for NO$_2$, 83.7% for CO, 85.1% for particulate matter (PM), and no scaler for VOCs. These scalers may remain uncertain and are not expected to represent precisely the anthropogenic emission levels in 2019–2020, but this is inconsequential here as we prefer to use machine learning model to correct the model bias as will be described later. Anthropogenic and biomass burning emissions (van der Werf et al. 2017) are fixed for 2019 and 2020. Natural emissions of biogenic VOCs (Guenther et al. 2012), lightning NO$_X$ (Murray et al. 2012), and soil NO$_X$ (Hudman et al. 2012, Lu et al. 2021) are calculated online in the model and thus respond to meteorological parameters.

We run global simulation at 2° × 2.5° resolution from January 2019 to August 2020. The model results on 1 April 2019 and 2020 were then interpolated to high resolution (0.25° × 0.3125°) over the nested domain (70°E–140°E, 15°N–55°N) to initialize the nested model simulation. Results from the nested model for May–August in both years are analyzed. Since the anthropogenic emissions are fixed, simulated ozone difference between 2020 (GC$_{2020}$) and 2019 (GC$_{2019}$) provides a means to quantify ozone change due to changes in meteorological conditions (GC$_{Met}$), estimated as:

$$\text{GC}_{\text{Met}} = \text{GC}_{2020} - \text{GC}_{2019}. \quad (1)$$

We can sequentially quantify the role of emission changes (GC$_{Emis}$) as:

$$\text{GC}_{\text{Emis}} = (\text{Obs}_{2020} - \text{Obs}_{2019}) - (\text{GC}_{2020} - \text{GC}_{2019}) \quad (2)$$

where Obs$_{2019}$ and Obs$_{2020}$ represents observations for 2019 and 2020, respectively.

This widely-used method assumes that CTMs can accurately simulate ozone sensitivity to interannual changes in meteorological parameters, but this is very likely problematic because of model bias due to errors in emissions estimates, chemical mechanism, and sub-grid-scale local processes (Young et al. 2018, Lu et al. 2019a). We use a machine learning model in addition to the GEOS-Chem results to address this issue.

### 2.4. XGBoost machine learning model to correct GEOS-Chem bias

We apply the XGBoost model to correct the bias of hourly GEOS-Chem ozone predictions at each observation site. XGBoost uses the Gradient Boosting Decision Tree framework to iteratively train the systematic observation-model bias in a stagewise manner (Jerome 2001, Chen and Guestrin 2016, Keller et al. 2021). We use hourly observations in 2019 from each site as learning samples, and GEOS-Chem input of emissions (total of anthropogenic and natural emissions) and meteorological parameters, output of concentrations of atmospheric chemical components, and time information (e.g. hour, day, month) as training input data (table S2), following (Keller et al. 2021). These parameters are central to ozone chemistry and transport. All data have been standardized ($Z_i = \frac{X_i - \mu}{\sigma}$, where $X_i$ represent the $i$th item in the dataset, and $\mu$ and $\sigma$ are the average and standard deviation of dataset $X_i$ respectively). We choose a learning rate of 0.35, maximum tree depth of $6, I_1$ and $I_2$ regularizarion terms of 0 and 1, the loss function of mean square, and evaluation metrics of root-mean-square error.

Our base estimates apply a five-fold cross validation strategy with the default learning rate and maximum tree depth following (Keller et al. 2021). The five-fold cross validation is designed to reduce overfitting and auto-correlation signal (Kleiner et al. 2021), and to test the robustness of XGBoost model. For each site, we first group all sample data into five subsets, and then train the model for five iterations, with each time taking four subsets as training dataset and the remaining one as testing data. We take the ensemble mean of these five iterations as the base estimate. We also conduct several sensitivity tests by altering the learning rate from 0.35 to 0.3 and 0.4 with the same five-fold cross validation strategy, and by altering the maximum tree depth of $6–4$ and $8$, yielding another 20 ensembles. The range of the total 25 ensemble are used to represent the uncertainty from the GEOS-Chem-XGBoost model.

The combination of GEOS-Chem and XGBoost model (hereafter GEOS-Chem-XGBoost, or GCB) is expected to provide a close fit to 2019 ozone observations. As GEOS-Chem simulation uses the same anthropogenic emissions in 2020 as in 2019, and observations for 2020 are not included in bias training, applying the GEOS-Chem-XGBoost model in 2020 then predicts ozone evolution in 2020 (GCB$_{2020}$) with 2019 anthropogenic emission levels at each observation site. Examination of the probability density functions of key ozone precursors and meteorological parameters shows that the training data in 2019 cover the range of variations in these factors in 2020 at individual cities (figures S1 and S2), supporting the application of the GEOS-Chem-XGBoost model to predict ozone in summer 2020 if anthropogenic emissions were unchanged from 2019 levels.
Comparison of the GEOS-Chem-XGBoost predictions to the actual 2020 observations then quantifies ozone changes due to perturbation of emissions (GCB_Emis), and sequentially the contribution from meteorology (GCB_Met):

\[ \text{GCB}_{-}\text{Emis} = \text{Obs}_{2020} - \text{GCB}_{2020} \]

\[ \text{GCB}_{-}\text{Met} = (\text{Obs}_{2020} - \text{Obs}_{2019}) - (\text{Obs}_{2020} - \text{GCB}_{2020}) = \text{GCB}_{2020} - \text{Obs}_{2019}. \]

A major advantage by applying this approach is that it corrects the systematic bias in GEOS-Chem ozone predictions, allowing a more accurate ozone sensitivity to changes in meteorology and emissions, as will be discussed later. We report results based on the GEOS-Chem-XGBoost approach but also compare with the GEOS-Chem results for consistency check.

3. Results and discussion

3.1. Widespread surface ozone decreases in Chinese cities in 2020

Figures 1(a) and (b) present the May–August mean MDA8 ozone concentrations at all available urban sites in 2019 and 2020. High ozone levels are concentrated in eastern China, especially in the Beijing–Tianjin–Hebei (BTH), the Fenwei Plain (FWP), and the Yangtze River Delta (YRD) city clusters (table S3), reflecting high anthropogenic emissions of ozone precursors in the regions. These city clusters have been identified by the MEE as key regions for ozone mitigation.

We find significant reduction of MDA8 ozone by 3.8 ± 0.5 ppbv (6%) (mean ± standard deviation across cities) averaged over all 366 cities and 5.5 ± 0.5 ppbv (8%) for 149 cities in eastern China in May–August 2020 compared to 2019 levels (figure 1(c)). This ozone reduction is unprecedented in the 2013–2020 period, following a continuous increase of surface MDA8 ozone levels from 2013 to 2019 by approximately 5% year\(^{-1}\) (figure 1(d)) (Lu et al. 2020, Li et al. 2021). The ozone reductions are widespread across the cities as indicated by the significant decrease in number of sites with MDA8 ozone higher than 75 ppbv (approximately the Chinese grade II air quality standard) from 150 in 2019 to only 9 in 2020. In particular, ozone decreases by 4.7 ± 0.5 ppbv (7%), 5.4 ± 0.6 ppbv (8%), and 5.9 ± 0.6 ppbv (10%) in the BTH, FWP, and YRD regions, respectively. The reductions are most prominent in June–August (figure 3).

3.2. Model performance on capturing observed ozone levels

We first compare the ability of GEOS-Chem and GEOS-Chem-XGBoost in capturing the observed ozone levels in 2019. Figure 2 shows the time series of observed and model predicted ozone averaged for all Chinese cities over eastern China and for the BTH, FWP, and YRD regions. We focus on eastern China and the three key city cluster hereafter since summertime ozone levels are higher, ozone decreases are more prominent, and influences from foreign ozone transport are smaller in these cities than others. The GEOS-Chem predictions generally capture the synoptic-scale variability of MDA8 ozone in these regions, but they show high mean bias (MB) of 7.7 ppbv (17.5%) across all cities in eastern China, reflecting the model bias as discussed above.

The GEOS-Chem-XGBoost model significantly improves the prediction of ozone levels compared to the GEOS-Chem CTM (figure 2). It shows no bias to the training data (MB = 0.1 ppbv, 0.2%) and very small bias to the testing data (MB = 0.6 ppbv, 1.2%) (figure 4, table S4), resulting in a mean bias of 0.3 ppbv (0.7%) to all 2019 ozone observations (figure 2). We also estimate the importance of input parameters in the XGBoost model for bias correction, using the SHapely Additive exPlanations (SHAP) approach (Lundberg et al. 2017). As shown in figure 5, meteorological parameters such as near-surface temperature and wind fields, the uncorrected GEOS-Chem predicted ozone, reactive nitrogen (e.g. NO\(_2\), PAN), and non-methane VOCs are the main factors for explaining the GEOS-Chem ozone bias, consistent with (Keller et al. 2021).

3.3. Attribution of summertime ozone reduction in 2020

We then attribute quantitatively the 2020 ozone reduction to changes in anthropogenic emissions and meteorological conditions following equations (3) and (4). Differences between the observed and GEOS-Chem-XGBoost predicted ozone in 2020 represent the emission-driven ozone changes in 2020 relative to 2019, as indicated by the shadings in figure 2. Figure 3 shows the spatial patterns of emission-driven versus meteorology-driven ozone changes, and figure 4 summarizes the mean contributions across eastern China and the key city clusters.

We find that the May–August ozone decreases in 2020 over eastern China can be largely attributed to anthropogenic emission changes, with 101 cities (69%) showing emission-driven ozone reduction of 0.2–15.3 ppbv though there are large variabilities in terms of magnitudes (figure 3). For the average of all eastern China cities, changes in emissions alone contribute to ozone decrease of 3.2 (2.9–3.6 from the ensemble range) ppbv, accounting for 57% (53%–66%) of the total ozone reduction (5.5 ± 0.5 ppbv) (figure 4). The estimated emission-driven ozone reductions are 2.5 (2.2–2.8) ppbv, 3.2 (2.9–3.6) ppbv, and 3.2 (2.8–3.6) ppbv in the BTH, FWP, and YRD city clusters, respectively.
These estimates are sufficiently large compared to the GEOS-Chem-XGBoost model bias (0.3 ppbv). The reductions may include some contributions from global emission reductions during the COVID-19 restrictions, which have been found to reduce ozone in the free troposphere (Steinbrecht et al 2021). However, these foreign contributions to surface ozone are small due to the short ozone lifetime in polluted city boundary layers and in summer (Lu et al 2019a, 2021), and our focus of eastern China here further minimizes the effect of foreign ozone transport (Ni et al 2018, Lu et al 2019a). Thus, the emission-driven ozone reductions are more likely due to local anthropogenic emission changes in 2020.

We examine changes of HCHO and NO$_2$ from TROPOMI measurements to understand the anthropogenic driver of the ozone decreases from 2019 to 2020 in figure 5. We find notable decreases in observed tropospheric HCHO (4.1 ± 1.1% averaged for cities in eastern China) and NO$_2$ (6.0 ± 1.2%) columns in 2020 compared to 2019 levels in most regions of eastern China (figures 5(a) and (b)). These changes may partly come from meteorological influences on biogenic sources as will be discussed later, but also reflect the decline in anthropogenic emissions of NO$_x$ and non-methane VOCs (NMVOCs) supported by the newly released bottom-up estimates (Zheng et al 2021) (figures 5(c) and (d)). The national total anthropogenic emissions of NO$_x$ and NMVOCs in May-August decreased by 1%–3% and 2%–5% in 2020 compared to 2019, respectively, with most regions in eastern China showing decreasing emissions of about 5%. These reductions are linked to both the ongoing NO$_x$ emission mitigation (Lu et al 2019a) and the new implementation of The 2020 action plan on VOCs mitigations by MEE in June 2020 (The Chinese Ministry of Environmental and Ecology (MEE) 2020), which issues a number of control measures including implementation of stringent VOCs emission standards, replacement of raw and auxiliary materials with low VOCs content, and mitigation of unorganized emissions, as summarized in table S1. The larger emission declines in areas surrounding Beijing may also be linked to the extension of COVID-19 lockdown measures (Zheng et al 2021), but at the country level these measures should play a much smaller role. Zheng et al (2021) shows that China's thermal electricity generation and travel demands in May–August 2020 are 1.6%–9.0% higher than those in the same months of 2019, with the loosening of COVID-19 lockdown measures from April in most regions.
Figure 2. Observed and model predicted ozone evolution of summertime (May–August) ozone in 2019 and 2020. Figures are for (a) all eastern China cities, (b) the BTH region, (c) the FWP region, and (d) the YRD region. Observed ozone values are denoted by black solid lines. GEOS-Chem predictions are denoted by gray dashed lines. GEOS-Chem model predictions have notable bias to observations, and we corrected the bias in 2019 by applying the XGBoost machine learning model. The GEOS-Chem-XGBoost predictions as shown in the purple dashed lines thus present an improved fit to 2019 observations. GEOS-Chem-XGBoost predictions for 2020 then predicts ozone evolution in 2020 with 2019 emission levels. Comparison of the GEOS-Chem-XGBoost predictions to the actual 2020 observations then quantifies ozone changes due to perturbation of emissions. Blue (red) shadings represent where GEOS-Chem-XGBoost predictions are higher (lower) than the actual observations in 2020, indicating that emission changes lead to ozone decrease (increase) in 2020. All values shown are 7 d average for presentation purpose. See the text for more information.

Figure 3. Attribution of summertime ozone changes for cities over eastern China in 2020 relative to the 2019 levels. (a) Ozone changes attributable to anthropogenic emissions, (b) ozone changes attributable to meteorological conditions.

Our analyses suggest that concurrent reductions of anthropogenic NO\textsubscript{x} and VOCs emissions based on 2019 emission levels can be effective for ozone mitigation in eastern China. This result can be expected from several recent observational and modeling studies. Previous studies showed ozone increases in Chinese cities from 2013 were driven by the decline of PM through impacts on heterogeneous chemistry and radiation, and decline in anthropogenic NO\textsubscript{x} emissions in regions where ozone chemical formation...
is in VOC-limited regime (Li et al 2019a, Liu and Wang 2020) while VOCs emissions have not been reduced. However, recent studies based on satellite observations of HCHO/NO₂ ratios have detected a shift of ozone chemical sensitivity from VOC-limited regime to transitional regime in eastern China from 2016 to 2019 with the continuous decline in NOₓ levels (Wang et al 2021a), indicating that emission controls of both NOₓ and VOCs based on 2019 levels would benefit ozone mitigation. Regional chemical models also predict decreases of summertime ozone levels with further reduction of VOCs emissions in years after 2017–2019 (Li et al 2019b, Liu and Wang 2020, Chen et al 2021, Kang et al 2021), when the impacts of PM on ozone formation also decline because of the continuous reductions of PM concentrations since 2013. However, our analyses could not distinguish which specific measures on controlling what chemical species are the most responsive for ozone reduction. We also note that there are still large variabilities of the ozone response to emission changes among the cities (figure 3), reflecting the different efficiency of city-level emission control measures and different ozone chemical regimes.

Changes in meteorological conditions contribute to 2.3 (1.9–2.6) ppbv (43%, 35%–47%) of the ozone reduction averaged over cities in eastern China, and reduce ozone by 2.2 (1.9–2.5) ppbv, 2.2 (1.8–2.5) ppbv, and 2.7 (2.3–3.1) ppbv in the BTH, FWP, and YRD city clusters, respectively (figures 3 and 4). Meteorological conditions influence surface ozone by modulating emissions from natural sources, chemical kinetics, dry deposition, and transport (Lu et al 2019b). In summer 2020, the eastern and southern China experienced anomaly strong or even record-breaking rainfalls (China Meteorological Administration 2021), leading to significant decreases in daily maximum temperature and increases in specific humidity and cloud fractions compared to the 2019 levels (figure 5), especially in June–August (figures S9–S11). These weather conditions inhibit biogenic VOCs emissions (figure S12), slow down ozone chemical production, and facilitate the ventilation of ozone and its precursors (Gong and Liao 2019, Ma et al 2019, Lu et al 2019a, Jiang et al 2021), and therefore contribute to ozone decrease.

3.4. Comparison between GEOS-Chem-XGBoost and GEOS-Chem estimates

We compare the estimated ozone contribution of emissions and meteorology by the GEOS-Chem-XGBoost with those by the GEOS-Chem CTM only (figure 4 vs figure S14). Both methods agree that changes in anthropogenic emission play a significant role in explaining the ozone decrease over eastern China and for the three city clusters in 2020, supporting the main claim of this study, while the absolute magnitudes differ with each other (e.g. 3.2 vs 2.3 ppbv on the emission-driven ozone contribution). Ozone attribution estimated from the GEOS-Chem-only method using equations (1) and (2) assumes that the GEOS-Chem model can accurately simulate ozone sensitivity to changes in
meteorological parameters. We test this assumption by simply comparing the correlation coefficients ($r$) between key meteorological parameters and ozone concentration at afternoon (2 p.m.) in 2019 from observations and GEOS-Chem predictions (figure S14). The GEOS-Chem predictions successfully capture the expected overall positive correlation coefficients between ozone and temperature, and the negative correlations between ozone and specific humidity, cloud fraction, and precipitations, but large discrepancies are found in terms of the absolute values for individual cities, indicating that the model may overestimate/underestimate the ozone sensitivity to meteorological changes. We find that the GEOS-Chem-XGBoost predictions obtained from the testing dataset significantly improve the predicted ozone-meteorology relationship, although this improvement is not necessarily from a better representation of physical process. Thus, we expect that the GEOS-Chem-XGBoost method is more likely to provide an accurate estimate on attribution of ozone change, representing a major advantage in methodology in this study.

4. Conclusion

In summary, we find that the unprecedented summertime ozone decrease (5.5 ppbv) over eastern China in 2020 relative to the 2019 levels are half attributed to domestic anthropogenic emissions...
reductions (3.2, 2.9–3.6 ppbv from GEOS-Chem-XGBoost ensemble), while the wetter and cooler weather conditions contribute comparatively (2.3, 1.9–2.6 ppbv). It indicates that the current emissions control measures on both NOx and NMVOCs may have started to achieve initial success, but ozone changes in future years should be continuously tracked to evaluate emission control strategies rigorously. We also reveal important potential to combine the mechanism-based, state-of-art atmospheric chemical models with machine learning model to improve the attribution of ozone drivers. However, our correction strategy used here is only tested for 1 year, and does not directly improve the chemical model description of physical and chemical processes, which may consequently bring uncertainties to the estimated attribution of ozone drivers. Our analyses are not able to determine which specific measures on controlling what species are the most effective for ozone mitigation. More studies are required to address this important issue.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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ORCID iDs

Hao Yin https://orcid.org/0000-0002-4399-5752
Xiao Lu https://orcid.org/0000-0002-5989-0912
Youwen Sun https://orcid.org/0000-0003-3126-3252
Bo Zheng https://orcid.org/0000-0001-8344-3445
Cheng Liu https://orcid.org/0000-0002-3759-9219

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