Anthropogenic drivers of 2013–2017 trends in summer surface ozone in China

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Observations of surface ozone available from ∼1,000 sites across China for the past 5 years (2013–2017) show severe summertime pollution and regionally variable trends. We resolve the effect of meteorological variability on the ozone trends by using a multiple linear regression model. The residual of this regression shows increasing ozone trends of 1–3 ppbv a−1 in megacity clusters of eastern China that we attribute to changes in anthropogenic emissions. By contrast, ozone decreased in some areas of southern China. Anthropogenic NOx emissions in China are estimated to have decreased by 21% during 2013–2017, whereas volatile organic compounds (VOCs) emissions changed little. Decreasing NOx would increase ozone under the VOC-limited conditions thought to prevail in urban China while decreasing ozone under rural NOx-limited conditions. However, simulations with the Goddard Earth Observing System Chemical Transport Model (GEOS-Chem) indicate that a more important factor for ozone trends in the North China Plain is the ∼40% decrease of fine particulate matter (PM2.5) over the 2013–2017 period, slowing down the aerosol sink of hydroperoxy (HO2) radicals and thus stimulating ozone production.

Results and Discussion

Observed Summer Ozone Air Quality, Meteorologically Driven Variability, and Residual Trend. Fig. 1 shows the 5-y average (2013–2017) values of the surface mean and maximum MDA8 ozone at the ensemble of sites operated by the China Ministry of Ecology and Environment. The Chinese National Ambient Air Quality Standard for MDA8 ozone is 160 μg m−3, corresponding to 82 ppbv at 298 K and 1 atm. Surface ozone in China is a major air pollutant harmful to human health (1) and to terrestrial vegetation (2, 3). Ozone pollution is a serious issue in China (4–8). Summer mean values of the maximum daily 8-h average (MDA8) ozone concentration exceed 60 ppbv over much of eastern China (9, 10), and episodes exceeding 120 ppbv occur frequently in megacities such as Beijing, Shanghai, and Guangzhou (4). Better understanding of the causes of elevated ozone in China is important for developing effective emission control strategies.

Ozone is produced rapidly in polluted air by photochemical oxidation of volatile organic compounds (VOCs) in the presence of nitrogen oxides (NOx ≡ NO + NO2). VOCs originate from both anthropogenic and biogenic sources. NOx is mainly from fuel combustion. Ozone sensitivity to anthropogenic emissions depends on the photochemical regime for ozone formation, i.e., whether ozone production is NOx-limited or VOC-limited (11). Observational and modeling studies suggest that ozone production in urban centers is VOC-limited, whereas ozone production in rural regions is NOx-limited, with megacity cluster regions in a transitional regime (4, 12).

Several studies have reported increasing ozone trends of 1–2 ppbv a−1 at urban and background sites in eastern China over the 2001–2015 period (7, 13–15). Surface ozone data were very sparse before 2013. Starting in 2013 the surface monitoring network greatly expanded, and detailed hourly data across all of China became available from the China Ministry of Ecology and Environment. In the same year, the Chinese government launched the Air Pollution Prevention and Control Action Plan to reduce anthropogenic emissions (www.gov.cn/zwwx/2013-09/12/content_2486773.htm). Fine particles with an aerodynamic diameter of 2.5 μm or smaller (PM2.5) concentration has decreased significantly since then, but ozone pollution has not decreased and is seemingly getting worse (8, 16). NOx emissions are estimated to have decreased by more than 20% over 2013–2017 (17), in part to decrease nitrate PM2.5 (18–20), but this could have had a counterproductive effect on ozone under VOC-limited conditions. Decreases in PM2.5 could further affect ozone through changes in aerosol chemistry and photoysis rates (21, 22). On the other hand, meteorological variability could also have a large effect on ozone trends over a 5-y period.

The aim of this work is to better understand the factors controlling ozone trends across China during 2013–2017, separating anthropogenic and meteorological influences, to diagnose the effect of emission reductions even though a 5-y record is relatively short. We focus on the summer season [June–July–August (JJA)] when ozone pollution in eastern China is most severe (4). We use a statistical model to isolate the meteorological contribution to month-to-month variability of ozone and infer a residual trend attributable to anthropogenic emissions. We interpret this residual trend in terms of changing emissions using the Goddard Earth Observing System Chemical Transport Model (GEOS-Chem) driven by 2013–2017 emissions from Multiresolution Emission Inventory for China (MEIC) (17).

Significance

Drastic air pollution control in China since 2013 has achieved sharp decreases in fine particulate matter (PM2.5), but ozone pollution has not improved. After removing the effect of meteorological variability, we find that surface ozone has increased in megacity clusters of China, notably Beijing and Shanghai. The increasing trend cannot be simply explained by changes in anthropogenic precursor [NOx and volatile organic compound (VOC)] emissions, particularly in North China Plain (NCP). The most important cause of the increasing ozone in NCP appears to be the decrease in PM2.5, slowing down the sink of hydroperoxy radicals and thus speeding up ozone production. Decreasing ozone in the future will require a combination of NOx and VOC emission controls to overcome the effect of decreasing PM2.5.
Fig. 1. Summer (Left) maximum and (Right) mean values of the MDA8 ozone concentration at the network of sites operated by the China Ministry of Ecology and Environment. Values are averages over 5 y (JJA 2013–2017) for each city. Rectangles identify the four megacity clusters designated by the Chinese government as targets for air pollution abatement: BTH (37°–41°N, 114°–118°E), YRD (30°–33°N, 118°–122°E), PRD (21.5°–24°N, 112°–115.5°E), and SCB (28.5°–31.5°N, 103.5°–107°E).

1,013 hPa. This standard is exceeded over much of eastern China. The highest concentrations are in the North China Plain, with values as high as 150 ppbv. Summer mean MDA8 ozone is also highest over the North China Plain, with values of 60–80 ppbv.

Fig. 2 shows the monthly mean MDA8 ozone trends for 2013–2017 in the four megacity clusters highlighted in Fig. 1: Beijing–Tianjin–Hebei (BTH), Yangtze River Delta (YRD), Pearl River Delta (PRD), and Sichuan Basin (SCB). These four megacity clusters are specific target areas in Chinese government plans to decrease air pollution (www.mee.gov.cn/hjzl/dqhj/cskqzlzkyb/).

The trends are presented as the anomalies for individual summer months relative to their 2013–2017 means. Also shown is the meteorologically driven variability as described by a multiple linear regression (MLR) model considering a number of meteorological variables from the NASA Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) reanalysis (Methods and Table 1) (23). We use only the top three meteorological predictors for each region (indicated in Fig. 2) to avoid overfitting the data. These include temperature, surface winds, relative humidity, and also surface pressure for PRD. These variables are frequently observed to be correlated with ozone air quality (24) and can be viewed as general indicators of stagnation. Temperature also affects ozone through its control of biogenic VOC emissions and peroxyacetyl nitrate chemistry (25). The coefficients of determination ($R^2$) for the MLR model in fitting the observed ozone anomalies range from 0.60 to 0.86 after removal of the residual linear trends (in black in Fig. 2).

The residual trends in Fig. 2 may be reasonably attributed to the effect of changing anthropogenic emissions. Fig. 3 shows the general trend of this MDA8 ozone residual across China for 2013–2017 after the meteorologically driven variability from the top three variables has been removed for each grid cell with the MLR model. Trends that are statistically significant above the 90% confidence level are marked with black dots. There is a general regional increase in eastern China between Shanghai (YRD) and Beijing (BTH). There are also patterns of decrease in southern and northeastern China away from the major population centers. The average trends for the focus megacity clusters are 3.1 ppbv $a^{-1}$ for BTH, 2.3 ppbv $a^{-1}$ for YRD, 0.56 ppbv $a^{-1}$ for PRD, and 1.6 ppbv $a^{-1}$ for SCB (SI Appendix, Table S1). The trend in BTH is larger than the earlier 2003–2015 trend of 1.1 ppbv $a^{-1}$ reported by ref. 14. PRD and SCB show increases even though they are in southern China, indicating some difference between urban centers and the broader region.

**Anthropogenic Drivers of Ozone Trend.** Chinese anthropogenic emissions estimated in the MEIC inventory decreased by 21% for NOx and increased by 2% for VOCs over the 2013–2017 period (17). Emissions of PM$_{2.5}$ and its precursors are estimated to have also decreased including by 59% for SO$_x$ (17). Trends for the four megacity cluster regions are given in SI Appendix, Table S2. Observed average PM$_{2.5}$ levels in summer during 2013–2017 decreased by 41% for BTH, 36% for YRD, 12% for PRD, and 39% for SCB. Aerosol optical depth (AOD) decreased by 20% in eastern China (SI Appendix, Fig. S1).

We examined the effects of these changes in NOx, emissions, VOC emissions, and PM$_{2.5}$ levels using the nested-grid GEOS-Chem model version 11-02 over Asia (60°–150°E, 10°S–55°N) with a resolution of 0.5° × 0.625°. The GEOS-Chem model includes detailed ozone–NOx–VOC–aerosol chemistry (26) and has been evaluated in previous studies simulating surface ozone in China (27–30). Our baseline simulation for 2013 is driven by MERRA-2 meteorological data with anthropogenic emissions from the MEIC inventory for China (17) and MIX inventory for other Asian countries (31). SI Appendix, Fig. S2, evaluates the simulation for 2017 with the mean summer MDA8 ozone observations for that year. Observed and simulated concentrations average 58.5 ± 15.4 and 63.0 ± 14.8 ppbv, respectively. Spatial correlation between simulated and observed ozone is high (correlation coefficient $R = 0.89$).

We then conducted sensitivity simulations with 2013–2017 changes taken together and separately in Chinese NOx and VOC emissions (SI Appendix, Fig. S3). PM$_{2.5}$ affecting aerosol chemistry, and AOD affecting photolysis rates (SI Appendix, Fig. S1) (Methods). All simulations were performed for the same meteorological conditions of JJA 2013 after 1 mo of initialization. Detailed description of the model configuration and the sensitivity simulations is given in SI Appendix.

Fig. 4 shows the differences in MDA8 ozone resulting from these 2013–2017 anthropogenic changes. Changes in NOx and VOC emissions (mainly due to decreased NOx emissions; SI Appendix, Fig. S4) increase ozone in the urban areas of BTH, YRD, and PRD and in the broader urban region around Beijing.
while decreasing ozone elsewhere, following expected patterns of VOC-limited and NOx-limited conditions. Ozone production in urban areas is expected to be VOC-limited because NOx concentrations are very high, but ozone production on a more regional scale in summer is expected to be NOx-limited. The modeled ozone sensitivity is generally consistent with previous measurement-based, satellite-retrieved, and model inferences of NOx- vs. VOC-limited conditions for ozone production in China (4, 12, 22).

However, we find that changes in PM2.5 are more important than changes in NOx or VOC emissions in driving ozone trends, particularly in the North China Plain, and this is mainly due to aerosol chemistry rather than photolysis (Fig. 4). The relevant aerosol chemistry involves reactive uptake of the gaseous precursors to ozone formation, as described in GEOS-Chem by first-order reactive uptake coefficients (32). This includes reactive uptake of the hydroperoxy radical (HO2) with coefficient γ = 0.2 and conversion to H2O or H2O2 (32–34) and reactive uptake of nitrogen oxides (NOx, NO3, and N2O5) with conversion to HNO3 (32, 35). Uptake of HO2 is by far the dominant effect (Fig. 4). It accounts in the model for most of the sink of hydrogen oxide radicals (HOx ≡ OH + peroxy) in eastern China (SI Appendix, Fig. S5). This suppresses the HO2 + NO reaction by which ozone is produced. The effect is particularly important in the North China Plain where PM2.5 concentrations are highest.

The importance of aerosol chemistry as a sink for ozone precursors in China has been previously pointed out in model studies (21, 22), which found ozone decreases of 6–12 and 10–20 ppb, respectively, over eastern China as a result of this chemistry. Ref. 21 found the dominant effect to be the reactive uptake of nitrogen oxides, but we find that effect to be small in part because of VOC-limited conditions and in part because summertime conditions are not conducive to nighttime NO3/N2O5 chemistry.

The HO2 uptake coefficient γ = 0.2 used in our simulation is consistent with a large body of experimental and modeling literature.

Fig. 2. Time series of monthly mean MDA8 ozone anomalies in summer (JJA) 2013–2017 for the four megacity clusters of Fig. 1: BTH, YRD, PRD, SCB. MDA8 ozone values for individual 0.5° × 0.625° grid cells are averaged over each cluster and month, and anomalies are computed relative to the 2013–2017 means for that month of the year. In each panel, observations (red line) are compared with results from an MLR model driven by meteorological variability (blue line). The linear trend of the 3-mo average residuals for each year is shown in black. The MLR model uses the top three meteorological predictors (Table 1) for each 0.5° × 0.625° grid cell in the cluster, and the results are then averaged for each cluster. The dominant variables in each cluster are indicated in legend with the sign of their correlation to MDA8 ozone. The coefficients of determination (R2) for the MLR model are shown in the right corner of each plot for the detrended time series (removing the residual linear trend).

Table 1. Meteorological variables considered as ozone covariates

| Variable name | Description |
|---------------|-------------|
| Tmax          | Daily maximum 2-m air temperature (K) |
| U10           | 10-m zonal wind (m s⁻¹)* |
| V10           | 10-m meridional wind (m s⁻¹)† |
| PBLH          | Mixing depth (m) |
| TCC           | Total cloud area fraction (%) |
| Rainfall      | Precipitation (mm d⁻¹) |
| SLP           | Sea level pressure (Pa) |
| RH            | Surface air relative humidity (%) |
| V850          | 850-hPa meridional wind (m s⁻¹)‡ |

Meteorological data from the NASA MERRA-2 reanalysis (23) with 0.5° × 0.625° grid resolution. The data are averaged over 24 h for use in the MLR model for ozone except for PBLH and TCC, which are averaged over daytime hours (8–20 local time), and for Tmax (daily maximum).

*Positive westerly.
†Positive southerly.
‡Positive easterly.
trends. The model underestimates the observed trend in BTH, possibly because the 50-km grid is too coarse to resolve strongly VOC-limited conditions in urban cores. Observations show ozone increases in western China, whereas the model suggests that emission controls should have produced decreases. Trends are high in that region so that ozone has a large background component (30), and the increasing trend could reflect the more general trend of increasing background ozone at northern midlatitudes (36). Anthropogenic emissions in western China may also be underestimated (31). Observations show mixed trends in the eastern peninsula of Shandong province as well as decreases in northeastern China that are not captured by the model. Eastern Shandong may be difficult to model due to marine influence. For northeastern China, the model simulates an ozone increase because of the PM$_{2.5}$ decrease, but it may overestimate the low PM$_{2.5}$ concentrations in that region (SI Appendix, Fig. S2).

There is a pressing need to continue to decrease PM$_{2.5}$ levels in China because of the benefit for public health. Our finding that decreasing PM$_{2.5}$ causes an increase in ozone calls for decreasing NOx and VOC emissions to overcome that effect. Model sensitivity simulations decreasing either NOx or VOC emissions relative to 2017 levels show ozone benefits from both in the four megacity clusters (Fig. 5), consistent with ozone production being in the transitional regime between NOx- and VOC-limited (12). The larger gains are from NOx, emission reductions become increasingly NOx-limited, but VOC emission reductions are important to decrease ozone in urban cores (SI Appendix, Fig. S7). Gains from decreasing NOx and VOC emissions are additive (37); thus, there is benefit in decreasing both.

In summary, we analyzed the factors driving 2013–2017 trends in summertime surface ozone pollution across China, taking advantage of the extensive network data available since 2013. We removed the effect of meteorological variability by using a multiple linear regression model fitting surface ozone to meteorological variables. The residual shows an increasing trend of 1–3 ppbv a$^{-1}$ in urban areas of eastern China that we attribute to changes in anthropogenic emissions. Decrease in anthropogenic NOx emissions can increase ozone in urban areas where ozone production is expected to be VOC-limited. However, we find that a more important and pervasive factor for the increase in ozone in the North China Plain is the rapid decrease in PM$_{2.5}$, slowing down the reactive uptake of NOx radicals by aerosol particles and thus stimulating ozone production. Decreasing ozone in the future will require a combination of NOx and VOC emission controls to overcome the effect of decreasing PM$_{2.5}$. There is a need to better understand HO$_2$ aerosol chemistry and its implications for ozone trends in China. Extending the observational record beyond the relatively short 5-y period will also provide more insights into the factors driving ozone trends in China.

Methods

Data Availability. All of the measurements, reanalysis data, and GEOS-Chem model code are openly available for download from the websites given below. The anthropogenic emission inventory is available from www.micemodel.org, and for more information, please contact Q.Z. (qiangzhang@tsinghua.edu.cn).

Surface Ozone Network Data. Hourly surface ozone concentrations for JJA 2013–2017 were obtained from the public website of the China Ministry of Ecology and Environment (MEE): beijingair.sinaapp.com/. The network had 450 monitoring stations in 2013 summer, growing to 1,500 stations by 2017 and including about 320 cities. Average the hourly data on the 0.5° latitude $\times$ 0.625° longitude MERRA-2 grid and compute daily MDA8 ozone on that grid. Trend analyses use all available data for a given year. Only using sites with 5-y records does not change the results. Most sites in the four focused megacity clusters were already operational in 2013.

Meteorological Data. Meteorological fields for 2013–2017 were obtained from the MERRA-2 reanalysis produced by the GEOS of the NASA Global Modeling and Assimilation Office (accessible online through https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2) (23). The MERRA-2 data have a spatial resolution of 0.5° $\times$ 0.625°. They match well with observed daily maximum temperature and relative humidity at Chinese weather stations (SI Appendix, Fig. S8) (38).
and provide us with a full gridded ensemble of meteorological variables. We average them over either 24 h or daytime hours (8–20 local time), depending on the variable (Table 1). All data are normalized for use in the MLR model (see below) by subtracting their 2013–2017 mean for that day of the year and dividing by the standard deviation.

**Multiple Linear Regression Model.** A number of previous studies have examined meteorological influences on ozone variability in China (4, 9, 39, 40). On the basis of these studies we considered the correlation of MDA8 ozone across China with a large number of candidate meteorological variables from the MERRA-2 archive (SI Appendix, Table S3 and Fig. S9). This led us to adopt nine variables as featuring the strongest correlations (Table 1). We applied a stepwise MLR model for each 0.5° × 0.625° grid cell:

\[
y = \beta_0 + \sum_{k=1}^{9} \beta_k x_k + \text{interaction terms},
\]

where \(y\) is the normalized daily MDA8 ozone concentration and \(x_1, \ldots, x_9\) are the nine meteorological variables. The interaction terms are up to second order. The regression coefficients \(\beta_k\) are determined by a stepwise method adding and deleting terms based on Akaike information criterion statistics to obtain the best model fit (41). Similar MLR models have been successfully applied to quantify the effect of meteorological variability on air pollutants in North America, Europe, and China (42–44).

We first apply the MLR model to identify the key meteorological variables driving the variability of daily surface ozone for each grid cell. Only the three locally dominant meteorological variables are regressed onto deseasonalized monthly MDA8 ozone to fit the effect of 2013–2017 meteorological variability on ozone within a 0.5° × 0.625° grid cell. This is done to avoid overfitting. We find that the dominant meteorological variables driving ozone variability are consistent across grid cells on a regional scale.

**GEOS-Chem Simulations.** The ozone simulations use the nested-grid version of the GEOS-Chem chemical transport model with detailed oxidant–aerosol chemistry, driven by MERRA-2 assimilated meteorological data and with a horizontal resolution of 0.5° × 0.625° over East Asia (version 11-02; acmg.seas.harvard.edu/geos). Anthropogenic emissions in China are from the MEIC inventory (see below). The base simulation is for the summer of 2013, and sensitivity simulations examine the effects of 2013–2017 changes in Chinese anthropogenic emissions, PM\(_{2.5}\), and AOD, as described below. Additional sensitivity simulations isolate the effects of PM\(_{2.5}\) and AOD changes on photolysis rates, NO\(_x\) aerosol chemistry, and HO\(_2\) aerosol chemistry. Results presented in Fig. 4 are differences between the sensitivity simulations and the base simulation. Further details on the GEOS-Chem simulations are in SI Appendix.

**Anthropogenic Emission Inventory.** The MEIC (www.meicmodel.org) is used to estimate China’s anthropogenic emissions and their trends from 2013 to 2017 (17, 31). MEIC is a widely used bottom-up emission inventory framework that follows a technology-based methodology to calculate emissions from more than 700 anthropogenic source types in China.

**PM\(_{2.5}\) and Aerosol Optical Depth Data.** Observed PM\(_{2.5}\) concentrations during 2013–2017 are from the same MEE observation network as ozone. Local changes in PM\(_{2.5}\) concentrations from 2013 to 2017 affecting aerosol chemistry are applied as scaling factors to GEOS-Chem aerosol surface areas in the boundary layer below 1.3 km. AOD trends for 2013–2017 are from the monthly level 3 product of the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument aboard the Aqua satellite, reported at 550-nm wavelength with a resolution of 1° × 1° (https://ladsweb.modaps.eosdis.nasa.gov). These trends in AOD are applied as scaling factors to simulated AOD in the GEOS-Chem calculation of photolysis rates (see details in SI Appendix, sections 1 and 2).

![Anthropogenic drivers of 2013–2017 changes in summer MDA8 ozone](https://www.pnas.org/cgi/doi/10.1073/pnas.1812168116)

**Fig. 4.** Anthropogenic drivers of 2013–2017 changes in mean summertime MDA8 ozone in China. (A–C) GEOS-Chem model results for the changes in MDA8 ozone resulting from: (A) combined effects of 2013–2017 changes in NO\(_x\) and VOC emissions together with changes in PM\(_{2.5}\); (B) effects of 2013–2017 changes in NO\(_x\) and VOC emissions alone; and (C) effects of 2013–2017 PM\(_{2.5}\) changes alone including contributions from aerosol chemistry and photolysis rates. (D–F) The different effects of 2013–2017 PM\(_{2.5}\) changes on ozone are separated: (D) radiative effect on photolysis rates, (E) effect of HO\(_2\) uptake, and (F) effect of nitrogen oxide (NO\(_x\), NO, and N\(_2\)O\(_x\)) uptake.
Ozone changes under future emission reductions

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1. Anenberg SC, et al. (2012) Global air quality and health co-benefits of mitigating near-term climate change through methane and black carbon emission controls. Environ Health Perspect 120:831–839.
2. Tai APK, Martin MV, Headl CL (2014) Threat to future global food security from climate change and air pollution. Nat Clim Chang 4:817–821.
3. Yue X, et al. (2017) Ozone and haze pollution weakens net primary productivity in China. Atmos Chem Phys 17:6073–6089.
4. Wang T, et al. (2017) Ozone pollution in China: A review of concentrations, meteorological influences, chemical precursors, and effects. Sci Total Environ 575:1582–1596.
5. Hu J, Chen J, Ying Q, Zhang H (2016) One-year simulation of ozone and particulate matter in China using WRF/Chem modeling system. Atmos Chem Phys 16:10333–10350.
6. Li N, et al. (2018) Impacts of biogenic and anthropogenic emissions on summertime ozone formation in the Guanzhong Basin, China. Atmos Chem Phys 18:7489–7507.
7. Sun L, et al. (2016) Significant increase of summertime ozone at Mount Tai in central eastern China. Atmos Chem Phys 16:10637–10650.
8. Lu X, et al. (2018) Severe surface ozone pollution in China: A global perspective. Environ Sci Technol Lett 5:487–494.
9. Zhao Z, Wang Y (2017) Influence of the West Pacific subtropical high on surface ozone daily variability in summertime over Eastern China. Atmos Environ 170:197–204.
10. Zhu J, Liao H (2016) Future ozone air quality and radiative forcing over China owing to future changes in emissions under the Representative Concentration Pathways (RCPs). J Geophys Res Atmos 121:1978–2001.
11. Kleinman LI (1994) Low and high NOx tropospheric photochemistry. J Geophys Res Atmos 99:16831–16838.
12. Jin XM, Hovington J (2015) Spatial and temporal variability of ozone sensitivity over China observed from the Ozone Monitoring Instrument. J Geophys Res Atmos 120:7229–7246.
13. Gao W, et al. (2017) Long-term trend of O3 in a mega City (Shanghai), China: Characteristics, causes, and interactions with precursors. Sci Total Environ 603-604:425–433.
14. Mo Z, et al. (2016) Significant increase of surface ozone at a rural site, north of Eastern China. Atmos Chem Phys 16:3969–3977.
15. Tang G, Li X, Wang Y, Xin J, Ren X (2009) Surface ozone trend details and interpretations in Beijing, 2001–2006. Atmos Chem Phys 9:8813–8823.
16. Chen SQ, et al. (2018) The fifth assessment on air quality: Regional air pollution in “2+31” cities during 2013-2017. (Beijing), p 82. Available at www.stat-center.pku.edu.cn/
17. Zheng B, et al. (2018) Trends in China’s anthropogenic emissions since 2010 as the consequence of clean air actions. Atmos Chem Phys 18:14095–14111.
18. Li K, Liao H, Zhu J, Moch JM (2016) Implications of RCP emissions on future PM2.5 air quality and direct radiative forcing over China. J Geophys Res Atmos 121:12985–13008.
19. Li HY, et al. (2018) Nitrate-driven urban haze pollution during summertime over the North China Plain. Atmos Chem Phys 18:5259–5306.
20. Zhang L, et al. (2015) Source attribution of particulate matter pollution over North China with the adjoint method. Environ Res Lett 10:304801.
21. Lou S, Liao H, Zhu B (2014) Impacts of aerosols on surface-layer ozone concentrations in China through heterogeneous reactions and changes in photolysis rates. Atmos Environ 85:123–138.
22. Li J, et al. (2018) Radiative and heterogeneous chemical effects of aerosols on ozone and inorganic aerosols over East Asia. Sci Total Environ 622–623:1327–1342.
23. Gelaro R, et al. (2017) The modern-era retrospective analysis for research and applications, version 2 (MERRA-2). J Clim 30:5419–5454.