



Impacts of Meteorological Uncertainties on the Haze Formation in Beijing-Tianjin Hebei (BTH) during Wintertime: A case study

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13 Abstract: In the present study, a persistent heavy haze episode from 13 to 20 January 2014 in 14 Beijing-Tianjin-Hebei (BTH) is simulated using the WRF-CHEM model through ensemble 15 simulations to investigate impacts of meteorological initial uncertainties on the haze formation. Model results have shown that uncertainties in meteorological initial conditions 16 17 substantially influence the aerosol constituent simulations at an observation site in Beijing, 18 and the ratio of the ensemble spread to ensemble mean (RESM) exceeds 50%. The ensemble 19 mean generally preforms well in reproducing the fine particles $(PM_{2.5})$ temporal variations 20 and spatial distributions against measurements in BTH. The initial meteorological 21 uncertainties do not alter the PM2.5 distribution pattern in BTH principally or dominate the haze formation and development, but remarkably affect the simulated PM2.5 level, and the 22 23 RESM of PM2.5 concentrations can be up to 30% at the region scale. In addition, the rather 24 large RESM in PM_{2.5} simulations at the city scale also causes difficulties in implementation 25 of the control strategies. Therefore, our results suggest that the ensemble simulation is 26 imperative to avoid the impact of the initial meteorological uncertainties on the haze 27 prediction. 28

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33 1 Introduction

Over the past three decades, rapid industrialization and urbanization have caused severe air pollution in China, particularly during wintertime heavy haze with extremely high levels of fine particles (PM_{2.5}) frequently engulfs the north of China (e.g., Chan and Yao, 2008; Fang et al., 2009; Zhao et al., 2013; Huang et al., 2014; Guo et al., 2014; Wu et al., 2017; Li et al., 2017). Elevated atmospheric aerosols or PM_{2.5} not only influence the Earth climate system, but also remarkably impair visibility and potentially cause severe health defects (e.g., Penner et al., 2001; Pope and Dockery, 2006; Zhang et al., 2007).

41 Meteorological condition is critical for understanding the formation, transformation, 42 diffusion, transport, and removal of the pollutants in the atmosphere. Dabberdt et al. (2004) have listed the meteorological research needs for improving air quality forecasting, one of 43 44 which is to provide the model uncertainty information through ensemble prediction 45 capabilities and quantify uncertainties and feed-backs between meteorological and air quality 46 modeling components. Numerous studies have been performed in China to explore the role of 47 meteorological conditions in the air pollution formation (e.g., Gao et al., 2011; Zhang et al., 48 2012; Wu et al. 2013; Wang et al. 2014; Zhang et al. 2015; Bei et al. 2016a; 2016b). Most 49 recently, Liu et al. (2017) have investigated the meteorological impacts on the PM_{25} 50 concentrations over Beijing-Tianjin-Hebei (BTH) in December 2015. Their results have 51 demonstrated that the unfavorable meteorological conditions are the main reason for 52 deterioration of the air quality in BTH, while the undertaken emission control measures have 53 only mitigated the air pollution slightly.

Previous studies on the air quality forecasting sensitivity to meteorological uncertainties mainly include Monte Carlo simulations (e.g. Dabberdt and Miller, 2000; Beekmann and Derognat, 2003) and adjoint sensitivity studies (e.g. Menut, 2003). The ensemble approach has also been applied to photochemical and secondary organic aerosol





(SOA) simulations in various numerical models (e. g. Galmarini et al., 2004; McKeen et al., 58 59 2005), photo-chemical reactions (e. g. Delle Monache and Stull, 2003), emission scenarios (e. 60 g. Delle Monache et al., 2006), physical parameterizations (e. g. Mallet and Sportisse, 2006), 61 and meteorological initial conditions (e. g. Zhang et al. 2007; Bei et al. 2012). The ensemble 62 means have generally performed better than most of individual models. Uncertainties in 63 meteorological initial conditions have been shown to substantially influence both ozone (O_3) 64 and SOA simulations, including the peak time concentrations, the horizontal distributions, 65 and the temporal variations (Zhang et al. 2007; Bei et al. 2012). Recently, Sharma et al. (2016) 66 have evaluated uncertainties in surface O₃ simulations over the South Asian region during the pre-monsoon season due to different emission inventories and different chemical mechanisms. 67 They have suggested that the assessment of the tropospheric O_3 budget and its implications 68 69 on public health and agricultural output should be conducted prudently considering the huge 70 uncertainties caused by emission inventories and chemical mechanisms. Solazzo et al. (2017) 71 have emphasized the high interdependencies among meteorological and chemical variables 72 and the related errors, indicating that the evaluation of the air quality model performance 73 needs to be confirmed by more complementary analysis of meteorological fields and 74 chemical precursors.

The purpose of the present study is to explore impacts of the uncertainties in meteorological initial conditions on the $PM_{2.5}$ simulations or forecasts in BTH through ensemble simulations using the WRF-CHEM model. The methodology and model are presented in Section 2. The analyses, results, and discussions are included in Section 3. The summary and conclusions are given in Section 4.

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81 2 Model and Methodology

82 2.1 WRF-CHEM Model





83 A specific version of the WRF-CHEM model is used to examine impacts of the uncertainties in meteorological initial conditions on the $PM_{2.5}$ simulations or the haze 84 formation in BTH, which is developed by Li et al. (2010; 2011a, b; 2012) at the Molina 85 86 Center for Energy and the Environment. The model includes a new flexible gas phase 87 chemical module and the CMAQ/Models-3 aerosol module developed by US EPA 88 (Binkowski and Roselle, 2003). The inorganic aerosols are predicted using the ISORROPIA 89 Version 1.7 (Nenes et al., 1998). The SOA formation is simulated using a non-traditional 90 SOA module, including the volatility basis-set (VBS) modeling method and the SOA 91 contributions from glyoxal and methylglyoxal. Detailed description of the WRF-CHEM 92 model can be found in Li et al. (2010; 2011a, b; 2012). A persistent heavy haze pollution 93 episode from 13 to 20 January 2014 in BTH is simulated. The model simulation domain is 94 shown in Figure 1, and detailed model configurations can be found in Table 1.

95 2.2 Ensemble Initialization Method

96 The ensemble initialization method used in the present study is called "climatological 97 ensemble initialization method" in which dynamically consistent initial and boundary 98 conditions are statistically sampled from a seasonal meteorological data set (Aksoy et al., 99 2005; Zhang et al., 2007; Bei et al. 2012). To represent the wintertime climatological 100 statistics, a data set during the period from 1 November 2013 to 28 February 2014 is generated using NCEP-FNL 1°×1° reanalysis data. Thirty ensemble perturbations are 101 102 randomly selected from this climatological data set. Similarly, boundary conditions for each 103 ensemble member are produced from the same data set beginning at the randomly selected 104 initial time of the given member, and extended for the same length of time as the simulated 105 episode. Deviations of the initial and boundary condition data for each member from the 106 climatological mean for the entire period are then scaled down to be 20% to reduce the ensemble spread to be less than typical observation error magnitudes (Nielsen-Gammon et al., 107





108 2007) and added to the unperturbed initial and boundary conditions derived directly from the 109 NCEP-FNL analyses valid at 12:00 UTC on 12 January 2014, which are used for the 6-km 110 domain ensemble simulation. Figures 2a-d show the vertical distribution of the average initial ensemble spread. The average spread is 0.5-3.0 m s⁻¹ for horizontal winds (U and V 111 component), 0.5–1.1 K for temperature, 0.02–0.48 hPa for pressure, and 0–0.15 g kg⁻¹ for the 112 113 water vapor mass mixing ratio. The initial ensemble spreads of meteorological variables are 114 generally less than their typical observation error magnitudes. It is worth noting that all the 115 ensemble simulations used the same initial and boundary conditions for chemical fields, as 116 well as the same anthropogenic emission inventory.

117 2.3 Pollutants Measurements

118 The hourly near-surface CO, SO₂, NO₂, O₃, and PM_{2.5} mass concentrations in BTH are 119 released by the China's Ministry of Environmental Protection (China MEP) and can be 120 downloaded from the website http://www.aqistudy.cn/. The Aerodyne High Resolution Timeof-Flight Aerosol Mass Spectrometer (HR-ToF-AMS) with a novel PM2.5 lens is used to 121 122 measure the sulfate, nitrate, ammonium, and organic aerosols (OA) from 9 to 26 January 123 2014 at the Institute of Remote Sensing and Digital Earth (IRSDE), Chinese Academy of 124 Sciences (40.00°N, 116.38°E) in Beijing (Figure 1). The Positive Matrix Factorization (PMF) technique is utilized to analyze the mass spectra of OA and five components are separated, 125 126 including hydrocarbon-like OA (HOA), cooking OA (COA), biomass burning OA (BBOA), 127 coal combustion OA (CCOA), and oxygenated OA (OOA). HOA, COA, BBOA, and CCOA 128 are interpreted as surrogates of primary OA (POA), and OOA is a surrogate of SOA. Detailed 129 information about the HR-ToF-AMS measurement can be found in Elser et al. (2016). A lidar 130 has also been deployed at IRSDE and the aerosol backscatter signal is used to retrieve the 131 planetary boundary layer (PBL) height.





133 **3** Results and Discussions

134 3.1 Synoptic Overview

135 Figure 3 shows temporal evolutions of the observed PM_{2.5} mass concentrations 136 averaged over 13 cities (see Figure 1) in BTH during the severe haze episode from 13 to 21 January 2014. The observed $PM_{2.5}$ mass concentrations are frequently more than 250 μg m⁻³ 137 138 in the 13 cities during the episode, exceeding the standard of severe pollutions (hourly PM_{2.5} mass concentration exceeding 250 µg m⁻³) according to China National Air Quality Standard 139 140 (Feng et al., 2016). The haze in BTH is in the stage of development from January 13 to 15, with the gradual increase of the $PM_{2.5}$ concentration. BTH is most polluted when the haze is 141 in the maturity stage on January 16, with the $PM_{2.5}$ concentration exceeding 400 μg m⁻³ in 142 most of the cities. From January 17 to 19, the PM_{2.5} concentrations fluctuate considerably, 143 144 which is primarily caused by the transition between different synoptic situations. During nighttime on January 19, the haze in BTH rapidly dissipates, with the PM2.5 concentration 145 decrease of several hundreds of µg m⁻³ in two or three hours. In addition, the diurnal cycles 146 147 of the observed PM2.5 mass concentrations are not clear, demonstrating the obvious regional 148 pollution characteristics in BTH. For the four mega-cities in BTH, The $PM_{2.5}$ level in 149 Shijiazhuang and Baoding are much higher than Beijing and Tianjin, which is caused by the 150 massive local emissions in Shijiazhuang and Baoding.

NCEP-FNL reanalysis data is used in the study to examine the effect of synoptic conditions on the air pollution during the haze episode in BTH. Figures s1-s3 show the synoptic conditions at the surface level, 850 hPa, and 500 hPa, respectively. On January 13, BTH is on the north of a high pressure at the surface level, causing the southerly wind in/on the east of BTH, and sandwiched between the trough in the northeast of BTH and the high pressure in the southwest of BTH at 850 hPa, inducing the westerly surface wind in the west of BTH. At 500 hPa, the BTH is situated in the rear of the trough, and the westerly airflow is





158 dominant. The air pollutants in BTH are subject to be transported to the east but hindered by 159 the southerly wind, causing accumulation of air pollutants. On January 14, the high pressure 160 system begins to control BTH at the surface level and 850 hPa, and the wind is varied and 161 weak, which is favorable for the accumulation of air pollutants in BTH. On January 15, the 162 BTH is still controlled by the high pressure at the surface level and 850 hPa, and the westerly 163 wind is prevailing at the 500 hPa. The calm or weak surface wind, together with the stable 164 stratification, further facilitates accumulation of air pollutants in the BTH. On January 16, a 165 trough develops over the BTH at 850 hPa and 500 hPa, and the BTH is situated near the 166 trough line, in which the northerly and southerly wind occurs at the same time. At the surface 167 level, the northerly wind is prevailing in the north of BTH and the southerly wind is prevalent 168 in the south of BTH, leading to evacuation of air pollutants in the north of BTH and the high 169 level of air pollutants in the south of BTH. On January 17, the trough at 850 hPa commences 170 to weaken and the controlling region of the trough at 500 hPa becomes narrow. The 171 northwesterly wind is dominant over BTH, leading to divergence of the air pollutants in BTH. 172 On January 18, the BTH is located near the ridgeline at 850hPa and at the verge of the high 173 pressure at the surface level. The controlling scope of high-pressure system on the surface 174 level is wide, inducing the varied wind over the BTH and is not conductive to the evacuation 175 of air pollutants in BTH. On January 19, the prevailing southerly wind in the south of BTH 176 and the strong westerly wind in the west of BTH lead to the convergence of air pollutants at 177 the surface level. At 850 hPa and 500 hPa, BTH is situated in the southeast of the trough and 178 southwesterly wind is prevalent. On January 20, the BTH is located in the southwest of the 179 trough at 500 hPa and 850 hPa, and the strong northwesterly wind is prevailing over the BTH. 180 At the surface level, the BTH is situated between the high pressure in the west and the low 181 pressure in the east, inducing the strong northwesterly wind over BTH. The clod clean air 182 sweeps BTH and efficiently decreases the air pollutant concentrations in BTH.





183 **3.2** Uncertainties in Meteorological Simulations

184 Figures 4a-d provide the temporal profiles of the ensemble simulations of the surface meteorological fields and the corresponding observations at the meteorological site in Beijing 185 186 from 13 to 20 January 2014. The U component exhibits larger ensemble spread than the V 187 component (Figure s4), but the ensemble mean (ENSM) of the U component generally yields 188 the observed diurnal variations. The ensemble prediction of the V component fails to 189 reproduce the observed intensified southerly or northerly winds. The meteorological site is 190 located on the north of the Yanshan Mountains, substantially influenced by the mountain-191 valley circulation (MVC). Apparently, the WRF-CHEM model lacks the ability to well 192 simulate the occurrence and development of MVC, causing the considerable biases of the 193 ensemble prediction of the V component. The ensemble prediction performs well in producing the diurnal variation of the surface temperature, but the underestimation or 194 195 overestimation is still large when the V component prediction is biased. The relative 196 humidity (RH) shows the rather large ensemble spread (Figure s4d), and the ENSM 197 reasonably tracks the observed diurnal variation, i.e., the simulated RH is high during 198 nighttime and low in the afternoon. The RH simulation is sensitive to that of the surface 199 temperature. Generally, the overestimation of the surface temperature well corresponds to the 200 underestimation of the RH, or vice versa. The ENSM considerably overestimates the PBL 201 height during daytime on January 13 and 14, and underestimates on January 15 (Figure 4e). 202 In addition, most of the ensemble members frequently underestimate the observed PBL 203 height during nighttime, and all ensemble members fail to produce the peak PBL height on 204 January 17 and 20. The PBL height is principally determined by the vertical shear of 205 horizontal winds and the ground thermal condition. Therefore, uncertainties of wind and 206 temperature field simulations cause large biases of the PBL height simulation.

207 3.3 Uncertainties in Aerosol Species Simulations





208 Figure 5 shows the temporal profiles of the ensemble simulations of the aerosol species 209 and the observations at IRSDE in Beijing. The ENSM reasonably produces the observed 210 variations of the POA concentrations. However, all ensemble members fail to capture the 211 peaks in the morning on January 16 and in the evening on January 17, indicating that the 212 underestimation might not be caused by the meteorological uncertainties, but by the emission 213 biases. The POA in the atmosphere are contributed by multi sources, including the direct 214 emissions from vehicles, cooking, biomass and coal combustion. Diurnal variations of those 215 sources might constitute one of the major reasons for the biases of the POA simulations. The 216 ENSM generally performs reasonably well in simulating the SOA concentration against the 217 measured OOA. The ratio of the ensemble spread to the ensemble mean (RESM) for the SOA 218 prediction is large compared to that of POA (Figures s5a, b). Four SOA formation pathways 219 are included in simulations: oxidations of anthropogenic and biogenic volatile organic 220 compounds (VOCs), oxidation and partition of HOA treated as semi-volatile, and irreversible 221 uptake of glyoxal and methylglyoxal on aerosol surfaces. Therefore, uncertainties in 222 meteorological fields not only influence the transport of the SOA precursors but also the 223 SOA formation processes in the atmosphere, causing the rather large RESM of SOA 224 simulations. The ENSM generally reproduces the observed variations of sulfate, nitrate and 225 ammonium (SNA), but the RESM of SNA is also considerably large (Figures s5c-d). During haze days, sulfate is primarily formed through heterogeneous reactions of SO₂ on aerosol 226 227 surfaces, which is highly dependent on the relative humidity (Li et al., 2017). Nitrate 228 formation is determined by the HNO₃ and N₂O₅ originated from the NO₂ oxidation, sensitive 229 to the temperature and relative humidity and also influenced by the level of sulfate in the 230 particle phase and ammonia in the atmosphere. The ammonium aerosol is formed through 231 neutralization of sulfate and nitrate aerosols by NH₃. Additionally, in the present study, 232 ISORROPIA (Version 1.7) is used to calculate the thermodynamic equilibrium between the





sulfate-nitrate-ammonium-water aerosols and their gas phase precursors H_2SO_4 -HNO₃-NH₃water vapor. Therefore, uncertainties of meteorological fields propagate to the transport, atmospheric oxidation, and thermal dynamic processes, which all have contributions to the large RESM of the SNA simulations. Apparently, uncertainties in meteorological initial conditions substantially affect the aerosol species simulations at a single observation site, which is consistent with the previous studies (Bei et al., 2012).

239 3.4 Uncertainties in PM_{2.5} Simulations in BTH

240 Heavy haze with high levels of PM_{2.5} frequently constitutes a regional pollution event, 241 so Figure 6 shows the temporal profiles of the ensemble simulations and observations of air 242 pollutants averaged at the monitoring sites in BTH from 13 to 20 January 2014. The RESM 243 of the average air pollutants is much less than those of aerosol species at the single 244 observation site (Figure s6). For the primary air pollutants, SO₂ and CO, the ENSM generally 245 tracks reasonably the observed variations. However, sometimes all the ensemble members 246 underestimate or overestimate the observation. There are two possible reasons for the biases 247 of ensemble simulations of SO₂ and CO: uncertainties of emissions and systematic errors of 248 meteorological fields. In the evening on January 15, the ensemble prediction substantially 249 overestimates the observed SO_2 concentration, but CO overestimation is not large. In the 250 contrast, in the morning on January 16, the ensemble prediction slightly underestimates the 251 SO₂ observation but remarkably underestimates the CO concentration. Therefore, the 252 overestimation of SO_2 on January 15 and underestimation of CO on January 16 might be 253 primarily contributed by the emission uncertainties. In the morning on January 18, the 254 ensemble prediction significantly underestimates both SO₂ and CO observations, indicating 255 the plausible uncertainties caused by the systematic errors of meteorological fields.

The ENSM of the average surface O_3 and NO_2 over the monitoring sites in BTH is in good agreement with observations. The ensemble prediction is subject to underestimate the





258 O3 observation during nighttime, but well consistent with the NO2 observation. Considering the massive NO_x emission and the titration of NO, the nighttime O_3 concentrations are 259 260 generally very low, particularly during wintertime when the daytime O_3 concentrations are 261 not high. Hence, the underestimation of nighttime O₃ concentrations is perhaps caused by the 262 observation uncertainties, such as the setting of lower detection limit. In addition, the ENSM 263 does not reproduce the high O₃ level during nighttime on January 19 when the northwesterly 264 wind is intensified to evacuate the air pollutants in BTH. Rapid increase of the observed O_3 265 concentrations during nighttime shows the substantial contribution of the background O_3 266 transport. Therefore, the background O_3 uncertainties constitute the major reason for the O_3 267 underestimation on January 19.

The ENSM also exhibits good performance in replicating the observed PM₂₅ 268 269 observation, except the underestimation on January 16 and 18. However, the RESM of the 270 $PM_{2.5}$ simulations is larger than those of O₃, NO₂, SO₂, and CO (Figure s6). The average 271 ENSM of the PM_{2.5} concentration over the monitoring sites during the simulation period is 189.5 μ g m⁻³, close to the observed 197.6 μ g m⁻³. In addition, the ensemble member of 16 272 and 30 (EN-16 and EN-30, respectively) produces the highest and lowest $PM_{2.5}$ level, with 273 the average $PM_{2.5}$ concentrations of 231.5 and 167.3 µg m⁻³, respectively. The $PM_{2.5}$ mainly 274 275 include the primary aerosols which are determined by direct emissions, and the secondary 276 aerosols which are determined by their precursors emissions and the homogeneous and heterogeneous oxidation process in the atmosphere. Therefore, the large RESM of SOA and 277 278 SNA simulations enhances the ensemble spread of the PM_{2.5} simulations.

Figure 7 presents the spatial distributions of ENSM and observations of the daily average near-surface $PM_{2.5}$ mass concentrations during the haze episode, along with the simulated wind fields. The ENSM predicted $PM_{2.5}$ spatial patterns are generally in good agreement with the observations at the ambient monitoring sites in BTH. The ENSM





283 successfully reproduces the haze development and maturity stages from January 13 to 16, 284 2014. From January 17 to 18, the northeasterly wind develops and decreases the PM2.5 level 285 in BTH, but not strong enough to evacuate the air pollutants. The PM_{2.5} pattern of ENSM is 286 well consistent with observations, but on January 18, the PM2.5 concentrations are remarkably 287 underestimated in four cities in BTH. On January 19, the westerly wind is prevailing in BTH, 288 causing the divergence of the PM2.5. On January 20, the intensified northwesterly wind 289 commences to empty the $PM_{2.5}$ in BTH. However, apparently, the occurrence of the 290 intensification of the northwesterly wind is early, causing considerable underestimation of the 291 PM_{2.5} concentration in the ENSM.

292 The uncertainties of initial meteorological fields are generally less than observational 293 and analysis errors, but the ensemble simulations still exhibit considerable spreads. In order 294 to contrast the PM2.5 simulations of different ensemble members, we have selected two 295 members: EN-16 and EN-30, representing the highest and lowest PM_{2.5} simulations in BTH, 296 respectively. Figure 8 provides the horizontal distributions of the daily average surface PM_{2.5} 297 concentrations along with surface winds during the episode in EN-16 and EN-30. Similar 298 PM2.5 distribution patterns are simulated in EN-16 and EN-30, showing that the initial 299 meteorological uncertainties do not dominate the haze formation and development principally. 300 The PM_{2.5} level in EN-16 is much higher than that in EN-30 in BTH, which is mainly caused 301 by the considerable discrepancies in the surface winds between the two members. The 302 simulated southerly wind in EN-16 is generally more intense than that in EN-30, but the 303 northerly wind in EN-16 is weak compared to EN-30, which is more favorable for the air 304 pollutants accumulation in EN-16 than EN-30. On January 13 and 14, the winds in EN-30 are 305 weak or calm in BTH and the PM_{2.5} is mainly attributed to the local production. However, in 306 EN-16, the prevailing south winds also deliver the air pollutants from the south areas to BTH, 307 substantially enhancing the PM_{2.5} level. On January 15, although EN-16 and EN-30 both





308 produce the prevailing southerly wind in BTH, the westerly wind in EN-30 is intense 309 compared to EN-16, considerably decreasing the PM2.5 level in EN-30. On January 16, the 310 northeasterly wind in EN-30 is intensified and evacuates the $PM_{2.5}$ in the north of BTH. 311 However, in EN-16, the simulated northeasterly wind is weak and the PM_{2.5} level in the north 312 of BTH still remains high. On January 17, the simulated northerly wind in EN-16 is weak 313 compared to that in EN-30, causing higher PM_{2.5} concentration in EN-16 than EN-30 in BTH. 314 On January 18, the intensified southerly wind in EN-16 considerably increases the PM_{2.5} 315 level in BTH compared to EN-30. On January 19, the westerly wind is prevalent in EN-30 316 and the PM_{2.5} level commences to decrease, but in EN-16, the southwesterly wind still causes 317 high $PM_{2.5}$ concentrations in BTH. On January 20, the stronger northeasterly wind in EN-30 318 more efficiently evacuates the $PM_{2.5}$ than that in EN-16.

319 **3.5** Uncertainties in PM_{2.5} Simulations in Mega-cities

320 EN-16 and EN-30 both predict the haze occurrence and development in BTH during 321 the episode, although the difference of the PM2.5 level between those two members are 322 considerable, showing that the initial meteorological uncertainties do not dominate the 323 regional haze formation. Previous studies have shown that the meteorological uncertainties 324 substantially impact the air quality simulations at the city-scale (Bei et al., 2012). Figure 10 325 presents the temporal variation of the ensemble simulations and observations averaged at four 326 mega-cities in BTH during the episode. The ENSM of the $PM_{2.5}$ concentrations in Beijing, 327 Tianjin, and Baoding is in good agreement with the observation. However, the ENSM 328 remarkably underestimates the observed PM2.5 concentration in Shijiazhuang from January 329 16 to 19, which is hardly interpreted by the emission biases. The ENSM performs well in 330 simulating the PM_{2.5} variations from January 13 to 15, and overestimates the observation on 331 January 20 in Shijiazhuang. One of the possible reasons for the underestimation in





332 Shijiazhuang is that the westerly wind is systematically overestimated from January 16 to 19 along the foothills of the Taihang Mountains, causing the haze plume to move eastwardly. 333 334 Although the ENSM produces reasonably well the PM2.5 variations in the four mega-335 cities against the measurement, the initial meteorological uncertainties still cause large 336 uncertainties of the PM_{2.5} concentration (Figure s7). During the first three days of the episode, 337 the ENSM is well consistent with the observations in the four mega-cites, but the PM2.5 level discrepancy between the members with the highest and lowest PM2.5 concentrations is rather 338 339 large, causing troubles for the implementation of the control strategies. For example, in Shijiazhuang, the average PM2.5 concentrations during the first three days in the members 340 with the highest and lowest $PM_{2.5}$ concentrations are 403.5 and 213.8 µg m⁻³, respectively, 341 and the difference is about 190 µg m⁻³. In Beijing, the average PM_{2.5} concentrations in the 342 two members are 103.9 and 196.3 μ g m⁻³. It is worth noting that, according to the Chinese air 343 quality standard released in 2012, the PM_{2.5} concentration of 103.9 µg m⁻³ is defined as 344 "lightly polluted condition", but 196.3 µg m⁻³ defined as "heavily polluted condition". If the 345 heavy air pollution occurs, the control strategies will be implemented. Therefore, it is 346 347 necessary to use the ensemble simulation to avoid the impact of the initial meteorological 348 uncertainties on the haze prediction.

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Summary and Conclusions

351 In the present study, the uncertainties in simulating haze formation due to 352 meteorological initial uncertainties are investigated using the WRF-CHEM model through 353 ensemble simulations. A persistent heavy haze episode occurred in BTH from 13 to 20 is 354 simulated. Climatological ensemble initialization approach is used to produce the initial and 355 boundary conditions for each ensemble member.





The ENSM of the aerosol constituents is generally in good agreement with the observations at an observation site in Beijing, including the sharp buildup of the aerosol constituents in the evening on January 15 and rapid falloff in the morning on January 20. However, the ENSM considerably underestimates the observed secondary aerosols in the evening on January 17. The ensemble spread is rather large for the aerosol constituent simulations, and the RESM exceeds 50%, respectively.

362 The ENSM performs well in simulating the temporal variations of the average surface 363 CO, SO₂, NO₂, O₃ and PM_{2.5} mass concentrations over the monitoring sites in BTH, and the 364 RESM of the air pollutants is generally less than 30%. The RESM of PM_{2.5} simulations is 365 larger than the other air pollutants, which is due to the complicated composition of PM_{2.5}, including the contributions of primary and secondary aerosols. The initial meteorological 366 367 uncertainties do not principally dominate the haze formation and development, but considerably alter the simulated PM2.5 level. The average PM2.5 difference during the episode 368 exceeds 60 μ g m⁻³ between the two members with the highest and lowest PM_{2.5} simulations. 369

Although the initial meteorological uncertainties do not dominate the regional haze formation, they still substantially influence the $PM_{2.5}$ simulations at city-scale. The ENSM reasonably well predicts the $PM_{2.5}$ variations in the four mega-cities against the measurement, including Beijing, Tianjin, Baoding and Shijiazhuang, but the RESM of the $PM_{2.5}$ simulations is rather large, causing troubles for the implementation of the control strategies. Therefore, the ensemble simulation is needed to avoid the impact of the initial meteorological uncertainties on the haze prediction.

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558 559	58 Figure Captions 59	
560 561 562 563 564	Figure 1 WRF-CHEM simulation domain. The filled red (in BTH) and blue (outside of BTH) circles represent centers of cities with ambient monitoring site. The size of the circle denotes the number of ambient monitoring sites of cities. The filled black triangle and rectangle denote the deployment location of the HR-ToF-AMS and the surface meteorological site in Beijing.	
565 566 567	Figure 2 Vertical distribution of the mean of initial ensemble spreads for (a) horizontal winds (U and V components), (b) temperature, (c) pressure, and (d) water vapor mixing ratio.	
568 569 570 571	Figure 3 Observed hourly PM _{2.5} concentrations averaged in 13 cities of BTH during the period from January 13 to 20, 2014. The blue, red, brown, and black lines represent the observations in Beijing, Tianjin, Baoding, and Shijiazhuang, respectively. The green lines denote the observations in other cities of BTH.	
572 573 574 575 576	Figure 4 Temporal evolution of the surface (a) U component, (b) V component, (c) temperature, and (d) relative humidity at the meteorological site, and (e) the PBL height at IRSDE in Beijing from each ensemble member (thin green lines), the ensemble mean (bold black line), and observations (black dots) from January 13 to 20, 2014.	
577 578 579 580	Figure 5 Temporal evolution of the (a) POA, (b) SOA, (c) sulfate, (d) nitrate, and (e) ammonium mass concentrations at IRSDE in Beijing from each ensemble member (thin green lines), the ensemble mean (bold black line), and observations (black dots) from January 13 to 20, 2014.	
581 582 583 584	Figure 6 Temporal evolution of the (a) PM _{2.5} , (b) O ₃ , (c) NO ₂ , (d) SO ₂ , and (e) CO mass concentrations averaged over monitoring sites in BTH from each ensemble member (thin green lines), the ensemble mean (bold black line), and observations (black dots) from January 13 to 20, 2014.	
585 586 587 588	Figure 7 ENSM of the daily average surface PM _{2.5} concentration distributions (color contour) along with the ENSM of the daily average surface winds (black arrows) from January 13 to 20, 2014. The colored circles denote the PM _{2.5} measurements in cities.	
589 590	Figure 8 Same as Figure 7, but for the ensemble member of 16 with the highest simulated $PM_{2.5}$ concentration.	
591 592	Figure 9 Same as Figure 7, but for the ensemble member of 30 with the lowest simulated $PM_{2.5}$ concentration.	
593 594 595 596 597 598	Figure 10 Temporal evolution of the PM _{2.5} mass concentrations averaged in (a) Beijing, (b) Tianjin, (c) Baoding, and (d) Shijiazhuang from each ensemble member (thin green lines), the ensemble mean (bold black line), and observations (black dots) during the period from January 13 to 20, 2014. The red and blue lines represent the simulations in the members with highest and lowest PM _{2.5} concentrations, respectively.	
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602 Table 1 WRF-CHEM model configurations

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Regions	Beijing-Tianjin-Hebei (BTH)			
Simulation period	January 13 to 21, 2014			
Domain size	200 imes 200			
Domain center	39°N, 117°E			
Horizontal resolution	6km × 6km			
Vertical resolution	35 vertical levels with a stretched vertical grid with spacing ranging from 30 m near the surface, to 500 m at 2.5 km and 1 km above 14 km			
Microphysics scheme	WSM 6-class graupel scheme (Hong and Lim, 2006)			
Boundary layer scheme	MYJ TKE scheme (Janjić, 2002)			
Surface layer scheme	MYJ surface scheme (Janjić, 2002)			
Land-surface scheme	Unified Noah land-surface model (Chen and Dudhia, 2001)			
Longwave radiation scheme	Goddard longwave scheme (Chou and Suarez, 2001)			
Shortwave radiation scheme	Goddard shortwave scheme (Chou and Suarez, 1999)			
Meteorological boundary and initial conditions	NCEP 1°×1° reanalysis data			
Chemical initial and boundary conditions	MOZART 6-hour output (Horowitz et al., 2003)			
Anthropogenic emission inventory	Developed by Zhang et al. (2009)			
Biogenic emission inventory	MEGAN model developed by Guenther et al. (2006)			

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Figure 1 WRF-CHEM simulation domain. The filled red (in BTH) and blue (outside of BTH)
circles represent centers of cities with ambient monitoring site. The size of the circle denotes
the number of ambient monitoring sites of cities. The filled black triangle and rectangle
denote the deployment location of the HR-ToF-AMS and the surface meteorological site in
Beijing.







Figure 2 Vertical distribution of the mean of initial ensemble spreads for (a) horizontal winds
(U and V components), (b) temperature, (c) pressure, and (d) water vapor mixing ratio.

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630 631 632 Figure 3 Observed hourly PM2.5 concentrations averaged in 13 cities of BTH during the 633 period from January 13 to 20, 2014. The blue, red, brown, and black lines represent the 634 observations in Beijing, Tianjin, Baoding, and Shijiazhuang, respectively. The green lines 635 denote the observations in other cities of BTH.

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Figure 4 Temporal evolution of the surface (a) U component, (b) V component, (c)
temperature, and (d) relative humidity at the meteorological site, and (e) the PBL height at
IRSDE in Beijing from each ensemble member (thin green lines), the ensemble mean (bold
black line), and observations (black dots) from January 13 to 20, 2014.







Figure 5 Temporal evolution of the (a) POA, (b) SOA, (c) sulfate, (d) nitrate, and (e)
ammonium mass concentrations at IRSDE in Beijing from each ensemble member (thin
green lines), the ensemble mean (bold black line), and observations (black dots) from January
13 to 20, 2014.







Figure 6 Temporal evolution of the (a) PM_{2.5}, (b) O₃, (c) NO₂, (d) SO₂, and (e) CO mass
concentrations averaged over monitoring sites in BTH from each ensemble member (thin
green lines), the ensemble mean (bold black line), and observations (black dots) from January
13 to 20, 2014.







6740 10 sitesPM2.5 concentration (µg m³)2.0 m s¹675Figure 7 ENSM of the daily average surface PM2.5 concentration distributions (colored676contour) along with the ENSM of the daily average surface winds (black arrows) from677January 13 to 20, 2014. The colored circles denote the PM2.5 measurements in cities.678







Figure 8 Same as Figure 7, but for the ensemble member of 16 with the highest simulatedPM_{2.5} concentration.

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Figure 9 Same as Figure 7, but for the ensemble member of 30 with the lowest simulated
 PM_{2.5} concentration.









Figure 10 Temporal evolution of the PM_{2.5} mass concentrations averaged in (a) Beijing, (b)
Tianjin, (c) Baoding, and (d) Shijiazhuang from each ensemble member (thin green lines),
the ensemble mean (bold black line), and observations (black dots) during the period from
January 13 to 20, 2014. The red and blue lines represent the simulations in the members with
highest and lowest PM_{2.5} concentrations, respectively.

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