



1 **Assessment of strict autumn-winter emission controls on air** 2 **quality in the Beijing-Tianjin-Hebei region**

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18 **Abstract.** Strict seasonal emission controls are a popular measure in China for addressing severe air pollution, in
19 particular fine particulate matter (PM_{2.5}). Here we evaluate the efficacy of these measures, with a particular focus
20 on the strict emission controls imposed on pollution sources in 28 cities in and around the Beijing-Tianjin-Hebei
21 region (BTH) in autumn-winter 2017/2018. For this we use the GEOS-Chem chemical transport model and air
22 pollutant measurements from the national and Beijing local monitoring networks, after evaluating the network
23 data with independent measurements and correcting large biases in the bottom-up emissions inventory. The
24 network measurements are temporally consistent ($r > 0.9$ for PM_{2.5} and $r > 0.7$ for gases) with the independent
25 measurements, though with systematic differences of 5–17% for nitrogen dioxide (NO₂) and 16–28% for carbon
26 monoxide (CO). The average decrease in monitoring network PM_{2.5} in BTH in autumn-winter 2017/2018 relative
27 to the previous year is 27%, declining from 103 to 75 $\mu\text{g m}^{-3}$. The regional decline in PM_{2.5} in the model is 20%,
28 exceeding the regional target of 15%. According to the model, pollution control measures led to decline in PM_{2.5}
29 precursor emissions of 0.27 Tg NO_x (as NO), 0.66 Tg sulfur dioxide (SO₂), 70 Gg organic carbon (OC), and 50
30 Gg black carbon (BC). We find though that these alone only lead to an 8% decline in PM_{2.5} and that interannual
31 variability in meteorology accounts for more than half (57%) the decline. This demonstrates that year-on-year
32 comparisons are misleading for assessing the efficacy of air pollution measures and should be taken into
33 consideration when extending such measures beyond BTH.

34 **1 Introduction**

35 Strict seasonal emission controls are an increasingly popular measure to reduce severe air pollution in China, in
36 particular elevated concentrations of fine particles, or PM_{2.5}, in autumn-winter. The Chinese government improved
37 such measures in 28 cities in and around the Beijing-Tianjin-Hebei region (BTH) (so-called “2+26” cities) in



northern China in autumn and winter 2017/2018. Targets were set to reduce regional mean $PM_{2.5}$ by 15% and city-specific $PM_{2.5}$ by 10–25% relative to the previous year (MEE, 2017). BTH experiences severe air pollution in China despite substantial decline in $PM_{2.5}$ of ~40% from 2013 to 2017 from enacting emission controls as part of the 5-year Action Plans (Zhang et al., 2019). Annual mean $PM_{2.5}$ in BTH in 2017 was $64 \mu g m^{-3}$ (Wang et al., 2019); far greater than the national standard of $35 \mu g m^{-3}$ (MEE, 2012) and the World Health Organization (WHO) guideline of $10 \mu g m^{-3}$. Severe pollution days (defined as days with 24-hour mean $PM_{2.5} \geq 150 \mu g m^{-3}$), mostly in autumn and winter, have declined in frequency, but still occurred in 78 days in 2016. Down from 122 days in 2013 (Li et al., 2019a). Severe $PM_{2.5}$ pollution is due to a combination of large primary emissions of particles and gas-phase precursors from multiple sources (Zhang et al., 2018), very active heterogeneous chemistry enhancing formation of secondary inorganic and organic aerosols (Huang et al., 2014), and accumulation of pollution due to meteorological conditions such as low windspeeds, shallow planetary boundary layer and high relative humidity (RH) (An et al., 2019; Bei et al., 2020; Le et al., 2020; Wu et al., 2019).

Dominant local $PM_{2.5}$ sources in BTH in autumn-winter include sustained contributions from the energy sector and road traffic (Tong et al., 2020), and seasonal contributions from industrial and residential combustion of coal and other solid fuels (Ma et al., 2017; Yun et al., 2020), and widespread burning of crop residue (Li et al., 2020c). Mitigation measures in China have led to a nation-wide decrease in emissions of the primary $PM_{2.5}$ components black carbon (BC) and organic carbon (OC) of 28 % for BC and 32 % for OC from 2013 to 2017 (Zheng et al., 2018). Emissions of prominent gas-phase $PM_{2.5}$ precursors such as nitrogen oxides ($NO_x \equiv NO + NO_2$) and sulfur dioxide (SO_2) have declined by 21% for NO_x and 59% for SO_2 over the same time period. Trends in other $PM_{2.5}$ precursors are less certain. Emissions of ammonia (NH_3), mostly from agriculture, are likely to have increased or remained constant (Zheng et al., 2018). Similar to NH_3 , emissions of non-methane volatile organic compounds (NMVOCs), mostly from industrial activity and solvent use, are either stable or increasing (Li et al., 2019c; Liu et al., 2018b; Zhang et al., 2017a; Zheng et al., 2018). Non-local sources also make a substantial contribution to $PM_{2.5}$ in BTH throughout the year. Dong et al. (2020) used a regional air quality model to estimate that regional transport of non-local $PM_{2.5}$ accounted for 33–68% of total monthly mean $PM_{2.5}$ in BTH in 2017.

Many mitigation measures were implemented in autumn-winter 2017/2018 to reduce $PM_{2.5}$ in the 28 cities in and around BTH. These are detailed in the “Air Pollution Action Plan in Autumn and Winter of 2017–2018 for the Beijing-Tianjin-Hebei Region and its Surrounding Areas” report by the Chinese Ministry of Ecology and Environment (MEE) (MEE, 2017). Briefly, these include a sector-wide cap on total consumption of coal, phase-out of small inefficient and outdated industrial coal-fired boilers, reduction in production capacity of heavy industries such as iron and cement, switching from coal to cleaner fuels in homes, and mandated controls on construction site fugitive dust emissions. Other short-term and reactionary measures included shutdown of intensive industries and construction sites throughout the emission control period and instantaneous shutdown of additional industrial plants in response to forecasts of elevated $PM_{2.5}$. Tougher emission standards and higher quality vehicular fuel were imposed on on-road vehicles. Agricultural residue burning was banned and strictly enforced, and installation of emission control technologies were mandated for all large emitters of industrial NMVOCs. The MEE used national network observations of $PM_{2.5}$ to determine that regional reduction targets were achieved in BTH and that only 3 of the 28 cities did not meet their city-specific targets (MEE, 2018).



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 79 As demonstrated by studies assessing changes in air quality during the lockdown period in response to the SARS-
 80 CoV-2 pandemic, variability in meteorology is also a large contributor to fluctuations in air quality in BTH (Le et
 81 al., 2020; Shi et al., 2021). This necessitates that assessment of the efficacy of such measures includes detailed
 82 understanding of the contribution of strict emission controls and other factors like meteorology. A recent study
 83 by Zhang et al. (2021) assessed city-scale changes in air quality in each of the 28 cities using the high-resolution
 84 Community Multi-Scale Air Quality model coupled to the Weather Research and Forecasting Model for
 85 meteorology (CMAQ-WRF). CMAQ-WRF was driven with a national bottom-up inventory for the year preceding
 86 the emission controls and a regional bottom-up emission inventory for the year of the emission control period.
 87 They determined that the contribution of emission controls to the decrease in simulated $PM_{2.5}$ in each city ranged
 88 from 2% to 82% and that meteorology was often a dominant contributor, ranging from 18% to 98%. Here we take
 89 a regional perspective, after correcting for large biases in the bottom-up emission inventories for BTH with the
 90 China national and Beijing regional monitoring network observations which we also assess against independent
 91 measurements. We apply the corrected inventory to the GEOS-Chem chemical transport model (CTM) to
 92 determine regional-scale emission reductions resulting from strict mitigation measures in autumn-winter
 93 2017/2018 and the contribution of these and meteorology to improved regional air quality, as such measures are
 94 now widely adopted in China.

95 **2 Air pollutant concentration changes detected with the national and local monitoring networks**

96 Ambient monitoring of $PM_{2.5}$ and trace gases in BTH includes reference monitors from the China National
 97 Environmental Monitoring Network (CNEMN) and the local Beijing Municipal Environmental Monitoring
 98 Network (BJMEMN) (Zhang et al., 2020). We use observations of hourly SO_2 , NO_2 , CO, and $PM_{2.5}$ for the
 99 autumn-winter emission reduction period (2017/2018) and the preceding year (2016/2017) at sites operational in
 100 both years: 402 for CNEMN and 35 for BJMEMN. Data from both networks are from the Sina Air Quality Data
 101 Platform (<http://beijingair.sinaapp.com/>; last accessed 17 October 2020, now hosted at <https://quotsoft.net/air/>).
 102 Data from both networks have been extensively used to quantify changes in surface air pollution (Li et al., 2019b;
 103 Silver et al., 2018; Wan et al., 2021; Wang et al., 2014; Zhai et al., 2019), though independent evaluation of the
 104 measurements is limited. A previous study used statistical techniques and intercomparison of air pollutant
 105 measurements to determine that outliers make only a small contribution ($\leq 1\%$) to measurements of air pollutants
 106 relevant to this work (Wu et al., 2018).

107
 108 We assess CNEMN and BJMEMN measurements against $PM_{2.5}$ from the US Embassy in Beijing and $PM_{2.5}$ and
 109 trace gas (SO_2 , NO_2 , and CO) measurements from the winter portion of the intensive Atmospheric Pollution &
 110 Human Health in a Chinese Megacity (APHH) campaign, hereafter referred to as APHH. The APHH campaign
 111 included a comprehensive suite of aerosol and gas-phase measurements from the 325-m tower at the urban
 112 Institute of Atmospheric Physics (IAP) measurement site and a few air quality measurements at a rural site (Pinggu)
 113 located ~60 km from the Beijing city centre (Shi et al., 2019). APHH data are from the National Environmental
 114 Research Council (NERC) Centre for Environmental Data Archive (CEDA) (Fleming et al., 2017). US Embassy
 115 $PM_{2.5}$ measurements in Beijing, obtained with US EPA measurement and quality control protocols (Martini et al.,
 116 2015), are from the US Department of State Air Quality Monitoring Program (<http://www.stateair.net/>; last



accessed 17 October 2020) for autumn-winter 2016/2017 and from the OpenAQ data portal (<http://www.openaq.org/>; last accessed 17 October 2020) for autumn-winter 2017/2018. We use APHH data for November-December 2016 and US Embassy PM_{2.5} for October 2016-March 2017 and October 2017-March 2018. These are compared to the nearest national and local monitoring network sites. For APHH, these are the CNEMN Aotizhongxin site (39.98°N, 116.40°E) and the BJMEMN Xizhimenbei site (39.95°N, 116.35°E), each located ~3 km from the APHH urban site (39.97°N 116.37°E). For the US Embassy, these are the CNEMN site Nongzhanguan (39.94°N, 116.46°E) and the BJMEMN site Dongsihuan (39.94°N, 116.48°E), each ~1 km from the US Embassy (39.95°N, 116.47°E).

Figure 1 compares hourly CNEMN and BJMEMN PM_{2.5} to APHH and US Embassy PM_{2.5}. PM_{2.5} from both CNEMN and BJMEMN are temporally consistent with APHH and US Embassy PM_{2.5} ($r \geq 0.96$). The surface monitoring networks also reproduce the variance in hourly PM_{2.5} (Slopes of 1.0-1.1). Network sites are systematically higher than APHH by 10% for CNEMN and 17% for BJMEMN, though compared to US Embassy site PM_{2.5} the difference is small, ranging from negligible (0.2% less) to 6.4% more than US Embassy PM_{2.5}. In general, the BJMEMN measurements are 6-17% more than APHH, likely due to spatial variability in local emissions. The decline in PM_{2.5} in the control period relative to the previous year at these sites is 43% according to US Embassy PM_{2.5}, decreasing from 97 $\mu\text{g m}^{-3}$ to 55 $\mu\text{g m}^{-3}$. A similar decline is obtained with the nearby BJMEMN (43% decline) and CNEMN (42% decline) sites shown in Fig. 1.

Figure 2 compares hourly trace gas measurements from CNEMN, BJMEMN and APHH. The CNEMN and BJMEMN trace gas instruments include chemiluminescence for NO₂, UV fluorescence for SO₂, and IR absorption for CO. Though CO is not a precursor of PM_{2.5}, its abundance affects the oxidative potential of the atmosphere and also offers a means to indirectly assess PM_{2.5} precursor emissions of NMVOCs that oxidize to form CO. Most measurements from the local and national networks, with the exception of 31% of the CNEMN SO₂ data and 16% of the BJMEMN SO₂ data, are above the instrument detection limit (indicated in Fig. 2). The surface network is temporally consistent with APHH ($r > 0.7$ for all species). CNEMN NO₂ is <10% more than NO₂ from APHH, likely due to susceptibility of the monitoring network instruments to interference from decomposition of NO_x reservoir compounds to NO₂ (Dunlea et al., 2007; Reed et al., 2016). Shah et al. (2020) estimate a positive bias of ~6% due to this interference. Differences in CNEMN SO₂ (19% less than APHH) and CO (16% more than APHH) are large and reflect differences in variance (CNEMN vs APHH SO₂ slope of 0.8, CNEMN vs APHH CO slope of 1.4). BJMEMN exceeds APHH by 17-28% for all trace gases.

To aid interpretation of the differences between the network sites and independent measurements, we also assess consistency between CNEMN and BJMEMN for the sites shown in Figs. 1 and 2. These are ~5 km apart and the BJMEMN site is closer to a heavily trafficked ring road than the CNEMN site. The sites are strongly correlated for PM_{2.5} ($r = 0.97$) and all trace gases ($r = 0.89$ - 0.92), but CNEMN is less than BJMEMN by 11% for NO₂, 33% for SO₂, 9% for CO, and 6% for PM_{2.5} due to the lower relative influence of road traffic sources. This is consistent with the relatively large positive differences between BJMEMN and the independent measurements in Figs. 1 and 2.



Both networks also measure ozone, but we do not consider this here, as ozone pollution is most severe in spring and summer in China (Yang et al., 2020). We estimate mean ozone of 15–19 $\mu\text{g m}^{-3}$ at the two monitoring network sites used in Fig. 2. This can be compared to the summer mean ozone air quality metric, mean maximum daily 8-h average ozone, of 120–160 $\mu\text{g m}^{-3}$ in northern China (Li et al., 2019b).

We show in Fig. 3 the spatial distribution of the network observed changes in air pollutant concentrations in and around BTH in the control period (autumn–winter 2017/2018) relative to the preceding year (autumn–winter 2016/2017). In what follows, we refer to these time periods as AW2017 for autumn–winter 2017/2018 and AW2016 for autumn–winter 2016/2017. Only CNEMN and BJMEMN sites that are operational in both periods are used. These include 164 sites within the control domain (region shaded grey in Fig. 3) and 273 sites in the surrounding area. The decline in air pollutant concentrations in AW2017 relative to AW2016 at sites within the emission control region is 16% for NO_2 , 44% for SO_2 , 31% for CO, and 29% for $\text{PM}_{2.5}$, surpassing the 15% $\text{PM}_{2.5}$ reduction target set for BTH. Surface concentrations of ozone (not shown) increase by 19% in response to decline in NO_x . Even with this increase, ozone is still substantially lower than in spring and summer (Liu et al., 2018a). Smaller reductions of 0.5% for NO_2 , 31% for SO_2 , 13% for CO, and 10% for $\text{PM}_{2.5}$ occur in the surrounding area. In the southeast portion of the domain shown in Fig. 3, both NO_2 and $\text{PM}_{2.5}$ increase by 5–8%. Fang et al. (2019) reported an increase in emissions from industries in the non-control area that in Fig. 3 appear to offset air quality improvements that would be expected from decline in influence of pollution from BTH.

3 BTH air pollution and emissions for the year preceding emission controls

We use the GEOS-Chem model (version 12.0.0; <https://doi.org/10.5281/zenodo.1343547>) with the evaluated surface network measurements to constrain precursor emissions of $\text{PM}_{2.5}$ in and around BTH. The model is nested over East Asia (11°S – 55°N , 60° – 150°E) at a horizontal resolution of $0.5^\circ \times 0.625^\circ$ (latitude \times longitude). The model is driven with assimilated meteorology from the NASA Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) updated hourly for 2D fields and every 3 hours for 3D fields. Dynamic (3-hourly) boundary conditions are from a global simulation at $4^\circ \times 5^\circ$. Monthly anthropogenic emissions for China in AW2016 are from the regional bottom-up Multi-resolution Emission Inventory for China (MEIC) (<http://www.meicmodel.org/>; last accessed 4 March 2020) available for 2000–2017 at $0.5^\circ \times 0.625^\circ$. MEIC includes emissions of SO_2 , NO_x , CO, NMVOCs, NH_3 , and primary particles from ~700 anthropogenic sources (Zheng et al., 2018; Li et al., 2017). In its implementation in GEOS-Chem, MEIC emissions are lumped into five sectors: industry, power plants, transportation, agriculture and residential. Primary particles are emitted as hydrophobic and hydrophilic BC and OC, and speciated NMVOCs are mapped to those in GEOS-Chem using the NMVOCs species mapping tables in Li et al. (2014).

The model includes detailed coupled gas- and aerosol-phase chemistry to represent the formation and loss of $\text{PM}_{2.5}$. Individual aerosol components are modelled as externally mixed. These include sulfate, nitrate, ammonium (Park et al., 2004; Wang et al., 2013), OC (Heald et al., 2006), BC (Li et al., 2016), dust (Fairlie et al., 2007), and sea salt (Jaegle et al., 2011). Formation of secondary sulfate–nitrate–ammonium aerosols are computed with ISORROPIA-II (Fountoukis and Nenes, 2007). Physical loss processes include dry and wet deposition (Amos et al., 2012; Liu et al., 2001; Wang et al., 1998). We implement a revised treatment of wet scavenging described and



196 first implemented in GEOS-Chem by Luo et al. (2019). This replaces fixed values of in-cloud condensation water
 197 with dynamic values from MERRA-2. This leads to more rapid wet deposition rates and addresses a positive bias
 198 in modelled nitrate and ammonium, in particular in winter, when compared to surface observations in China,
 199 Europe, and the US (Luo et al., 2020). We sample the model in AW2016 and AW2017 following two months
 200 spin-up before each period of interest for chemical initialization.

201

202 We find from initial comparison of the model to the surface observations that the model in AW2016 is
 203 considerably less than observed NO_2 (by 48%), SO_2 (by 42%), and CO (by 57%) over the entire domain shown
 204 in Fig. 3. We attribute this to an underestimate in precursor emissions of these in the MEIC. Previous studies
 205 reported that MEIC trends in NO_x , SO_2 , and CO emissions are consistent with trends in satellite observations of
 206 column densities and weather-normalised surface measurements (Vu et al., 2019; Zheng et al., 2018), but studies
 207 assessing and identifying similar underestimates to ours are limited to very local assessment of the inventory.
 208 Squires et al. (2020) determined that MEIC NO_x and CO emissions are overestimated at the urban APHH site
 209 from comparison to fluxes calculated using the eddy-covariance method, though their comparison was for
 210 different years (measurements in 2016, MEIC in 2013). We calculate scale factors to apply to the MEIC based on
 211 our initial comparison to the network site measurements. These include spatially uniform scale factors of 1.5
 212 applied to NO_x emissions and 2.4 applied to CO emissions across the whole domain shown in Fig. 3. Spatially
 213 variable scale factors of 2.1-6.8 are applied to seven grid squares for the MEIC SO_2 emissions. These are
 214 concentrated in Shanxi province west of BTH, a region with large coal-fired power plants (Xie et al., 2018). These
 215 grids account for the majority of the domain average 42% underestimate in modelled SO_2 concentrations. Local
 216 enhancements in CO can include primary emissions and secondary contributions from oxidation of NMVOCs.
 217 Emission inventory estimates of NMVOCs are subject to large uncertainties, mainly due to poorly quantified
 218 industrial emissions (Li et al., 2017) and lack of reliable data for scattered areal sources such as residential coal
 219 burning (Li et al., 2019c; Peng et al., 2019; Shi et al., 2020). We find though that modelled CO is relatively
 220 unaffected by NMVOCs emissions. A sensitivity simulation with MEIC NMVOCs emissions increased by 50%
 221 only increases surface CO concentrations by 0.2%. Given this, we attribute the model underestimate in CO surface
 222 concentrations to the emissions. We do not adjust MEIC primary emissions of BC and OC, due to limited
 223 constraints on these from the observations. APHH eddy covariance fluxes of BC obtained in winter suggest a
 224 large overestimate (59 times) in MEIC BC emissions (Joshi et al., 2021), though this may be due to very local
 225 influence of traffic that is diluted at the resolution of the MEIC (Joshi et al., 2021).

226

227 Figure 4 compares GEOS-Chem and monitoring network air pollutant concentrations for BTH and the
 228 surrounding area after applying scale factors to MEIC emissions of SO_2 , NO_x , and CO. Emissions scaling of NO_x
 229 improves the modelled variance in NO_2 . The regression slope increases from 0.86 (not shown) to 0.93 (Fig. 4).
 230 There is still an underestimate in modelled background NO_2 (intercept = $-12.8 \mu\text{g m}^{-3}$) that leads to a model NO_2
 231 normalized mean bias (NMB) of -33%. The monitoring network includes sites close to busy roads that may be
 232 influenced by local traffic emissions that would be diluted at the 50-67 km resolution of the model. The BJMEMN
 233 sites are categorised by location and we find that excluding roadside sites leads to a 5-8% decrease in mean
 234 BJMEMN NO_2 (2-8% decrease for the other pollutants) and would only partially resolve the remaining
 235 underestimate in modelled NO_2 in Fig. 4. Other factors that could contribute to the remaining discrepancy include



short atmospheric lifetime of NO_2 , relatively coarse model resolution, and a positive 5-17% bias in the monitoring network measurements (Fig. 2). Any further increases in MEIC NO_x emissions would worsen the model NMB in $\text{PM}_{2.5}$ of 15%, as nitrate from oxidation of NO_x is the dominant component of $\text{PM}_{2.5}$ (29% in AW2016 for the entire domain in Fig. 3, according to GEOS-Chem).

Emissions scaling of SO_2 improves spatial consistency for concentrations of SO_2 from $r = 0.54$ (not shown) to $r = 0.90$ (Fig. 4). There is still a model bias -29% mostly due to 2 grids in Shanxi province with observed SO_2 of $161\text{--}200\ \mu\text{g m}^{-3}$ and modelled SO_2 of $109\text{--}122\ \mu\text{g m}^{-3}$ (Fig. 4). The model underestimate in CO decreases from -57% to -14% and the remaining model bias may be due to a 16-28% positive bias in the monitoring network (Fig. 2). The improvement in spatial correlation for CO is marginal, increasing from $r = 0.35$ to $r = 0.45$. Scaling MEIC emissions of SO_2 and NO_x increases the modelled $\text{PM}_{2.5}$ NMB from 8% with the original emissions to 15% with the scaled emissions. This may be due to remaining uncertainties in MEIC emissions of BC, OC, and NH_3 .

Figure 5 compares observed and modelled $\text{PM}_{2.5}$ composition at the urban and rural APHH sites. The model overestimates total $\text{PM}_{2.5}$ by 10% at the urban site and 34% at the rural site. Components are measured with a semicontinuous analyzer for OC and BC (Han et al., 2014; Kondo et al., 2006) and ion chromatography following particle collection with a Partisol for sulfate, nitrate, and ammonium (Taiwo et al., 2014; Xu et al., 2021). OC is compared instead of organic aerosol (OA), due to uncertainties in conversion of OC to OA (Xing et al., 2013). According to the observations, OC is the dominant $\text{PM}_{2.5}$ component, with a carbon mass contribution to total $\text{PM}_{2.5}$ of 23% at the urban site and 33% at the rural site. The total contribution of secondary inorganic aerosols is similar (31%) at both sites and includes 9% sulfate, 13% nitrate, and 9% ammonium at the urban site and similar contributions (8% sulfate, 13% nitrate, and 10% ammonium) at the rural site. BC is 4% of total $\text{PM}_{2.5}$ at both sites. The model underestimates OC (9% urban, 10% rural) and sulfate (both 4%), overestimates nitrate (28%, 30%), slightly overpredicts BC (4%, 5%), and is similar for ammonium (both 10%).

Previous studies have reported similar biases in simulated OC, sulfate and nitrate in China from GEOS-Chem (Miao et al., 2020) and other CTMs (Chen et al., 2019; Gao et al., 2018). Miao et al. (2020) reported a year-round underestimate in OA that they attribute to biases in precursor emissions and lack of seasonality in fixed secondary OA (SOA) yields used to estimate SOA formation from precursor emissions of NMVOCs. They also identified a year-round underestimate in sulfate that peaks at 54% in winter (Miao et al., 2020), similar to the 50% underestimate we obtain at the urban IAP site. The model underestimate in sulfate may in part be due to the remaining underestimate in MEIC SO_2 emissions (Fig. 4) after scaling MEIC SO_2 emissions. The model may also be missing key sulfate formation processes during haze events (Bloss et al., 2021; Wang et al., 2016; Wang et al., 2020), though the measurements may also be impacted by interference from hydroxymethane sulfonate (HMS) (Moch et al., 2018; Song et al., 2019). The overestimate in modelled nitrates is a common issue and has been attributed by Miao et al. (2020) to an overestimate in aerosol nitrate precursors at night exacerbated by errors in boundary layer dynamics. Despite biases in $\text{PM}_{2.5}$ composition, the model reproduces day-to-day variability in 24-hour mean $\text{PM}_{2.5}$ ($r = 0.66\text{--}0.71$) and its components ($r = 0.50\text{--}0.78$) at both sites.



Figure 6 shows total anthropogenic emissions of gaseous $\text{PM}_{2.5}$ precursors and primary $\text{PM}_{2.5}$ (OC and BC) for AW2016 obtained after applying scaling factors to the MEIC based on discrepancies in modelled and observed air pollutant concentrations. Total anthropogenic emissions in BTH (area shaded grey in Fig. 3) in AW2016, the year prior to the control period, are 2.4 Tg NO_x as NO, 1.6 Tg SO_2 , 150 Gg BC, 240 Gg OC, and 41 Tg CO. NMVOCs (2.0 Tg C) and NH_3 (0.64 Tg) are not shown in Fig. 6, as these are unchanged from AW2016 to AW2017. Though emissions of NO_x , CO and SO_2 increase in AW2016 relative to the default MEIC emissions due to our emissions scaling, there is no change in the relative contribution of different sectors. The major sector contributions include industry for NO_x (44%), SO_2 (56%), and CO (39%), transport for NO_x (34%), and residential fuel use for domestic heating and cooking for SO_2 (28%), CO (42%), BC (47%) and OC (79%).

4 Influence of emissions and meteorology on air quality in AW2017

To estimate the emission changes in the model due to controls implemented in BTH in AW2017, we regrid the relative changes in the surface air quality observations (Fig. 3) to a $1^\circ \times 1.25^\circ$ resolution grid to achieve reasonably extensive coverage across the whole domain shown in Fig. 3. For grids without surface observations (17% of the grids in the emission control region, 51% outside it), we interpolate across nearest neighbouring grids. Anthropogenic emissions beyond the geographic limits in Fig. 3 are unchanged. Due to lack of observations of OC and BC concentrations, we initially use the relative change in total measured $\text{PM}_{2.5}$. This ranges from a decrease in AW2017 relative to AW2016 of 5% to 53% in BTH. We find with this initial approach that the model underestimates the percent reduction in $\text{PM}_{2.5}$ in AW2017 relative to AW2016. This suggests that the decline in primary $\text{PM}_{2.5}$ may be greater than the decline in total $\text{PM}_{2.5}$, corroborated by the greater decline in primary $\text{PM}_{2.5}$ emissions in the bottom-up inventories used by Zhang et al. (2021) than the decline in measured total $\text{PM}_{2.5}$ for around half of the 28 cities. This may be because the regulations mostly targeted sources that have large primary $\text{PM}_{2.5}$ emissions, such as coal combustion, industry, vehicles, fugitive dust and biomass burning (Zhang et al., 2017b; Zheng et al., 2017). We iterate to obtain BC and OC emissions scaling factors that are 1.4 times more than the percent change in total $\text{PM}_{2.5}$.

Figure 7 shows the spatial distribution of modelled and observed $\text{PM}_{2.5}$ concentrations and relative changes in $\text{PM}_{2.5}$ in and around BTH. The average decrease in observed $\text{PM}_{2.5}$ is 28% in BTH, declining from $103 \mu\text{g m}^{-3}$ in AW2016 to $75 \mu\text{g m}^{-3}$ in AW 2017. A similar decline is obtained with the model for grids coincident with the sites (25% decrease from $112 \mu\text{g m}^{-3}$ in AW2016 to $85 \mu\text{g m}^{-3}$ in AW2017). The decline in modelled $\text{PM}_{2.5}$ for all BTH grids is 20% and compared to 16% for the whole domain. In Beijing, observed $\text{PM}_{2.5}$ decreases from $96 \mu\text{g m}^{-3}$ in AW2016 to $57 \mu\text{g m}^{-3}$ in AW2017, a 40% reduction. The decline in the model for all 13 grids covering Beijing ($39.25\text{--}41.25^\circ\text{N}$, $115.3125\text{--}117.8125^\circ\text{E}$) is more modest (33% decline from $75 \mu\text{g m}^{-3}$ in AW2016 to $50 \mu\text{g m}^{-3}$ in AW2017) than the grids coincident with the monitoring network sites. Regardless, both values exceed the 25% target set for Beijing (MEE, 2017).

Figure 8 further compares observed and modelled relative changes in $\text{PM}_{2.5}$. This confirms the skill of the model at reproducing the relative change in $\text{PM}_{2.5}$, despite an overall positive bias in total $\text{PM}_{2.5}$ (Figs. 4 and 7) and individual $\text{PM}_{2.5}$ components (Fig. 5). The modelled relative changes in $\text{PM}_{2.5}$ are somewhat more spatially consistent with the observations in BTH ($r = 0.82$) than the surrounding area ($r = 0.76$). The variance is closer to



unity for BTH (slope = 0.84) than the surrounding area (slope = 0.74). The relative change in $PM_{2.5}$ outside the emission control domain is -10% according to the observations, and -11% in the coincident model grids. During the emission control period, the area surrounding BTH in the domain shown in Fig. 7 is likely influenced by anthropogenic emissions from neighbouring regions that are the same in AW2017 and AW2016. This may account for the differences in the direction of change for 14 model grids (decline) compared to the observations (increase) in Fig. 8.

The emissions that we estimate for the control period (AW2017) are also shown in Fig. 6. According to our approach, total emissions reductions in AW2017 compared to AW2016 in BTH are 0.27 Tg NO_x as NO , 0.66 Tg SO_2 , 9.7 Tg CO, 70 Gg OC, and 50 Gg BC. Emissions of NH_3 and NMVOCs are unchanged due to limited constraints on these. There is an Ammonia Monitoring Network in China (AMoN-China), but there are only 8 sites in BTH, and the data are not publicly available (Pan et al., 2018). Relating NH_3 concentrations to emissions is also complicated by its ability to partition to sulfate aerosols (Fu et al., 2017) that decline by 36%, according to the model, in AW2017 relative to AW2016 due to decline in SO_2 emissions. There were also no mandatory measures targeting NH_3 sources during AW2017. Agricultural activities such as fertilizer and livestock excreta (Huang et al., 2012), dominant NH_3 sources in China, are also at a minimum in autumn and winter (Kong et al., 2019). Zhang et al. (2021) reported that NH_3 emissions were relatively unchanged in almost half of the 28 cities and varied in others from a 35% decrease to a 33% increase. Controls in BTH in AW2017 should have targeted NMVOCs sources, but these have limited effect on $PM_{2.5}$ according to GEOS-Chem. The sensitivity simulation we conducted with a 50% increase in NMVOCs emissions only causes a 1% increase in surface concentrations of $PM_{2.5}$. Mechanisms leading to the formation of wintertime SOA are not well understood. Field campaigns in winter in Beijing suggest significant SOA formation from oxidation of NMVOCs (Li et al., 2020a; Li et al., 2020b), whereas Wang et al. (2021) propose that rapid aqueous-phase oxidation of primary OA dominates SOA formation and would resolve the observed decline in SOA in Beijing in winter at the same time that NMVOCs emissions have remained relatively constant.

We also quantify the contribution of meteorology to the decline in $PM_{2.5}$ in AW2017. To do this, we compare modelled $PM_{2.5}$ from the AW2017 simulation (Fig. 7) to a simulation with AW2017 emissions and AW2016 meteorology. The decline in $PM_{2.5}$ in BTH due to differences in AW2016 and AW2017 meteorology only is 12 $\mu g m^{-3}$ or 57% of the decline in $PM_{2.5}$ from changes in both emissions and meteorology. The contribution of meteorology is similar, 54%, in the surrounding area. Our estimate is slightly less than the city-scale study by Zhang et al. (2019). They attribute 70% of the decline in $PM_{2.5}$ in BTH to variation in meteorology using CMAQ driven with WRF meteorology and the national MEIC and regional Beijing emissions inventories. Zhang et al. (2021) identified large variability in the contribution of emissions and meteorology to decline in $PM_{2.5}$ across the 28 cities, of 2-82% for emissions and 18-98% for meteorology. We find that the meteorological factors contributing to decline in $PM_{2.5}$ in BTH in AW2017 include dilution and dispersion of pollution due to stronger south-easterly winds and a 7% higher planetary boundary layer in AW2017 than AW2016. Efficiency of formation of secondary inorganic aerosols would also be less in AW2017 than AW2016 in response to 5% lower RH. Interannual variability in RH has similarly been identified as the cause for sustained air pollution over BTH despite a dramatic decline in precursor emissions from lockdown measures imposed to mitigate the spread of the SARS-



CoV-2 virus (Le et al., 2020). The meteorological factors that we identified with GEOS-Chem are consistent with those identified by Zhang et al. (2021) using WRF.

5 Conclusions

Strict emission controls were implemented across 28 cities in and around the Beijing-Tianjin-Hebei region (BTH) in autumn-winter 2017/2018 to address severe air pollution, specifically fine particles ($\text{PM}_{2.5}$). We used national and local surface monitoring network observations of $\text{PM}_{2.5}$ and trace gases with the GEOS-Chem model to assess the efficacy of emission controls, following evaluation of the network with independent measurements.

$\text{PM}_{2.5}$ and trace gases (NO_2 , SO_2 and CO) from the surface networks are temporally consistent with independent measurements ($r > 0.9$ for $\text{PM}_{2.5}$ and $r > 0.7$ for gases) and exhibit discrepancies that are in large part due to variability of these in the urban environment. According to these networks, $\text{PM}_{2.5}$ in BTH decreased by 28% from $103 \mu\text{g m}^{-3}$ to $75 \mu\text{g m}^{-3}$ in the control period relative to the previous year, exceeding the regional target of 15%. The model with emissions scaled to address large biases in NO_x , SO_2 , and CO emissions, reproduces the spatial distribution in $\text{PM}_{2.5}$ ($r = 0.68$). Despite a 15% positive bias in total $\text{PM}_{2.5}$ and large biases in $\text{PM}_{2.5}$ composition, the model captures the relative decline in $\text{PM}_{2.5}$ in BTH of 25%. According to the model constrained with the network measurements, decline in emissions in BTH due to strict controls are 0.27 Tg NO_x as NO, 0.66 Tg SO_2 , 9.7 Tg CO, 70 Gg OC, and 50 Gg BC. These account for less than half the observed decline in $\text{PM}_{2.5}$ and alone lead to an 8% reduction in $\text{PM}_{2.5}$, falling shorting of $\text{PM}_{2.5}$ reduction target. The remainder is due to meteorology, specifically a deeper planetary boundary layer, stronger winds, and lower relative humidity during the control period.

This supports the need for much stricter emissions controls in BTH and other parts of China where these controls are now adopted.

Data Availability

The GEOS-Chem model outputs used in this study are available at:

https://github.com/GongdaLu/BTH_emission_control.

Author Contributions

GLu performed the GEOS-Chem simulations, analysed the model and measurement data, and prepared the manuscript. EAM assisted in the writing and provided supervisory guidance, with co-supervision and editorial contributions from ZS. JDL provided APHH gas concentration data. ZS, TVV and JX performed PM composition analyses and provided guidance on using APHH data. QZ provided the original MEIC emission inventory that LS processed for input to GEOS-Chem. GLuo and FY provided source codes for the updated wet scavenging scheme in GEOS-Chem.

Competing Interests

The authors declare that they have no conflicts of interest.



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References

- Amos, H. M., Jacob, D. J., Holmes, C. D., Fisher, J. A., Wang, Q., Yantosca, R. M., Corbitt, E. S., Galarneau, E., Rutter, A. P., Gustin, M. S., Steffen, A., Schauer, J. J., Graydon, J. A., St Louis, V. L., Talbot, R. W., Edgerton, E. S., Zhang, Y., and Sunderland, E. M.: Gas-particle partitioning of atmospheric Hg(II) and its effect on global mercury deposition, *Atmos. Chem. Phys.*, 12, 591-603, <https://doi.org/10.5194/acp-12-591-2012>, 2012.
- An, Z., Huang, R. J., Zhang, R., Tie, X., Li, G., Cao, J., Zhou, W., Shi, Z., Han, Y., Gu, Z., and Ji, Y.: Severe haze in northern China: A synergy of anthropogenic emissions and atmospheric processes, *Proc. Natl. Acad. Sci. USA*, 116, 8657-8666, <https://doi.org/10.1073/pnas.1900125116>, 2019.
- Bei, N., Li, X., Tie, X., Zhao, L., Wu, J., Li, X., Liu, L., Shen, Z., and Li, G.: Impact of synoptic patterns and meteorological elements on the wintertime haze in the Beijing-Tianjin-Hebei region, China from 2013 to 2017, *Sci. Total. Environ.*, 704, 135210, <https://doi.org/10.1016/j.scitotenv.2019.135210>, 2020.
- Bloss, W. J., Kramer, L., Crilley, L. R., Vu, T., Harrison, R. M., Shi, Z., Lee, J. D., Squires, F. A., Whalley, L. K., Slater, E., Woodward-Massey, R., Ye, C., Heard, D. E., Tong, S., Hou, S., Sun, Y., Xu, J., Wei, L., and Fu, P.: Insights into air pollution chemistry and sulphate formation from nitrous acid (HONO) measurements during haze events in Beijing, *Faraday Discuss.*, 226, 223-238, [10.1039/d0fd00100g](https://doi.org/10.1039/d0fd00100g), 2021.
- Chen, L., Gao, Y., Zhang, M. G., Fu, J. S., Zhu, J., Liao, H., Li, J. L., Huang, K., Ge, B. Z., Wang, X. M., Lam, Y. F., Lin, C. Y., Itahashi, S., Nagashima, T., Kajino, M., Yamaji, K., Wang, Z. F., and Kurokawa, J.: MICS-Asia III: multi-model comparison and evaluation of aerosol over East Asia, *Atmos. Chem. Phys.*, 19, 11911-11937, <https://doi.org/10.5194/acp-19-11911-2019>, 2019.
- Dong, Z., Wang, S., Xing, J., Chang, X., Ding, D., and Zheng, H.: Regional transport in Beijing-Tianjin-Hebei region and its changes during 2014-2017: The impacts of meteorology and emission reduction, *Sci. Total. Environ.*, 737, 139792, <https://doi.org/10.1016/j.scitotenv.2020.139792>, 2020.
- Dunlea, E. J., Herndon, S. C., Nelson, D. D., Volkamer, R. M., San Martini, F., Sheehy, P. M., Zahniser, M. S., Shorter, J. H., Wormhoudt, J. C., Lamb, B. K., Allwine, E. J., Gaffney, J. S., Marley, N. A., Grutter, M., Marquez, C., Blanco, S., Cardenas, B., Retama, A., Villegas, C. R. R., Kolb, C. E., Molina, L. T., and Molina, M. J.: Evaluation of nitrogen dioxide chemiluminescence monitors in a polluted urban environment, *Atmos. Chem. Phys.*, 7, 2691-2704, <https://doi.org/10.5194/acp-7-2691-2007>, 2007.
- Fairlie, T. D., Jacob, D. J., and Park, R. J.: The impact of transpacific transport of mineral dust in the United States, *Atmos. Environ.*, 41, 1251-1266, <https://doi.org/10.1016/j.atmosenv.2006.09.048>, 2007.
- Fang, D., Chen, B., Hubacek, K., Ni, R., Chen, L., Feng, K., and Lin, J.: Clean air for some: Unintended spillover effects of regional air pollution policies, *Sci. Adv.*, 5, eaav4707, <https://doi.org/10.1126/sciadv.aav4707>, 2019.
- Fleming, Z. L., Lee, J. D., Liu, D., Acton, J., Huang, Z., Wang, X., Hewitt, N., Crilley, L., Kramer, L., Slater, E., Whalley, L., Ye, C., and Ingham, T.: APHH: Atmospheric measurements and model results for the Atmospheric Pollution & Human Health in a Chinese Megacity, available at: <http://catalogue.ceda.ac.uk/uuid/648246d2bdc7460b8159a8f9daee7844> (last access: 04 March 2021), 2017.
- Fountoukis, C. and Nenes, A.: ISORROPIA II: a computationally efficient thermodynamic equilibrium model for K^+ - Ca^{2+} - Mg^{2+} - NH_4^+ - Na^+ - SO_4^{2-} - NO_3^- - Cl^- - H_2O aerosols, *Atmos. Chem. Phys.*, 7, 4639-4659, <https://doi.org/10.5194/acp-7-4639-2007>, 2007.
- Fu, X., Wang, S. X., Xing, J., Zhang, X. Y., Wang, T., and Hao, J. M.: Increasing Ammonia Concentrations Reduce the Effectiveness of Particle Pollution Control Achieved via SO_2 and NO_x Emissions Reduction in East China, *Environ. Sci. Tech. Lett.*, 4, 221-227, <https://doi.org/10.1021/acs.estlett.7b00143>, 2017.



- 435 Gao, M., Han, Z. W., Liu, Z. R., Li, M., Xin, J. Y., Tao, Z. N., Li, J. W., Kang, J. E., Huang, K., Dong, X. Y.,
 436 Zhuang, B. L., Li, S., Ge, B. Z., Wu, Q. Z., Cheng, Y. F., Wang, Y. S., Lee, H. J., Kim, C. H., Fu, J. S. S., Wang,
 437 T. J., Chin, M. A., Woo, J. H., Zhang, Q., Wang, Z. F., and Carmichael, G. R.: Air quality and climate change,
 438 Topic 3 of the Model Inter-Comparison Study for Asia Phase III (MICS-Asia III) - Part 1: Overview and model
 439 evaluation, *Atmos. Chem. Phys.*, 18, 4859–4884, <https://doi.org/10.5194/acp-18-4859-2018>, 2018.
- 440 Han, T. T., Liu, X. G., Zhang, Y. H., Qu, Y., Gu, J. W., Ma, Q., Lu, K. D., Tian, H. Z., Chen, J., Zeng, L. M., Hu,
 441 M., and Zhu, T.: Characteristics of Aerosol Optical Properties and Their Chemical Apportionments during
 442 CAREBeijing 2006, *Aerosol Air Qual. Res.*, 14, 1431–1442, <https://doi.org/10.4209/aaqr.2013.06.0203>, 2014.
- 443 Heald, C. L., Jacob, D. J., Turquety, S., Hudman, R. C., Weber, R. J., Sullivan, A. P., Peltier, R. E., Atlas, E. L.,
 444 de Gouw, J. A., Warneke, C., Holloway, J. S., Neuman, J. A., Flocke, F. M., and Seinfeld, J. H.: Concentrations
 445 and sources of organic carbon aerosols in the free troposphere over North America, *J. Geophys. Res. Atmos.*, 111,
 446 D23S47, <https://doi.org/10.1029/2006jd007705>, 2006.
- 447 Huang, R. J., Zhang, Y., Bozzetti, C., Ho, K. F., Cao, J. J., Han, Y., Daellenbach, K. R., Slowik, J. G., Platt, S.
 448 M., Canonaco, F., Zotter, P., Wolf, R., Pieber, S. M., Bruns, E. A., Crippa, M., Ciarelli, G., Piazzalunga, A.,
 449 Schwikowski, M., Abbaszade, G., Schnelle-Kreis, J., Zimmermann, R., An, Z., Szidat, S., Baltensperger, U., El
 450 Haddad, I., and Prevot, A. S.: High secondary aerosol contribution to particulate pollution during haze events in
 451 China, *Nature*, 514, 218–222, <https://doi.org/10.1038/nature13774>, 2014.
- 452 Huang, X., Song, Y., Li, M. M., Li, J. F., Huo, Q., Cai, X. H., Zhu, T., Hu, M., and Zhang, H. S.: A high-resolution
 453 ammonia emission inventory in China, *Global Biogeochem. Cy.*, 26, GB1030,
 454 <https://doi.org/10.1029/2011gb004161>, 2012.
- 455 Jaegle, L., Quinn, P. K., Bates, T. S., Alexander, B., and Lin, J. T.: Global distribution of sea salt aerosols: new
 456 constraints from in situ and remote sensing observations, *Atmos. Chem. Phys.*, 11, 3137–3157,
 457 <https://doi.org/10.5194/acp-11-3137-2011>, 2011.
- 458 Joshi, R., Liu, D. T., Nemitz, E., Langford, B., Mullinger, N., Squires, F., Lee, J., Wu, Y. F., Pan, X. L., Fu, P.
 459 Q., Kotthaus, S., Grimmond, S., Zhang, Q., Wu, R. L., Wild, O., Flynn, M., Coe, H., and Allan, J.: Direct
 460 measurements of black carbon fluxes in central Beijing using the eddy covariance method, *Atmos. Chem. Phys.*,
 461 21, 147–162, <https://doi.org/10.5194/acp-21-147-2021>, 2021.
- 462 Kondo, Y., Komazaki, Y., Miyazaki, Y., Moteki, N., Takegawa, N., Kodama, D., Deguchi, S., Nogami, M.,
 463 Fukuda, M., Miyakawa, T., Morino, Y., Koike, M., Sakurai, H., and Ehara, K.: Temporal variations of elemental
 464 carbon in Tokyo, *J. Geophys. Res. Atmos.*, 111, D12205, <https://doi.org/10.1029/2005jd006257>, 2006.
- 465 Kong, L., Tang, X., Zhu, J., Wang, Z., Pan, Y., Wu, H., Wu, L., Wu, Q., He, Y., Tian, S., Xie, Y., Liu, Z., Sui,
 466 W., Han, L., and Carmichael, G.: Improved Inversion of Monthly Ammonia Emissions in China Based on the
 467 Chinese Ammonia Monitoring Network and Ensemble Kalman Filter, *Environ. Sci. Technol.*, 53, 12529–12538,
 468 <https://doi.org/10.1021/acs.est.9b02701>, 2019.
- 469 Le, T., Wang, Y., Liu, L., Yang, J., Yung, Y. L., Li, G., and Seinfeld, J. H.: Unexpected air pollution with marked
 470 emission reductions during the COVID-19 outbreak in China, *Science*, 369, 702–706,
 471 <https://doi.org/10.1126/science.abb7431>, 2020.
- 472 Li, C., Li, Q., Tong, D., Wang, Q., Wu, M., Sun, B., Su, G., and Tan, L.: Environmental impact and health risk
 473 assessment of volatile organic compound emissions during different seasons in Beijing, *J. Environ. Sci. (China)*,
 474 93, 1–12, <https://doi.org/10.1016/j.jes.2019.11.006>, 2020a.
- 475 Li, J., Liao, H., Hu, J., and Li, N.: Severe particulate pollution days in China during 2013–2018 and the associated
 476 typical weather patterns in Beijing–Tianjin–Hebei and the Yangtze River Delta regions, *Environ. Pollut.*, 248, 74–
 477 81, <https://doi.org/10.1016/j.envpol.2019.01.124>, 2019a.



- 478 Li, K., Jacob, D. J., Liao, H., Shen, L., Zhang, Q., and Bates, K. H.: Anthropogenic drivers of 2013-2017 trends
 479 in summer surface ozone in China, *Proc. Natl. Acad. Sci. USA*, 116, 422-427,
 480 <https://doi.org/10.1073/pnas.1812168116>, 2019b.
- 481 Li, K., Liao, H., Mao, Y. H., and Ridley, D. A.: Source sector and region contributions to concentration and direct
 482 radiative forcing of black carbon in China, *Atmos. Environ.*, 124, 351-366,
 483 <https://doi.org/10.1016/j.atmosenv.2015.06.014>, 2016.
- 484 Li, M., Liu, H., Geng, G. N., Hong, C. P., Liu, F., Song, Y., Tong, D., Zheng, B., Cui, H. Y., Man, H. Y., Zhang,
 485 Q., and He, K. B.: Anthropogenic emission inventories in China: a review, *Natl. Sci. Rev.*, 4, 834-866,
 486 <https://doi.org/10.1093/nsr/nwx150>, 2017.
- 487 Li, M., Zhang, Q., Streets, D. G., He, K. B., Cheng, Y. F., Emmons, L. K., Huo, H., Kang, S. C., Lu, Z., Shao, M.,
 488 Su, H., Yu, X., and Zhang, Y.: Mapping Asian anthropogenic emissions of non-methane volatile organic
 489 compounds to multiple chemical mechanisms, *Atmos. Chem. Phys.*, 14, 5617-5638, [https://doi.org/10.5194/acp-](https://doi.org/10.5194/acp-14-5617-2014)
 490 14-5617-2014, 2014.
- 491 Li, M., Zhang, Q., Zheng, B., Tong, D., Lei, Y., Liu, F., Hong, C. P., Kang, S. C., Yan, L., Zhang, Y. X., Bo, Y.,
 492 Su, H., Cheng, Y. F., and He, K. B.: Persistent growth of anthropogenic non-methane volatile organic compound
 493 (NMVOC) emissions in China during 1990-2017: drivers, speciation and ozone formation potential, *Atmos. Chem.*
 494 *Phys.*, 19, 8897-8913, <https://doi.org/10.5194/acp-19-8897-2019>, 2019c.
- 495 Li, Q., Su, G., Li, C., Liu, P., Zhao, X., Zhang, C., Sun, X., Mu, Y., Wu, M., Wang, Q., and Sun, B.: An
 496 investigation into the role of VOCs in SOA and ozone production in Beijing, China, *Sci. Total. Environ.*, 720,
 497 137536, <https://doi.org/10.1016/j.scitotenv.2020.137536>, 2020b.
- 498 Li, X. R., Zhang, C. L., Liu, P. F., Liu, J. F., Zhang, Y. Y., Liu, C. T., and Mu, Y. J.: Significant influence of the
 499 intensive agricultural activities on atmospheric PM_{2.5} during autumn harvest seasons in a rural area of the North
 500 China Plain, *Atmos. Environ.*, 241, 117844, <https://doi.org/10.1016/j.atmosenv.2020.117844>, 2020c.
- 501 Liu, H., Jacob, D. J., Bey, I., and Yantosca, R. M.: Constraints from ²¹⁰Pb and ⁷Be on wet deposition and transport
 502 in a global three-dimensional chemical tracer model driven by assimilated meteorological fields, *J. Geophys. Res.*
 503 *Atmos.*, 106, 12109-12128, <https://doi.org/10.1029/2000jd900839>, 2001.
- 504 Liu, H., Liu, S., Xue, B. R., Lv, Z. F., Meng, Z. H., Yang, X. F., Xue, T., Yu, Q., and He, K. B.: Ground-level
 505 ozone pollution and its health impacts in China, *Atmos. Environ.*, 173, 223-230,
 506 <https://doi.org/10.1016/j.atmosenv.2017.11.014>, 2018a.
- 507 Liu, M. X., Huang, X., Song, Y., Xu, T. T., Wang, S. X., Wu, Z. J., Hu, M., Zhang, L., Zhang, Q., Pan, Y. P., Liu,
 508 X. J., and Zhu, T.: Rapid SO₂ emission reductions significantly increase tropospheric ammonia concentrations
 509 over the North China Plain, *Atmos. Chem. Phys.*, 18, 17933-17943, <https://doi.org/10.5194/acp-18-17933-2018>,
 510 2018b.
- 511 Luo, G., Yu, F. Q., and Moch, J. M.: Further improvement of wet process treatments in GEOS-Chem v12.6.0:
 512 impact on global distributions of aerosols and aerosol precursors, *Geosci. Model Dev.*, 13, 2879-2903,
 513 <https://doi.org/10.5194/gmd-13-2879-2020>, 2020.
- 514 Luo, G., Yu, F. Q., and Schwab, J.: Revised treatment of wet scavenging processes dramatically improves GEOS-
 515 Chem 12.0.0 simulations of surface nitric acid, nitrate, and ammonium over the United States, *Geosci. Model*
 516 *Dev.*, 12, 3439-3447, <https://doi.org/10.5194/gmd-12-3439-2019>, 2019.



- 517 Ma, Q. A., Cai, S. Y., Wang, S. X., Zhao, B., Martin, R. V., Brauer, M., Cohen, A., Jiang, J. K., Zhou, W., Hao,
 518 J. M., Frostad, J., Forouzanfar, M. H., and Burnett, R. T.: Impacts of coal burning on ambient PM_{2.5} pollution in
 519 China, *Atmos. Chem. Phys.*, 17, 4477–4491, <https://doi.org/10.5194/acp-17-4477-2017>, 2017.
- 520 Martini, F. M. S., Hasenkopf, C. A., and Roberts, D. C.: Statistical analysis of PM_{2.5} observations from diplomatic
 521 facilities in China, *Atmos. Environ.*, 110, 174–185, <https://doi.org/10.1016/j.atmosenv.2015.03.060>, 2015.
- 522 Ministry of Ecology and Environment, the People's Republic of China (MEE). Ambient air quality standards
 523 GB3095-2012 (in Chinese), available at:
 524 https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/dqhjbh/dqhjzlbz/201203/t20120302_224165.shtml (last access: 04
 525 March 2021), 2012.
- 526 Ministry of Ecology and Environment, the People's Republic of China (MEE). Air Pollution Comprehensive
 527 Management Action Plan in the Autumn and Winter of 2017-2018 for the Beijing-Tianjin-Hebei Region and its
 528 Surrounding Areas (in Chinese), available at:
 529 https://www.mee.gov.cn/gkml/sthjbgw/sthjbjw/201809/t20180927_630570.htm (last access: 04 March 2021),
 530 2017.
- 531 Ministry of Ecology and Environment, the People's Republic of China (MEE). Letter on notifying the completion
 532 of air quality targets in the Beijing-Tianjin-Hebei air pollution transmission channel cities in autumn and winter
 533 (in Chinese), available at: http://www.mee.gov.cn/gkml/sthjbgw/stbgh/201805/t20180503_435855.htm (last
 534 access: 04 March 2021), 2018.
- 535 Miao, R. Q., Chen, Q., Zheng, Y., Cheng, X., Sun, Y. L., Palmer, P. I., Shrivastava, M., Guo, J. P., Zhang, Q.,
 536 Liu, Y. H., Tan, Z. F., Ma, X. F., Chen, S. Y., Zeng, L. M., Lu, K. D., and Zhang, Y. H.: Model bias in simulating
 537 major chemical components of PM_{2.5} in China, *Atmos. Chem. Phys.*, 20, 12265–12284,
 538 <https://doi.org/10.5194/acp-20-12265-2020>, 2020.
- 539 Moch, J. M., Dovrou, E., Mickley, L. J., Keutsch, F. N., Cheng, Y., Jacob, D. J., Jiang, J. K., Li, M., Munger, J.
 540 W., Qiao, X. H., and Zhang, Q.: Contribution of Hydroxymethane Sulfonate to Ambient Particulate Matter: A
 541 Potential Explanation for High Particulate Sulfur During Severe Winter Haze in Beijing, *Geophys. Res. Lett.*, 45,
 542 11969–11979, <https://doi.org/10.1029/2018gl079309>, 2018.
- 543 Pan, Y., Tian, S., Zhao, Y., Zhang, L., Zhu, X., Gao, J., Huang, W., Zhou, Y., Song, Y., Zhang, Q., and Wang,
 544 Y.: Identifying Ammonia Hotspots in China Using a National Observation Network, *Environ. Sci. Technol.*, 52,
 545 3926–3934, <https://doi.org/10.1021/acs.est.7b05235>, 2018.
- 546 Park, R. J., Jacob, D. J., Field, B. D., Yantosca, R. M., and Chin, M.: Natural and transboundary pollution
 547 influences on sulfate-nitrate-ammonium aerosols in the United States: Implications for policy, *J. Geophys. Res.*
 548 *Atmos.*, 109, D15204, <https://doi.org/10.1029/2003jd004473>, 2004.
- 549 Peng, L. Q., Zhang, Q., Yao, Z. L., Mauzerall, D. L., Kang, S. C., Du, Z. Y., Zheng, Y. X., Xue, T., and He, K.
 550 B.: Underreported coal in statistics: A survey-based solid fuel consumption and emission inventory for the rural
 551 residential sector in China, *Appl. Energ.*, 235, 1169–1182, <https://doi.org/10.1016/j.apenergy.2018.11.043>, 2019.
- 552 Reed, C., Evans, M. J., Di Carlo, P., Lee, J. D., and Carpenter, L. J.: Interferences in photolytic NO₂ measurements:
 553 explanation for an apparent missing oxidant?, *Atmos. Chem. Phys.*, 16, 4707–4724, <https://doi.org/10.5194/acp-16-4707-2016>, 2016.
- 555 Shah, V., Jacob, D. J., Li, K., Silvern, R. F., Zhai, S. X., Liu, M. Y., Lin, J. T., and Zhang, Q.: Effect of changing
 556 NO_x lifetime on the seasonality and long-term trends of satellite-observed tropospheric NO₂ columns over China,
 557 *Atmos. Chem. Phys.*, 20, 1483–1495, <https://doi.org/10.5194/acp-20-1483-2020>, 2020.



- 558 Shi, Y. Q., Xi, Z. Y., Simayi, M., Li, J., and Xie, S. D.: Scattered coal is the largest source of ambient volatile
 559 organic compounds during the heating season in Beijing, *Atmos. Chem. Phys.*, 20, 9351-9369,
 560 <https://doi.org/10.5194/acp-20-9351-2020>, 2020.
- 561 Shi, Z., Song, C., Liu, B., Lu, G., Xu, J., Van Vu, T., Elliott, R. J. R., Li, W., Bloss, W. J., and Harrison, R. M.:
 562 Abrupt but smaller than expected changes in surface air quality attributable to COVID-19 lockdowns, *Sci. Adv.*,
 563 7, eabd6696, <https://doi.org/10.1126/sciadv.abd6696>, 2021.
- 564 Shi, Z. B., Vu, T., Kotthaus, S., Harrison, R. M., Grimmond, S., Yue, S., Zhu, T., Lee, J., Han, Y., Demuzere, M.,
 565 Dunmore, R. E., Ren, L. J., Liu, D., Wang, Y. L., Wild, O., Allan, J., Acton, W. J., Barlow, J., Barratt, B., Beddows,
 566 D., Bloss, W. J., Calzolari, G., Carruthers, D., Carslaw, D. C., Chan, Q., Chatzidiakou, L., Chen, Y., Crilley, L.,
 567 Coe, H., Dai, T., Doherty, R., Duan, F., Fu, P., Ge, B., Ge, M., Guan, D., Hamilton, J. F., He, K., Heal, M., Heard,
 568 D., Hewitt, C. N., Hollaway, M., Hu, M., Ji, D., Jiang, X. J., Jones, R., Kalberer, M., Kelly, F. J., Kramer, L.,
 569 Langford, B., Lin, C., Lewis, A. C., Li, J., Li, W., Liu, H., Liu, J. F., Loh, M., Lu, K. D., Lucarelli, F., Mann, G.,
 570 McFiggans, G., Miller, M. R., Mills, G., Monk, P., Nemitz, E., O'Connor, F., Ouyang, B., Palmer, P. I., Percival,
 571 C., Popoola, O., Reeves, C., Rickard, A. R., Shao, L. Y., Shi, G. Y., Spracklen, D., Stevenson, D., Sun, Y., Sun,
 572 Z. W., Tao, S., Tong, S. R., Wang, Q. Q., Wang, W. H., Wang, X. M., Wang, X. J., Wang, Z. F., Wei, L. F.,
 573 Whalley, L., Wu, X. F., Wu, Z. J., Xie, P. H., Yang, F. M., Zhang, Q., Zhang, Y. L., Zhang, Y. H., and Zheng,
 574 M.: Introduction to the special issue "In-depth study of air pollution sources and processes within Beijing and its
 575 surrounding region (APHH-Beijing)", *Atmos. Chem. Phys.*, 19, 7519-7546, [https://doi.org/10.5194/acp-19-7519-](https://doi.org/10.5194/acp-19-7519-2019)
 576 2019, 2019.
- 577 Silver, B., Reddington, C. L., Arnold, S. R., and Spracklen, D. V.: Substantial changes in air pollution across
 578 China during 2015-2017, *Environ. Res. Lett.*, 13, 114012, <https://doi.org/10.1088/1748-9326/aae718>, 2018.
- 579 Song, S. J., Gao, M., Xu, W. Q., Sun, Y. L., Worsnop, D. R., Jayne, J. T., Zhang, Y. Z., Zhu, L., Li, M., Zhou, Z.,
 580 Cheng, C. L., Lv, Y. B., Wang, Y., Peng, W., Xu, X. B., Lin, N., Wang, Y. X., Wang, S. X., Munger, J. W., Jacob,
 581 D. J., and McElroy, M. B.: Possible heterogeneous chemistry of hydroxymethanesulfonate (HMS) in northern
 582 China winter haze, *Atmos. Chem. Phys.*, 19, 1357-1371, <https://doi.org/10.5194/acp-19-1357-2019>, 2019.
- 583 Squires, F. A., Nemitz, E., Langford, B., Wild, O., Drysdale, W. S., Acton, W. J. F., Fu, P. Q., Grimmond, C. S.
 584 B., Hamilton, J. F., Hewitt, C. N., Hollaway, M., Kotthaus, S., Lee, J., Metzger, S., Pingintha-Durden, N., Shaw,
 585 M., Vaughan, A. R., Wang, X. M., Wu, R. L., Zhang, Q., and Zhang, Y. L.: Measurements of traffic-dominated
 586 pollutant emissions in a Chinese megacity, *Atmos. Chem. Phys.*, 20, 8737-8761, [https://doi.org/10.5194/acp-20-](https://doi.org/10.5194/acp-20-8737-2020)
 587 8737-2020, 2020.
- 588 Taiwo, A. M., Beddows, D. C., Calzolari, G., Harrison, R. M., Lucarelli, F., Nava, S., Shi, Z., Valli, G., and Vecchi,
 589 R.: Receptor modelling of airborne particulate matter in the vicinity of a major steelworks site, *Sci. Total. Environ.*,
 590 490, 488-500, <https://doi.org/10.1016/j.scitotenv.2014.04.118>, 2014.
- 591 Tong, R. P., Liu, J. F., Wang, W., and Fang, Y. Q.: Health effects of PM_{2.5} emissions from on-road vehicles during
 592 weekdays and weekends in Beijing, China, *Atmos. Environ.*, 223, 117258,
 593 <https://doi.org/10.1016/j.atmosenv.2019.117258>, 2020.
- 594 Vu, T. V., Shi, Z. B., Cheng, J., Zhang, Q., He, K. B., Wang, S. X., and Harrison, R. M.: Assessing the impact of
 595 clean air action on air quality trends in Beijing using a machine learning technique, *Atmos. Chem. Phys.*, 19,
 596 11303-11314, <https://doi.org/10.5194/acp-19-11303-2019>, 2019.
- 597 Wan, Y. T., Xu, M. Y., Huang, H., and Chen, S. X.: A spatio-temporal model for the analysis and prediction of
 598 fine particulate matter concentration in Beijing, *Environmetrics*, 32, e2648, <https://doi.org/10.1002/env.2648>,
 599 2021.
- 600 Wang, G., Zhang, R., Gomez, M. E., Yang, L., Levy Zamora, M., Hu, M., Lin, Y., Peng, J., Guo, S., Meng, J., Li,
 601 J., Cheng, C., Hu, T., Ren, Y., Wang, Y., Gao, J., Cao, J., An, Z., Zhou, W., Li, G., Wang, J., Tian, P., Marrero-
 602 Ortiz, W., Secrest, J., Du, Z., Zheng, J., Shang, D., Zeng, L., Shao, M., Wang, W., Huang, Y., Wang, Y., Zhu, Y.,



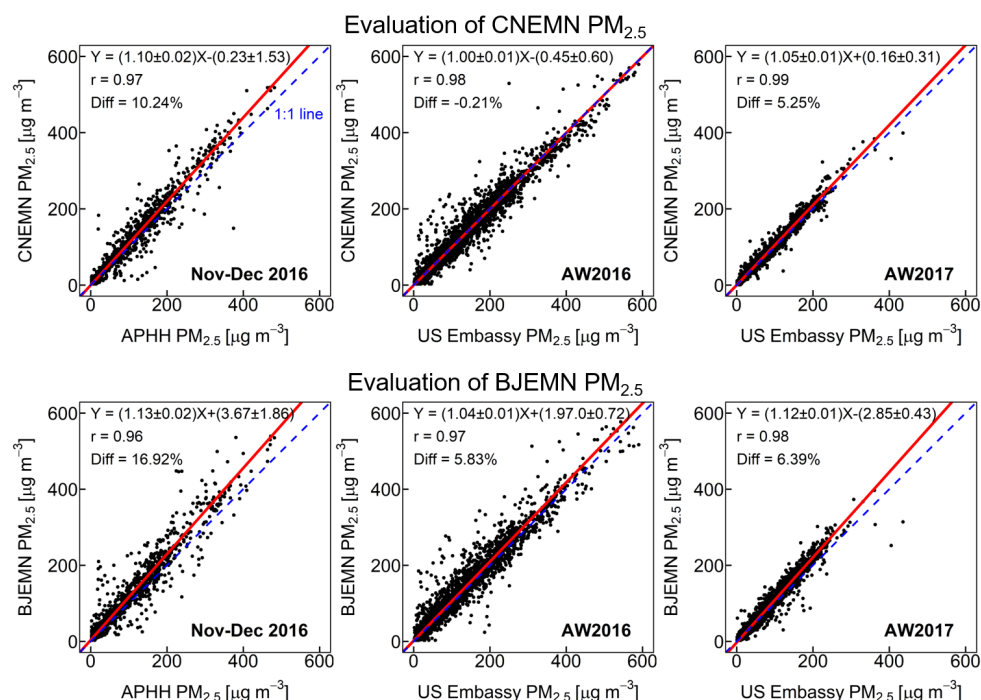
- 603 Li, Y., Hu, J., Pan, B., Cai, L., Cheng, Y., Ji, Y., Zhang, F., Rosenfeld, D., Liss, P. S., Duce, R. A., Kolb, C. E.,
 604 and Molina, M. J.: Persistent sulfate formation from London Fog to Chinese haze, *Proc. Natl. Acad. Sci. USA*,
 605 113, 13630-13635, <https://doi.org/10.1073/pnas.1616540113>, 2016.
- 606 Wang, J., Li, J., Ye, J., Zhao, J., Wu, Y., Hu, J., Liu, D., Nie, D., Shen, F., Huang, X., Huang, D. D., Ji, D., Sun,
 607 X., Xu, W., Guo, J., Song, S., Qin, Y., Liu, P., Turner, J. R., Lee, H. C., Hwang, S., Liao, H., Martin, S. T., Zhang,
 608 Q., Chen, M., Sun, Y., Ge, X., and Jacob, D. J.: Fast sulfate formation from oxidation of SO₂ by NO₂ and HONO
 609 observed in Beijing haze, *Nat. Commun.*, 11, 2844, <https://doi.org/10.1038/s41467-020-16683-x>, 2020.
- 610 Wang, J., Ye, J., Zhang, Q., Zhao, J., Wu, Y., Li, J., Liu, D., Li, W., Zhang, Y., Wu, C., Xie, C., Qin, Y., Lei, Y.,
 611 Huang, X., Guo, J., Liu, P., Fu, P., Li, Y., Lee, H. C., Choi, H., Zhang, J., Liao, H., Chen, M., Sun, Y., Ge, X.,
 612 Martin, S. T., and Jacob, D. J.: Aqueous production of secondary organic aerosol from fossil-fuel emissions in
 613 winter Beijing haze, *Proc. Natl. Acad. Sci. USA*, 118, e2022179118, <https://doi.org/10.1073/pnas.2022179118>,
 614 2021.
- 615 Wang, Y., Jacob, D. J., and Logan, J. A.: Global simulation of tropospheric O₃-NO_x-hydrocarbon chemistry: 1.
 616 Model formulation, *J. Geophys. Res. Atmos.*, 103, 10713-10725, <https://doi.org/10.1029/98jd00158>, 1998.
- 617 Wang, Y., Ying, Q., Hu, J., and Zhang, H.: Spatial and temporal variations of six criteria air pollutants in 31
 618 provincial capital cities in China during 2013-2014, *Environ. Int.*, 73, 413-422,
 619 <https://doi.org/10.1016/j.envint.2014.08.016>, 2014.
- 620 Wang, Y., Zhang, Q. Q., He, K., Zhang, Q., and Chai, L.: Sulfate-nitrate-ammonium aerosols over China: response
 621 to 2000-2015 emission changes of sulfur dioxide, nitrogen oxides, and ammonia, *Atmos. Chem. Phys.*, 13, 2635-
 622 2652, <https://doi.org/10.5194/acp-13-2635-2013>, 2013.
- 623 Wang, Y. S., Li, W. J., Gao, W. K., Liu, Z. R., Tian, S. L., Shen, R. R., Ji, D. S., Wang, S., Wang, L. L., Tang, G.
 624 Q., Song, T., Cheng, M. T., Wang, G. H., Gong, Z. Y., Hao, J. M., and Zhang, Y. H.: Trends in particulate matter
 625 and its chemical compositions in China from 2013-2017, *Sci. China Earth Sci.*, 62, 1857-1871,
 626 <https://doi.org/10.1007/s11430-018-9373-1>, 2019.
- 627 Wu, H. J., Tang, X., Wang, Z. F., Wu, L., Lu, M. M., Wei, L. F., and Zhu, J.: Probabilistic Automatic Outlier
 628 Detection for Surface Air Quality Measurements from the China National Environmental Monitoring Network,
 629 *Adv. Atmos. Sci.*, 35, 1522-1532, <https://doi.org/10.1007/s00376-018-8067-9>, 2018.
- 630 Wu, J., Bei, N., Hu, B., Liu, S., Zhou, M., Wang, Q., Li, X., Liu, L., Feng, T., Liu, Z., Wang, Y., Cao, J., Tie, X.,
 631 Wang, J., Molina, L. T., and Li, G.: Is water vapor a key player of the wintertime haze in North China Plain?,
 632 *Atmos. Chem. Phys.*, 19, 8721-8739, <https://doi.org/10.5194/acp-19-8721-2019>, 2019.
- 633 Xie, L. Y., Huang, Y., and Qin, P.: Spatial distribution of coal-fired power plants in China, *Environ. Dev. Econ.*,
 634 23, 495-515, <https://doi.org/10.1017/S1355770x18000098>, 2018.
- 635 Xing, L., Fu, T. M., Cao, J. J., Lee, S. C., Wang, G. H., Ho, K. F., Cheng, M. C., You, C. F., and Wang, T. J.:
 636 Seasonal and spatial variability of the OM/OC mass ratios and high regional correlation between oxalic acid and
 637 zinc in Chinese urban organic aerosols, *Atmos. Chem. Phys.*, 13, 4307-4318, <https://doi.org/10.5194/acp-13-4307-2013>, 2013.
- 639 Xu, J., Liu, D., Wu, X., Vu, T. V., Zhang, Y., Fu, P., Sun, Y., Xu, W., Zheng, B., Harrison, R. M., and Shi, Z.:
 640 Source apportionment of fine organic carbon at an urban site of Beijing using a chemical mass balance model,
 641 *Atmos. Chem. Phys.*, 21, 7321-7341, <https://doi.org/10.5194/acp-21-7321-2021>, 2021.
- 642 Yang, G., Liu, Y., and Li, X.: Spatiotemporal distribution of ground-level ozone in China at a city level, *Sci. Rep.*,
 643 10, 7229, <https://doi.org/10.1038/s41598-020-64111-3>, 2020.



- 644 Yun, X., Shen, G., Shen, H., Meng, W., Chen, Y., Xu, H., Ren, Y., Zhong, Q., Du, W., Ma, J., Cheng, H., Wang,
 645 X., Liu, J., Wang, X., Li, B., Hu, J., Wan, Y., and Tao, S.: Residential solid fuel emissions contribute significantly
 646 to air pollution and associated health impacts in China, *Sci. Adv.*, 6, eaba7621,
 647 <https://doi.org/10.1126/sciadv.aba7621>, 2020.
- 648 Zhai, S. X., Jacob, D. J., Wang, X., Shen, L., Li, K., Zhang, Y. Z., Gui, K., Zhao, T. L., and Liao, H.: Fine
 649 particulate matter (PM_{2.5}) trends in China, 2013-2018: separating contributions from anthropogenic emissions and
 650 meteorology, *Atmos. Chem. Phys.*, 19, 11031-11041, <https://doi.org/10.5194/acp-19-11031-2019>, 2019.
- 651 Zhang, F., Shi, Y., Fang, D., Ma, G., Nie, C., Krafft, T., He, L., and Wang, Y.: Monitoring history and change
 652 trends of ambient air quality in China during the past four decades, *J. Environ. Manage.*, 260, 110031,
 653 <https://doi.org/10.1016/j.jenvman.2019.110031>, 2020.
- 654 Zhang, Q., Zheng, Y., Tong, D., Shao, M., Wang, S., Zhang, Y., Xu, X., Wang, J., He, H., Liu, W., Ding, Y., Lei,
 655 Y., Li, J., Wang, Z., Zhang, X., Wang, Y., Cheng, J., Liu, Y., Shi, Q., Yan, L., Geng, G., Hong, C., Li, M., Liu,
 656 F., Zheng, B., Cao, J., Ding, A., Gao, J., Fu, Q., Huo, J., Liu, B., Liu, Z., Yang, F., He, K., and Hao, J.: Drivers of
 657 improved PM_{2.5} air quality in China from 2013 to 2017, *Proc. Natl. Acad. Sci. USA*, 116, 24463-24469,
 658 <https://doi.org/10.1073/pnas.1907956116>, 2019.
- 659 Zhang, X., Wu, Y., Liu, X., Reis, S., Jin, J., Dragosits, U., Van Damme, M., Clarisse, L., Whitburn, S., Coheur,
 660 P. F., and Gu, B.: Ammonia Emissions May Be Substantially Underestimated in China, *Environ. Sci. Technol.*,
 661 51, 12089-12096, <https://doi.org/10.1021/acs.est.7b02171>, 2017a.
- 662 Zhang, Y., Cai, J., Wang, S., He, K., and Zheng, M.: Review of receptor-based source apportionment research of
 663 fine particulate matter and its challenges in China, *Sci. Total. Environ.*, 586, 917-929,
 664 <https://doi.org/10.1016/j.scitotenv.2017.02.071>, 2017b.
- 665 Zhang, Y., Chen, X., Yu, S., Wang, L., Li, Z., Li, M., Liu, W., Li, P., Rosenfeld, D., and Seinfeld, J. H.: City-
 666 level air quality improvement in the Beijing-Tianjin-Hebei region from 2016/17 to 2017/18 heating seasons:
 667 Attributions and process analysis, *Environ. Pollut.*, 274, 116523, <https://doi.org/10.1016/j.envpol.2021.116523>,
 668 2021.
- 669 Zhang, Y. P., Li, X., Nie, T., Qi, J., Chen, J., and Wu, Q.: Source apportionment of PM_{2.5} pollution in the central
 670 six districts of Beijing, China, *J. Clean Prod.*, 174, 661-669, <https://doi.org/10.1016/j.jclepro.2017.10.332>, 2018.
- 671 Zheng, B., Tong, D., Li, M., Liu, F., Hong, C. P., Geng, G. N., Li, H. Y., Li, X., Peng, L. Q., Qi, J., Yan, L.,
 672 Zhang, Y. X., Zhao, H. Y., Zheng, Y. X., He, K. B., and Zhang, Q.: Trends in China's anthropogenic emissions
 673 since 2010 as the consequence of clean air actions, *Atmos. Chem. Phys.*, 18, 14095-14111,
 674 <https://doi.org/10.5194/acp-18-14095-2018>, 2018.
- 675 Zheng, M., Yan, C. Q., Wang, S. X., He, K. B., and Zhang, Y. H.: Understanding PM_{2.5} sources in China:
 676 challenges and perspectives, *Natl. Sci. Rev.*, 4, 801-803, <https://doi.org/10.1093/nsr/nwx129>, 2017.
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681 **Figure 1.** Evaluation of local and national network PM_{2.5} measurements. Points are hourly PM_{2.5} measurements. The top row
 682 compares CNEMN to the APHH urban site (left), and CNEMN to the US Embassy in autumn-winter 2016/2017 (AW2016)
 683 (centre) and 2017/2018 (AW2017) (right). The bottom row compares BJEMN to the APHH urban site (left), and BJEMN
 684 to the US Embassy in AW2016 (centre) and AW2017 (right). Reduced major axis (RMA) regression statistics, Pearson's
 685 correlation coefficients (r), and the percent difference (Diff = monitoring network minus independent measurement) are given.
 686 Lines are the RMA regression (red) and 1:1 line (blue dashed).

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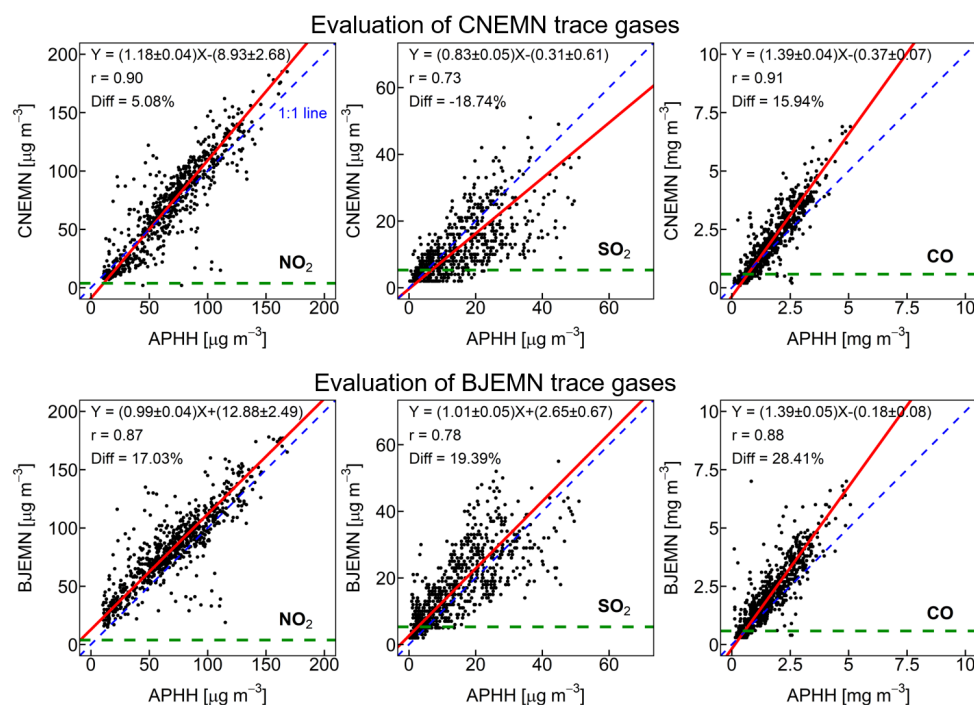
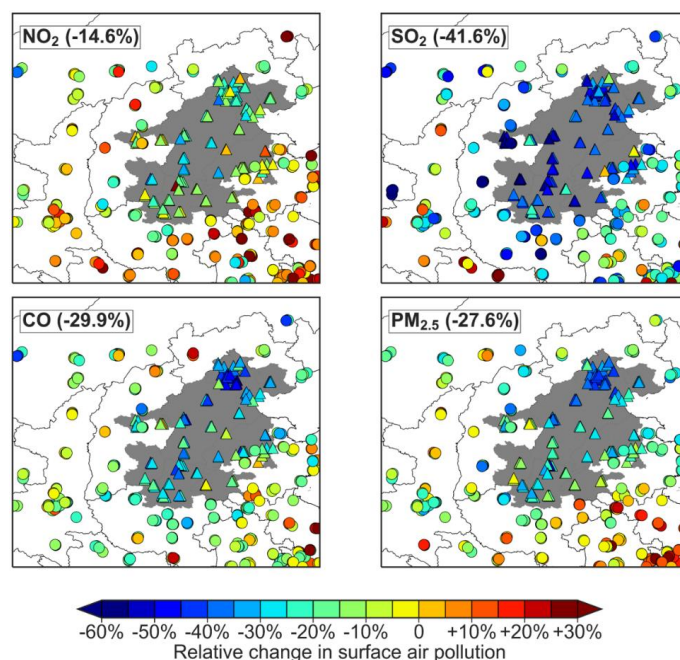


Figure 2. Evaluation of local and national network trace gas concentration measurements. Points are hourly measurements. Panels compare CNEMN (top) and BJEMN (bottom) NO_2 (left), SO_2 (centre) and CO (right) to the APHH urban site in November-December 2016. RMA regression statistics, Pearson's correlation coefficients (r), and the percent difference (Diff = monitoring network minus independent measurement) are given. Lines are the RMA regression (red) and 1:1 line (blue dashed). The green dashed line is the reported monitoring network instrument detection limit (MEE, 2012).



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Figure 3. Change in surface air pollution in BTH and the surrounding area in AW2017 relative to AW2016. Individual points are monitoring network site changes for the target region (triangles within area shaded grey) and the surrounding area (circles in the non-shaded area). Values inset give the percent change for sites in the grey domain only. Note the colourbar is uneven.

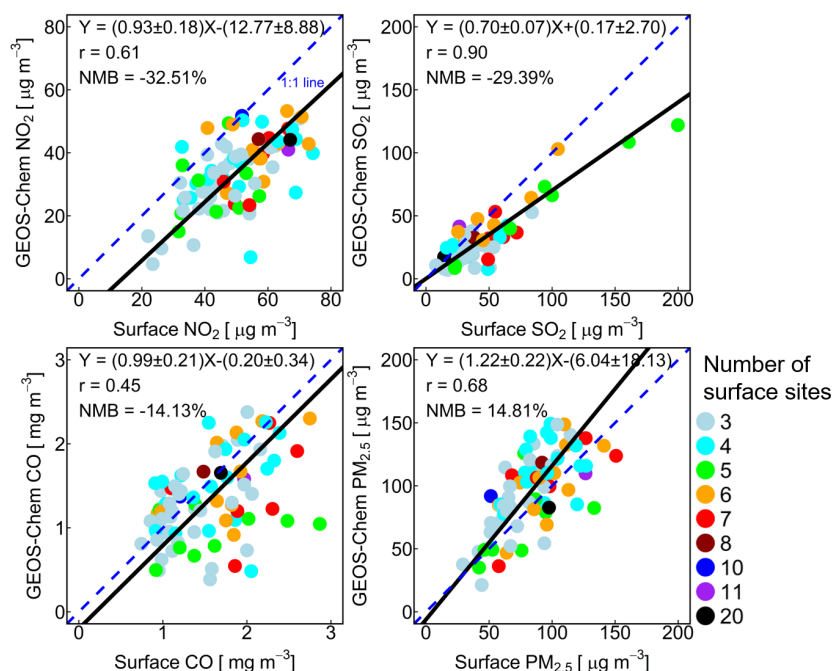


Figure 4. Evaluation of GEOS-Chem simulation of air pollutant concentrations in AW2016. Observations are averaged onto the GEOS-Chem grid. Points are simulated and observed NO₂ (top left), SO₂ (top right), CO (bottom left) and PM_{2.5} (bottom right) in the entire domain in Figure 3 for grid squares with at least three coincident surface sites. Points are coloured by the number of surface sites. The model uses scaled MEIC emissions (see text for details). RMA regression statistics, Pearson's correlation coefficients (r), and model normalized mean biases (NMB) are given. Lines are the RMA regression (black) and 1:1 line (blue dashed).

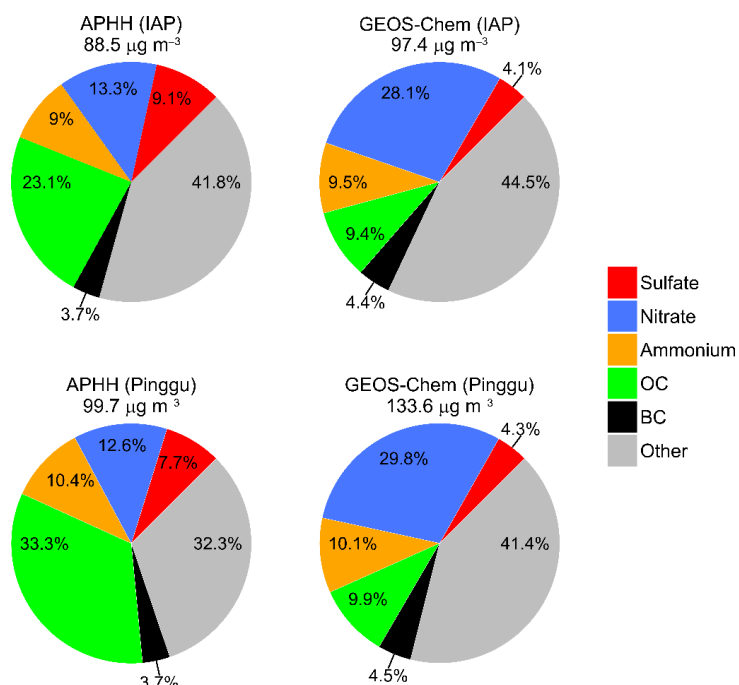
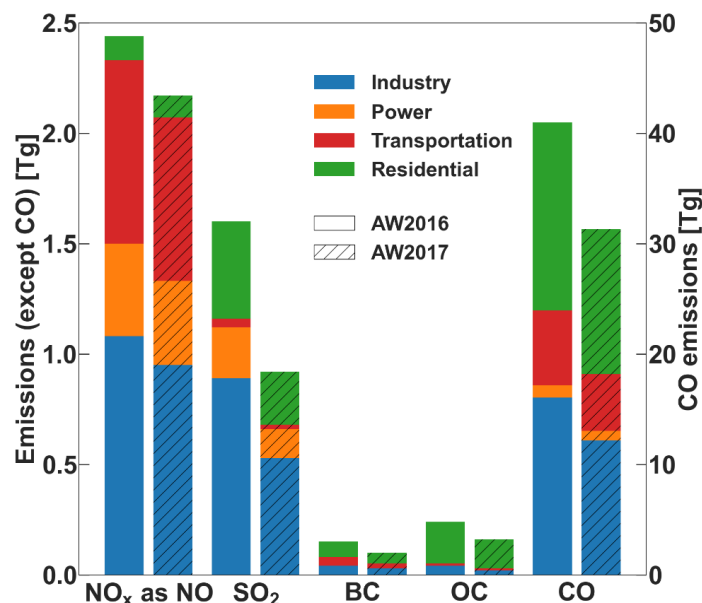


Figure 5. Relative contribution of individual PM_{2.5} components during the APHH campaign. Panels are measured (left) and modelled (right) percent contribution for the urban IAP (top) and rural Pinggu (bottom) sites. Components are sulfate, nitrate, ammonium, OC, BC and Other. Other is the sum of trace metals, mineral dust and other ions, the non-carbon portion of OC, and aerosol water at 33-35% relative humidity (RH) for the measurements and 35% RH for the model. Values above the pies are mean total PM_{2.5}.



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Figure 6. Total anthropogenic emissions in BTH in AW2016 and AW2017. Emissions are for grids covering the grey shaded area in Figure 3. Emissions are from the MEIC with scaling factors to address discrepancies between the model and observations for AW2016 and to reproduce the change in air pollutant concentrations in the AW2017 emission control period (see text for details). Vertical axes are emissions for NO, BC, OC, and SO₂ on the left axis and for CO on the right axis.

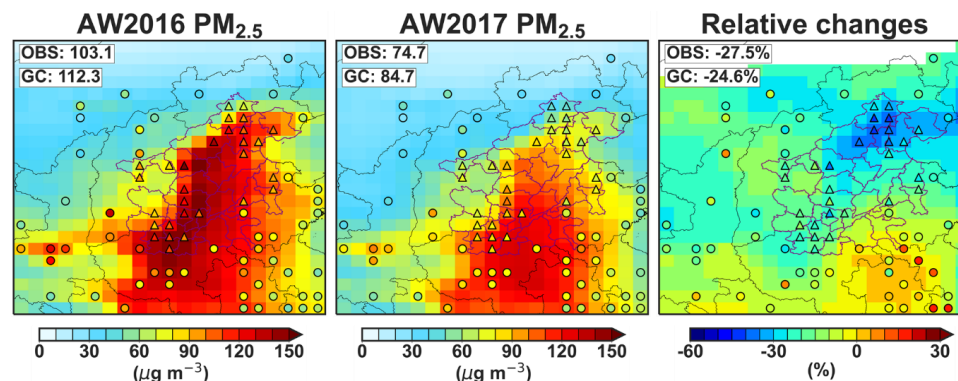
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Figure 7. Spatial distribution of absolute and relative changes in observed and modelled PM_{2.5} before and during the strict emission control period. The observed (shapes) and modelled (background) PM_{2.5} are shown for AW2016 (left) and AW2017 (centre). The right panel is the relative change in observed and modelled PM_{2.5}. Observations are distinguished as within (triangles) and outside (circles) the emission control region (grey area in Figure 3). Inset values are the observed (OBS) and modelled (GC) means for sites and coincident grids in the emission control domain. Note the uneven colour scale in the right panel.

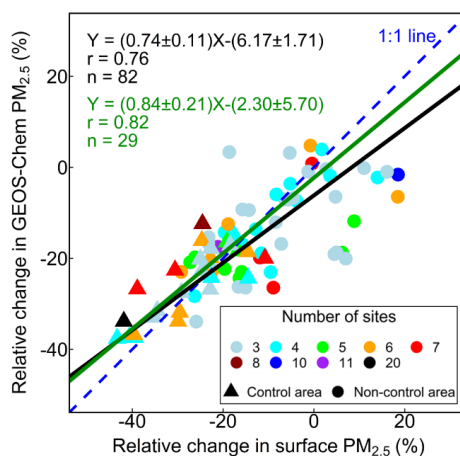


Figure 8. Comparison of observed and modelled relative changes in $PM_{2.5}$. Triangles indicate data in BTH (grey area in Figure 3) and circles indicate data outside BTH. These are coloured by the number of sites in each GEOS-Chem grid. The RMA regression statistics and lines, Pearson's correlation coefficients (r), and NMB are given for all points (black text) and for those in BTH (green text).