

# 1           **Confronting Uncertainties of Simulated Air Pollution Concentrations** 2           **during Persistent Cold Air Pool Events in the Salt Lake Valley, Utah**

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19   Abstract: Air pollutant accumulations during wintertime persistent cold air pool (PCAP) events in mountain  
20   valleys are of great concern for public health worldwide. Uncertainties associated with the simulated  
21   meteorology under stable conditions over complex terrain hinder realistic simulations of air quality using  
22   chemical transport models. We use the Community Multiscale Air Quality (CMAQ) model to simulate the  
23   gaseous and particulate species for one-month in January 2011 during the Persistent Cold Air Pool Study  
24   (PCAPS) in the Salt Lake Valley (SLV), Utah (USA). Results indicate that the temporal variability  
25   associated with the elevated NO<sub>x</sub> and PM<sub>2.5</sub> concentrations during PCAP events were captured by the model  
26   ( $r=0.20$  for NO<sub>x</sub> and  $r=0.49$  for PM<sub>2.5</sub>). However, concentrations were not at the correct magnitude (NMB=  
27    $-35\%/12\%$  for PM<sub>2.5</sub> during PCAPs/non-PCAPs) where PM<sub>2.5</sub> was underestimated during PCAP events and  
28   overestimated during non-PCAP periods. The underestimated PCAP strength is represented by valley heat  
29   deficit, which contributed to the underestimated PM<sub>2.5</sub> concentrations compared with observations due to  
30   the model simulating more vertical mixing and less stable stratification than what was observed. Based on  
31   observations, the dominant PM<sub>2.5</sub> species were ammonium and nitrate. We provide a discussion that aims  
32   to investigate the emissions and chemistry model uncertainties using the nitrogen ratio method and the  
33   thermodynamic ammonium nitrate regime method.

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34 Keywords: Chemical Transport Model; CMAQ; WRF; evaluation; air quality; temperature inversion;  
35 PCAP

## 36 **Synopsis**

37 We investigate air quality model uncertainties related to meteorology and chemistry for wintertime air  
38 pollution episodes in the mountainous western United States.

### 39 **1. Introduction**

40 Particulate matter (PM), especially with an aerodynamic diameter smaller than  $2.5\ \mu\text{m}$  ( $\text{PM}_{2.5}$ ),  
41 has adverse effects on human health that are commonly presented as respiratory and cardiovascular  
42 ailments [1]. It is well known that natural and anthropogenic emissions and meteorological  
43 conditions influence ambient  $\text{PM}_{2.5}$  concentrations. Topography also impacts air quality since it  
44 affects the local meteorology [2]. In valleys, cold air can be trapped near the valley floor for more  
45 than one day (24 hours) during wintertime with limited insolation, which is known as a persistent  
46 cold air pool (PCAP) [3]. PCAP events are characterized by a stably stratified atmospheric  
47 boundary layer, calm winds, and low boundary layer height [4]. PCAPs have been documented in  
48 multiple valleys and basins in the U.S. [3, 5-8], Asia [9, 10], and Europe [11-13], but the PCAP  
49 frequency, strength, and length depends on location. The PCAP strength, characterized by valley  
50 heat deficit, is correlated with  $\text{PM}_{2.5}$  concentrations based on data collected in western U.S. valleys  
51 [4, 14, 15].

52 The Community Multiscale Air Quality (CMAQ) model [16] is a regulatory tool that is used  
53 to simulate air quality and is employed in state implementation plans (SIPs) for regulatory planning  
54 purposes. There are three main uncertainties associated with chemical transport modeling (CTM):  
55 emissions estimates, meteorological modeling, and the model formulation of the atmospheric  
56 chemistry processes. Large discrepancies have been identified in global and regional emissions

57 inventories [17]. A case study in Houston suggested that uncertainties in emissions estimates were  
58 associated with uncertainties of 42%~52% in the simulated PM<sub>2.5</sub> concentrations [18]. Previous  
59 studies in U.S. cities have aimed at determining uncertainties in NO<sub>x</sub> emissions [19] [20], however  
60 there is not a consistent conclusion on whether they are over- or underestimated. To address the  
61 discrepancy in NO<sub>x</sub> emissions and PM<sub>2.5</sub> nitrate formation, some studies rely on model tuning, or  
62 simply adjusting the emissions rate so that the CMAQ model matches the observed ambient  
63 concentrations, which may improve the simulation accuracy but also misrepresent the actual  
64 emissions and therefore bias the chemical and physical processes. Emissions tuning is often used  
65 for SIPs modeling in the western U.S. where CTMs typically underestimate the elevated  
66 wintertime PM<sub>2.5</sub> concentrations associated with PCAPs [19, 21].

67 In addition to emission inventories, realistic simulation of the ambient air quality using CMAQ  
68 requires accurate meteorological inputs. The meteorology fields are provided by numerical  
69 weather prediction models, such as the Weather Research and Forecasting (WRF) model [22].  
70 Crippa et al. [23] found that simulated PM<sub>2.5</sub> concentrations in the eastern U.S. were sensitive to  
71 the selection of the planetary boundary layer (PBL) scheme in WRF as well as the aerosol scheme  
72 and emissions inventory. In the western U.S., the PBL scheme is expected to have an even greater  
73 impact on the simulated PM<sub>2.5</sub> concentrations because the mountainous terrain leads to increased  
74 uncertainties in WRF, especially during wintertime [24]. Previous studies have investigated  
75 whether numerical models can capture the PCAP evolution where the results differ based on the  
76 atmospheric scale of interest [25] [26] [27]. In general, these studies found that the large-scale  
77 dynamics associated with PCAP initiation and duration were well captured by WRF [10][13].  
78 However, the surface turbulence and boundary layer structure that impact pollutant accumulation  
79 and mixing were not well simulated [11][25]. Studies have shown that enhanced vertical resolution

80 can improve performance in simulating PCAP evolution [27] but not necessarily the decreased  
81 turbulent mixing. There is a critical need to better understand the NWP turbulence  
82 parameterizations during wintertime air quality events to reliably simulate the air quality [28].

83 To address this critical need, we evaluate the WRF-CMAQ model performance during PCAP  
84 events in the SLV, Utah. Model performance during non-PCAP events is also investigated to  
85 understand uncertainties related to emissions estimates and chemistry versus uncertainties related  
86 to meteorological conditions. The aims of our study are to understand how well the meteorology  
87 fields can be captured by the WRF model, how they impact the CMAQ model performance during  
88 PCAPs, and to investigate other possible sources of uncertainty associated with emissions and/or  
89 chemistry. Therefore, our simulation time period was selected to focus on a large scale PCAPs  
90 field study in the SLV to provide the most complete record of meteorological observations for  
91 PCAP events. The discussion provides insights into the potential uncertainties in the NO<sub>x</sub>  
92 chemistry of the CMAQ model that contributes to simulated PM<sub>2.5</sub> discrepancies with the aim of  
93 providing suggestions for future measurements needed from field campaigns to evaluate the  
94 CMAQ model more thoroughly during PCAP events.

## 95 **2. Material and Methods**

### 96 2.1 Model configuration

97 The meteorology fields used to drive the CMAQ model came from the WRF model (v3.7).  
98 Four configurations were applied in WRF using different PBL schemes, including the Asymmetric  
99 Convective Model version 2 (ACM2) PBL scheme, the Yonsei University (YSU) PBL scheme,  
100 the Mellor-Yamada-Janjic (MYJ) and Mellor-Yamada-Nakanishi-Niino (MYNN) schemes. The  
101 PBL schemes were paired with their intended surface layer schemes (See Table S1, Supporting  
102 Information, SI). The scenario names of model runs are abbreviated using the name of their PBL

103 schemes, ModACM2, ModYSU, ModMYJ, and ModMYNN. More information on the WRF  
104 configurations and model run setup are provided in the SI (Section S1).

105 To investigate the impacts of PBL schemes on simulated air quality, four sets of CMAQ  
106 (v5.2) simulations were performed covering the whole January of 2011, when three strong PCAP  
107 events occurred [29]. The outer domain covered the Contiguous United States (CONUS) with 12  
108 km horizontal resolution. The inner domain was centered on the Salt Lake Valley with 4 km  
109 horizontal resolution and 41 vertical levels with 20 levels below 1km (Figure S1). Previous studies  
110 have demonstrated that the horizontal and vertical resolution impacts the simulated meteorological  
111 fields [30], however, CTMs (CMAQ specifically) are more limited in the horizontal resolution  
112 than WRF. This is due to the computational power required for the chemistry and physics, and  
113 challenges in modeling the finer spatial resolution of the emissions estimates. The emissions were  
114 based on the 2011 National Emissions Inventory (NEI) developed by the U.S. Environmental  
115 Protection Agency (EPA). CMAQ was configured with the Carbon Bond version 6 gas-phase  
116 chemical mechanism [31], AERO6 aerosol module, and aqueous phase chemistry.

## 117 2.2 Observational datasets

118 The Persistent Cold Air Pool Study (PCAPS) provides the observational data of surface  
119 meteorology and surface energy fluxes at seven sites, and vertical profiles of temperature and wind  
120 speed and laser ceilometer data at National Center for Atmospheric Research (NCAR) Integrated  
121 Sounding System (ISS) site located in the SLV (Figure S2). The wintertime field campaign was  
122 conducted from December 2010 to February 2011. While the PCAPS field study was one of the  
123 largest field campaigns in recent years aimed at quantifying atmospheric processes governing the  
124 formation and evolution of PCAP events, there are limited observation data specifically related to  
125 the atmospheric chemistry of PCAP events. For this we rely on routinely monitored hourly

126 observations of gaseous and particulate pollutant concentrations, as well as speciated PM<sub>2.5</sub>  
127 concentrations measured at the Hawthorne site (HW, 49-035-3006; 40.73° N, 111.87° W) from  
128 the EPA's Air Quality System (AQS). The Hawthorne site is an EPA NCore (multipollutant) site  
129 [32] that also collects filter-based samples every 3<sup>rd</sup> day for speciated PM<sub>2.5</sub> as part of the EPA  
130 Chemical Speciation Network (CSN) [33]. The U.S. EPA Quality Objectives for measurement  
131 data set the precision range of PM<sub>2.5</sub>, NO<sub>x</sub>, and O<sub>3</sub> to be ±10%, ±10%, and ±7% respectively [34].

132 The outputs from CMAQ were paired with observations for evaluation using the Atmospheric  
133 Model Evaluation tool (AMET) [35]. The mean bias (MB), mean error (ME), normalized mean  
134 bias (NMB), normalized mean error (NME), index of agreement (IOA), and correlation coefficient  
135 (r) are calculated to evaluate the model performance for CMAQ. Readers can refer to Kelly et al.  
136 [36] and Henneman et al. [37] for reference evaluation statistics.

137 We use valley heat deficit to determine PCAP periods in the SLV. Valley heat deficit is a bulk  
138 measure of the atmospheric stability in the valley and is computed using Eq. 1 [14]:

$$H22 = c_p \int_{sfc}^{2200} \rho(z) [\theta_{2200m} - \theta(z)] dz \quad (\text{Eq. 1})$$

139 where H22 denotes the valley heat deficit from the surface to 2200 m, which is the ridge height of  
140 the western boundary of the SLV;  $c_p$  is the specific heat of air (J kg<sup>-1</sup> K<sup>-1</sup>), sfc is the surface,  $\rho$  is  
141 air density (kg m<sup>-3</sup>),  $\theta$  is the potential temperature (K), and  $z$  is the altitude (m). We use the criteria  
142 proposed by Whiteman et al. [14] where a PCAP exists when  $H22 > 4.04 \text{ MJ m}^{-2}$  for more than 36  
143 hours.

### 144 2.3 Identification of limiting precursor reagent for ammonium nitrate formation

145 Ammonium nitrate (NH<sub>4</sub>NO<sub>3</sub>) is the main component of the PM<sub>2.5</sub> mass during wintertime in  
146 northern Utah [38-41]. Identification of the limiting precursor reagent for NH<sub>4</sub>NO<sub>3</sub> is needed for

147 policy makers to make regulations that have effective PM<sub>2.5</sub> concentration reduction pathways.  
148 One method to identify the limiting reagent of NH<sub>4</sub>NO<sub>3</sub> is to inspect the aerosol liquid water  
149 content (LWC) variation with characteristic aerosol pH [42]. The thermodynamic framework  
150 considers the aerosol acidity, aerosol LWC, and temperature (271K in our case). Model simulated  
151 aerosol LWC was calculated as the sum of aerosol water for the Aitken and accumulation modes  
152 from the CMAQ hourly model raw outputs. The aerosol pH from CMAQ was determined by the  
153 ratio of H<sup>+</sup> concentration over the aerosol LWC. Aerosol pH data were excluded when aerosol  
154 LWC was below 0.01 μg m<sup>-3</sup> [43]. By plotting the CMAQ simulated pH versus LWC, the aerosol  
155 partitioning fraction can be visualized and compared to the characteristic pH values for ammonium  
156 nitrate formation, where four chemical domains can be identified on the plot [42]. Based on the  
157 location of the CMAQ pH relative to the characteristic pH, the sensitivity of aerosol formation to  
158 NH<sub>3</sub> or HNO<sub>3</sub> can be determined. The four sensitivity regimes for NH<sub>4</sub>NO<sub>3</sub> formation are i) NH<sub>3</sub>  
159 dominated, ii) HNO<sub>3</sub> dominated, iii) both NH<sub>3</sub> and HNO<sub>3</sub> dominated, and iv) insensitive to both  
160 NH<sub>3</sub> and HNO<sub>3</sub>, and regimes can be determined based on the location of the datapoints within the  
161 chemical domains. The aerosol pH and LWC sensitivity regime plot is discussed in Section 4.

162 Another method to investigate the limiting reagent of ammonium nitrate formation is the molar  
163 ratio of total nitrate (HNO<sub>3</sub>(g) + NO<sub>3</sub><sup>-</sup>(p)) to total reduced nitrogen (NH<sub>3</sub>(g) + NH<sub>4</sub><sup>+</sup>(p)) (Eq. 2)  
164 [21].

$$\text{Ratio} = \frac{HNO_3(g) + NO_3^-(p)}{NH_3(g) + NH_4^+(p)} \quad (\text{Eq. 2})$$

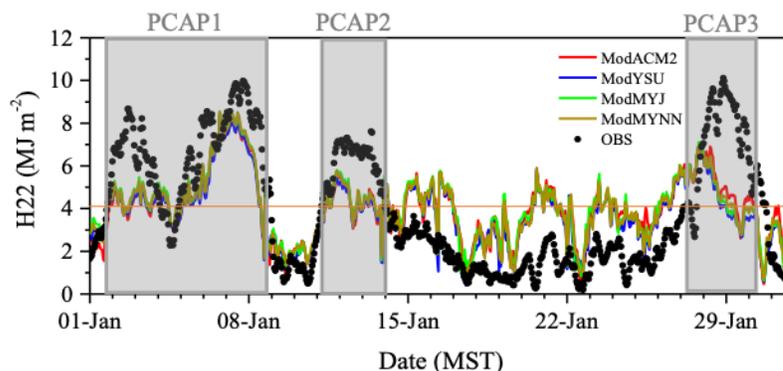
165  
166  
167 A nitrogen ratio larger than 1 indicates that the limiting reagent for NH<sub>4</sub>NO<sub>3</sub> formation is ammonia,  
168 and a ratio smaller than 1 indicates that nitric acid is the limiting reagent. This ratio was calculated

169 using the CMAQ results, and findings are discussed in Section 4 to highlight the model  
170 uncertainties related to chemistry and emissions.

### 171 3. Results

#### 172 3.1 Valley heat deficit and vertical profiles

173 Valley heat deficit is used to measure the CAP strength and has been reported to be correlated  
174 with  $PM_{2.5}$  in multiple studies [4, 14, 15]. The hourly modeled and observed H22 are shown in  
175 Figure 1. Three PCAP events were identified in January 2011 using the hourly sounding  
176 observations at the NCAR ISS site based on the aforementioned method (i.e.,  $H_{22} > 4.04 \text{ MJ m}^{-2}$   
177 lasting for more than one day): PCAP1 (1900 MST 1 Jan to 2300 MST 8 Jan), PCAP2 (0500 MST  
178 11 Jan to 0000 MST 14 Jan), and PCAP3 (0300 MST 27 Jan to 1800 MST 30 Jan).



179  
180 Figure 1 Time series of the hourly simulated valley heat deficit and hourly estimated values from observations at the  
181 NCAR ISS site in January 2011. The orange horizontal line indicates the threshold of  $H_{22}$  ( $4.04 \text{ MJ m}^{-2}$ ) for a PCAP  
182 event.

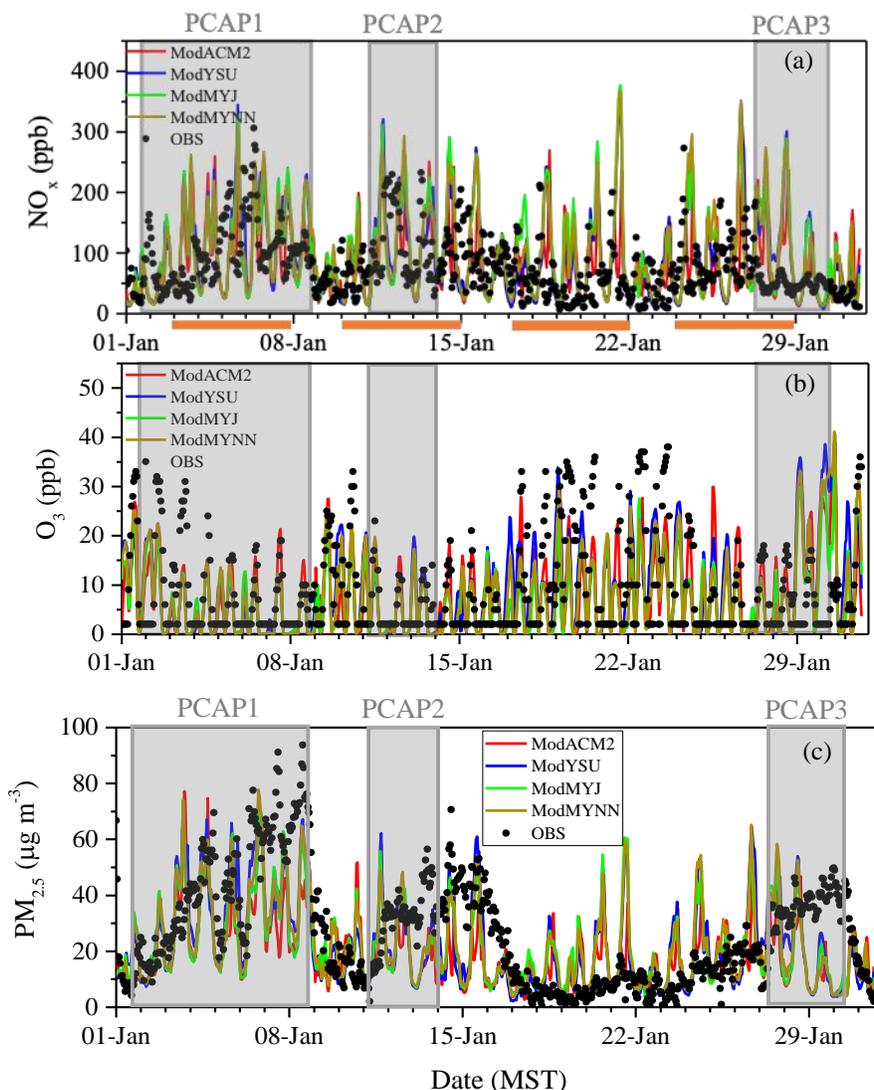
183 Compared with observations, the WRF model underestimated  $H_{22}$  during PCAP events and  
184 overestimated  $H_{22}$  during non-PCAP periods. The average simulated  $H_{22}$  during PCAP and non-  
185 PCAP events was  $4.88 \text{ MJ m}^{-2}$  and  $2.75 \text{ MJ m}^{-2}$ , respectively. This indicates that the WRF model  
186 is capable of successfully simulating the timing of a PCAP event but cannot accurately simulate  
187 the boundary layer bulk stability, i.e. the model simulated less stability during PCAP events and

188 more stability during non-PCAP events. The inability of the model to simulate the bulk stability  
189 under stable boundary layer events is consistent with prior studies [28]. The model simulated less  
190 stable atmospheric stratification compared with the ISS site observations during PCAP3 (0300  
191 MST 27 Jan to 1800 MST 30 Jan, Figure S3). Further inspections of the vertical profiles of  
192 simulated and observed potential temperature (Figure S4) suggest that WRF simulated less vertical  
193 mixing accompanied by a more stably stratified atmosphere, thus higher H22 during non-PCAPs.  
194 The four WRF scenarios generated nearly the same H22 values. This implies that the surface PM<sub>2.5</sub>  
195 simulation deficiencies stemming from unrealistic bulk stability (H22) should be similar in the  
196 four CMAQ simulations. However, this is not the only determinant meteorological factor, and  
197 discrepancies in simulated PM<sub>2.5</sub> in CMAQ will also result from other predicted meteorological  
198 variables, such as temperature and its impact on emissions and chemical reactions. The WRF  
199 model performance for other meteorological variables can be found in Figure S4. WRF has also  
200 been found to exhibit a positive bias in simulating surface turbulent fluxes during PCAP events  
201 [26].

### 202 3.2. Gaseous pollutants

203 Gas-phase pollutants serve as precursors for secondary aerosol formation (e.g., NO<sub>x</sub>) and  
204 can also directly impact human health (e.g., O<sub>3</sub>). Hourly variations of simulated and observed  
205 mixing ratios for NO<sub>x</sub> and O<sub>3</sub> are illustrated in Figure 2. Analysis of SO<sub>2</sub> simulation results are  
206 included in the SI (Figure S6-S8) because it was not the primary species impacting PM<sub>2.5</sub>  
207 concentrations in SLV during PCAPs [38, 44-50]. There were clear day-of-week patterns of NO<sub>x</sub>  
208 concentrations in the observations, i.e., high on weekdays and low on weekends. The weekly  
209 maximum NO<sub>x</sub> concentration was enhanced during PCAP events. For example, NO<sub>x</sub> levels were  
210 elevated during PCAP1 and PCAP2, reaching up to 306 ppb. The CMAQ model was able to

211 capture the NO<sub>x</sub> weekly pattern but not the amplitude. During the non-PCAP period (17 Jan-24  
212 Jan) between PCAP2 and PCAP3, the NO<sub>x</sub> levels were overestimated by the model. This is related,  
213 in part, to the overestimated H22 accompanied by more stratified potential temperature vertical  
214 profiles compared with observations during non-PCAPs, which may simulate higher pollutant  
215 concentrations confined in the boundary layer. Modeled NO<sub>x</sub> discrepancies may also be related to  
216 overestimated NO<sub>x</sub> in the emissions inventory, which has also been found by Canty et al. [51]. The  
217 observed low NO<sub>x</sub> mixing ratios during PCAP3 were related to the low weekend emissions (29  
218 Jan-30 Jan). The high simulated NO<sub>x</sub> during PCAP3 implies that the emissions inventory might be  
219 overestimating the NO emissions during PCAP3, which is the main contributor to NO<sub>x</sub>. The  
220 nighttime NO<sub>x</sub> underestimations were likely associated with the underestimated H22 during the  
221 three PCAP events. Overall, NO<sub>x</sub> was overestimated in CMAQ (see Table S2). The ModACM2  
222 run performed best in simulating NO<sub>x</sub> with the smallest NMB, ME, and NME.



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227 Figure 2 Time series of hourly simulated and observed mixing ratios of (a)  $\text{NO}_x$ , (b)  $\text{O}_3$ , and (c)  $\text{PM}_{2.5}$  at HW site.

228 The nighttime  $\text{O}_3$  concentrations reached below the instrument detection limit. The weekdays are indicated with  
 229 orange bars on the x axis.

230 The maximum observed  $\text{O}_3$  during January was 38 ppb.  $\text{O}_3$  had an opposite trend

231 compared to the  $\text{NO}_x$  since it is titrated through reactions with  $\text{NO}$ . Higher  $\text{O}_3$  was observed during

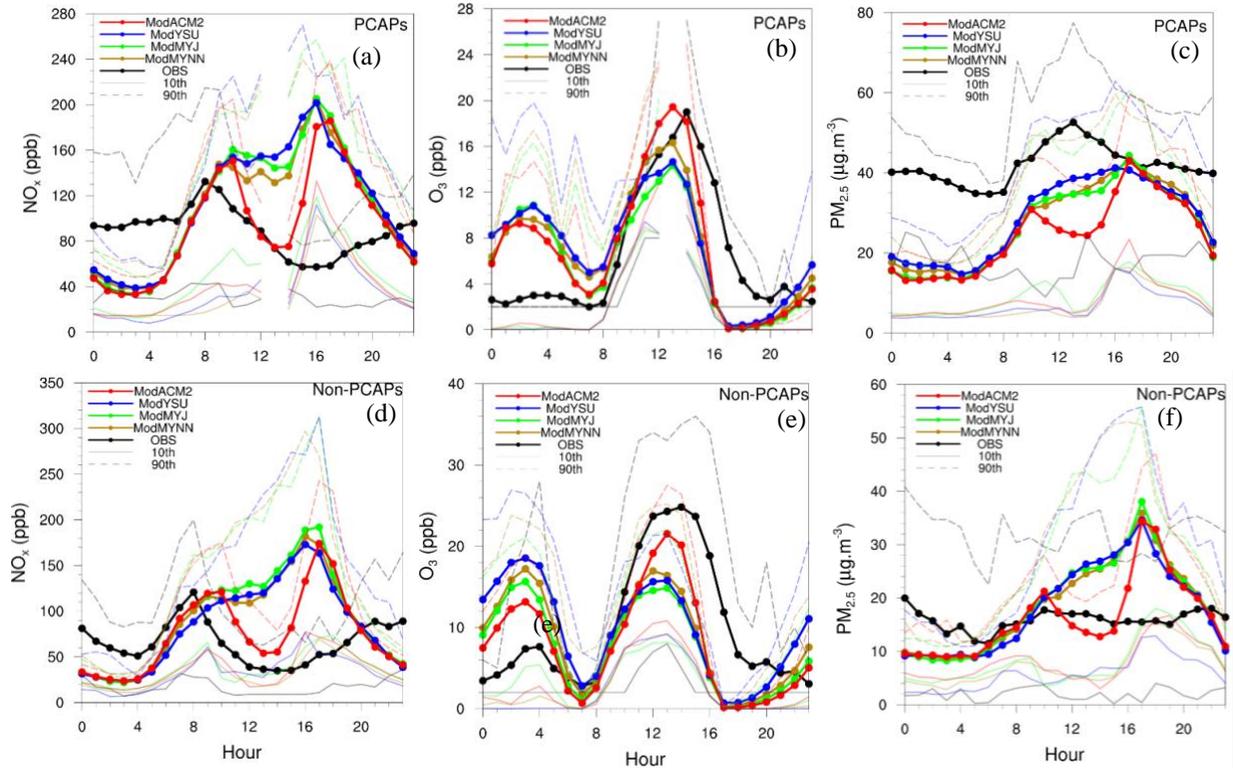
232 non-PCAPs with less rich  $\text{NO}_x$  than PCAPs. However, CMAQ simulated lower  $\text{O}_3$  accompanied

233 with an underestimation of  $\text{NO}_x$  for PCAP3. Net radiation was reasonably well-simulated by the

234 WRF model (Figure S5). We suspect the lower  $\text{O}_3$  in the CMAQ model might be related to the

235 modeled photolysis rates during PCAP3. Statistics show that O<sub>3</sub> was underestimated during non-  
236 PCAPs (Table S2), which is likely related to the NO<sub>x</sub> overestimation during the same time period.  
237 The snow cover during PCAP1 contributed to the observed high O<sub>3</sub> concentrations. However, the  
238 WRF model underestimated the snow cover [26], and correspondingly simulated less upward  
239 shortwave radiation reflected to the atmosphere. Thus, the O<sub>3</sub> concentrations in CMAQ were lower  
240 than the observations during PCAP1. The elevated simulated O<sub>3</sub> levels during PCAP3 were  
241 partially related to the warmer simulated T2 (Figure S5) compared to observations or unrealistic  
242 emissions estimates for the O<sub>3</sub> precursors. The ModMYJ case agreed better with observations in  
243 O<sub>3</sub> simulation with a lower ME and NME.

244 Diel variations of simulated and observed NO<sub>x</sub> and O<sub>3</sub> are presented in Figure 3. Observed  
245 NO<sub>x</sub> concentrations peaked at around 0800 MST and began to increase again after 1600 MST in  
246 the non-PCAP scenario, which were partially impacted by fresh on-road emissions. The CMAQ  
247 model was able to capture the morning NO<sub>x</sub> peak but generated a second peak faster than the  
248 observations at around 1800 MST. Observed NO<sub>x</sub> exhibited less variation during nighttime during  
249 the PCAP case compared with the non-PCAP case. Simulated diel patterns of NO<sub>x</sub> concentrations  
250 did not change but generated higher peak magnitudes in the PCAP case compared with non-PCAP.  
251 Overestimation of NO<sub>x</sub> mainly occurred during daytime and underestimation occurred during  
252 nighttime. The observed bimodal shape of the O<sub>3</sub> diel distribution with two peaks at around 0400  
253 and 1200 MST in the non-PCAP case were captured by the model but with a lower magnitude.  
254 The reason for the O<sub>3</sub> peak in the CMAQ simulations at nighttime might be related to the  
255 overestimated downward mixing from above. Observed O<sub>3</sub> remained depleted and nearly constant  
256 at nighttime in the PCAP case, which is attributed to the rich NO<sub>x</sub> concentrations at the same time.



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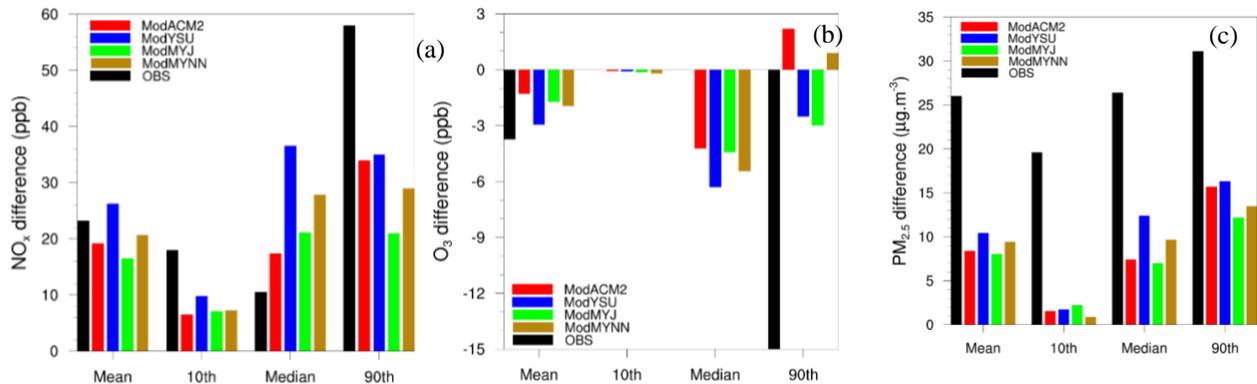
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260 Figure 3 Diel variations of observed and modeled hourly mean values of  $\text{NO}_x$ ,  $\text{O}_3$ , and  $\text{PM}_{2.5}$  during PCAP events in  
 261 (a), (b), and (c), respectively, and non-PCAP events in (d), (e), and (f), respectively. The lower (10<sup>th</sup>) and upper (90<sup>th</sup>)  
 262 decile values are presented for reference by opaque dashed lines and opaque solid lines, respectively. The data gaps  
 263 in the PCAPs panel are because there are not enough data to plot the lower and upper decile at that time.

264 In addition to the operational evaluations conducted above, dynamic evaluations were  
 265 undertaken to determine how much of the pollutant concentration change between PCAP and non-  
 266 PCAP events are captured by the model. Changes in the mean and percentiles of  $\text{NO}_x$ ,  $\text{O}_3$ , and  
 267  $\text{PM}_{2.5}$  based on hourly values from observations and the four simulations during PCAPs and non-  
 268 PCAPs (PCAPs-non-PCAPs) are displayed in Figure 4. Positive (negative) values indicate an  
 269 increase (decrease) of the concentration during PCAPs compared with non-PCAPs. The results  
 270 indicate that the mean changes of the two gaseous pollutants were reproduced relatively well by  
 271 the CMAQ model, including the increase of the  $\text{NO}_x$  mean, decrease of the  $\text{O}_3$  mean, and increase  
 272 of the  $\text{SO}_2$  mean during PCAP events. However, higher deficiencies occurred in simulating the  
 273 percentile changes, especially for the 90<sup>th</sup> percentile. The 90<sup>th</sup> percentile  $\text{NO}_x$  changes were

274 underestimated in the simulations, indicating that the model was not able to simulate the large  
 275 increase in NO<sub>x</sub> concentrations during PCAPs compared with non-PCAPs. The 10<sup>th</sup> and median  
 276 of observed O<sub>3</sub> changes happen to be zero. The model had mixed performance in simulating the  
 277 O<sub>3</sub> 90<sup>th</sup> percentile change. This indicates that the model performs well in simulating the overall  
 278 changes in gaseous species for PCAPs but loses accuracy in simulating high concentration changes.  
 279 There is no uniform model configuration that performs best for simulating all of the gaseous  
 280 species and the differences between PCAP and non-PCAP periods.



281  
 282  
 283 Figure 4 Bar chart of the observed and modeled difference in mean, 10<sup>th</sup> percentile, median, and 90<sup>th</sup> percentile of  
 284 (a) NO<sub>x</sub>, (b) O<sub>3</sub>, and (c) PM<sub>2.5</sub> between hourly values during PCAPs and non-PCAPs events (PCAPs-non-PCAPs).

### 285 3.3. PM<sub>2.5</sub>

#### 286 3.3.1 Mass concentration

287 Comparisons of simulated and observed hourly PM<sub>2.5</sub> concentrations at the HW site in January  
 288 are presented in Figure 2(c). Elevated PM<sub>2.5</sub> concentrations were observed during PCAP events,  
 289 reaching up to 93.7 µg m<sup>-3</sup> during PCAP1. This is expected due to the suppressed mixing  
 290 accompanied by the elevated H22 observed during PCAPs (Figure 1). Overall, the model  
 291 underestimated (overestimated) PM<sub>2.5</sub> during PCAP (non-PCAP) events (See Table S3, Supporting  
 292 Information).

293 The temporal variations of PM<sub>2.5</sub> were not well reproduced by the model. The observed daily  
294 increase of PM<sub>2.5</sub> concentrations during PCAP1, PCAP2, and PCAP3 using the daily maximum  
295 PM<sub>2.5</sub> concentrations (Figure S8) at the HW site were 11.5, 11.2, and 4.4 μg m<sup>-3</sup>/day, respectively.  
296 The PM<sub>2.5</sub> accumulation rate was not captured by the model, where the simulated daily PM<sub>2.5</sub>  
297 concentration increases were 3.5, -3.8, and -8.0 μg m<sup>-3</sup>/day, respectively for the three PCAP  
298 periods.

299 Observed PM<sub>2.5</sub> concentrations during PCAP3 were similar in magnitude to PCAP2, although  
300 PCAP3 had lower NO<sub>x</sub> levels. This is related to the higher observed H22 during PCAP3 compared  
301 to PCAP2, which may lead to higher PM<sub>2.5</sub> concentrations near ground level (i.e., increased  
302 stability traps pollutants). The model underestimated H22 during PCAP3 to a larger extent  
303 compared to PCAP2. This leads to negative biases in simulated PM<sub>2.5</sub>, despite NO<sub>x</sub> being  
304 overestimated at the same time. This highlights the importance of realistic simulated meteorology  
305 fields in air quality modeling, especially during PCAP events, as well as potential biases in  
306 modeled PCAP aerosol formation. Underestimated PCAP strength can lead to underestimated  
307 PM<sub>2.5</sub> concentrations even with overestimated emissions.

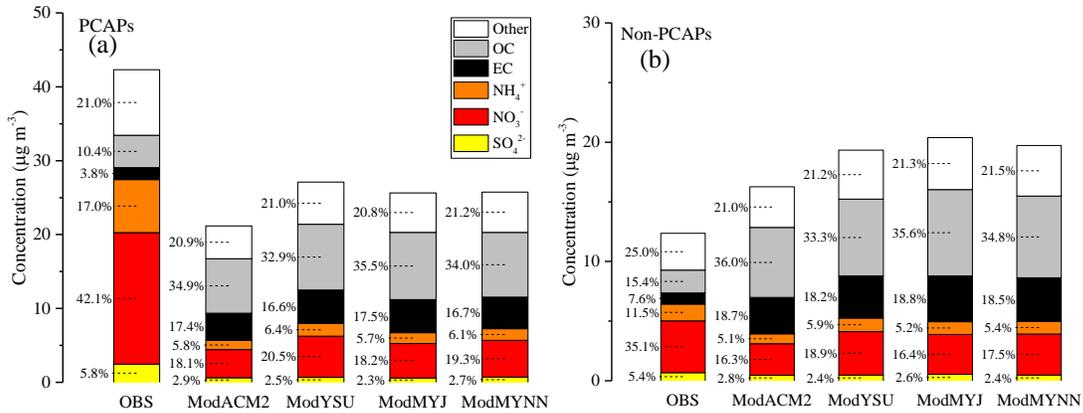
308 Nighttime aerosol nitrate formation and early morning transport has been found to contribute  
309 to PM<sub>2.5</sub> concentration increases during PCAPs based on observations [38] and box models [52].  
310 Diel variations of simulated and observed PM<sub>2.5</sub> during PCAPs and non-PCAPs are illustrated in  
311 Figure 3. Measured PM<sub>2.5</sub> levels were elevated in PCAPs compared to non-PCAPs during both  
312 daytime and nighttime. The observed mean PM<sub>2.5</sub> values reached a maximum at noon during the  
313 PCAPs. Underestimations of PM<sub>2.5</sub> existed all day with large underestimations occurring at night.  
314 There was less diel variability in the PM<sub>2.5</sub> concentration from observations for the non-PCAPs.  
315 The model overestimated PM<sub>2.5</sub> during daytime and underestimated PM<sub>2.5</sub> during nighttime. In

316 addition to the underestimated atmospheric stability, the high observed nighttime  $PM_{2.5}$   
317 concentrations were suspected to be related to the nighttime heterogeneous  $N_2O_5$  uptake  
318 mechanism for  $NH_4NO_3$  formation that is not well simulated in the CMAQ model.

319 The  $PM_{2.5}$  mean and percentile increases during PCAPs compared with non-PCAPs were  
320 captured by the model (Figure 4). However, the magnitudes of the change were largely  
321 underestimated. This indicates that the model was able to respond to stably stratified atmospheric  
322 boundary layer (ABL) conditions with enhanced pollutant concentrations but with smaller  
323 increments compared to observations. Recall that the median  $NO_x$  change was overestimated,  
324 whereas the median  $PM_{2.5}$  change was underestimated. This suggests that in addition to the  
325 meteorology fields, the  $PM_{2.5}$  simulation deficiencies during PCAPs in CMAQ may also be  
326 attributed to chemistry and dry deposition, which are further discussed in Section 4.

### 327 *3.3.2. Chemical composition*

328 Simulated speciated  $PM_{2.5}$  components are compared with observations (Figure 5). The  
329 observed  $PM_{2.5}$  chemical composition during PCAPs and non-PCAPs both show a large  
330 contribution from ammonium and nitrate, 59.1% and 46.6%, respectively. This is consistent with  
331 previous studies [38, 53] which found that the percentage of ammonium nitrate increased during  
332 inversion cases. The  $PM_{2.5}$  concentration increase during PCAP events was largely due to  
333 ammonium nitrate. The concentration of observed ammonium nitrate increased from  $5.76 \mu\text{g m}^{-3}$   
334 during non-PCAPs to  $25.00 \mu\text{g m}^{-3}$  during PCAPs.



335  
336 Figure 5 Stacked bar plots of average daily PM<sub>2.5</sub> chemical composition at the HW site during PCAP events (n=5)  
337 and non-PCAP events (n=5).

338 The CMAQ model simulations produced different PM<sub>2.5</sub> chemical composition compared to  
339 observations (Figure 5). Organic carbon (OC) shows the largest contribution of PM<sub>2.5</sub> mass  
340 concentration in CMAQ followed by nitrate and ammonium, both in PCAPs and non-PCAPs. The  
341 simulated ammonium nitrate percentage of the PM<sub>2.5</sub> mass concentration increased from 22.69%  
342 in non-PCAPs to 25.03% in PCAPs. The modeled percentage increase of ammonium and nitrate  
343 (2.3%) is not as significant as the observations (12.5%). These results indicate that uncertainties  
344 in the chemical processes are also contributing to the underestimated PM<sub>2.5</sub> concentrations in  
345 CMAQ.

#### 346 4. Discussion

347 It is well understood that stable boundary layer events, such as PCAPs, can dampen vertical  
348 mixing and lead to an accumulation of air pollution concentrations. Discrepancies in simulating  
349 atmospheric vertical mixing stem from two sources, one is the initial NWP outputs (WRF), the  
350 other is the CTM (CMAQ). In WRF, uncertainties associated with the simulated land-atmosphere  
351 interactions, which determine the heat and moisture exchange from the surface to the atmosphere,  
352 further impact the simulated boundary layer structure. Sun et al. [26] investigated the surface  
353 turbulent fluxes observed during the same field campaign (PCAPS) and found that WRF

354 overestimated the surface heat fluxes during PCAPs. They found that the surface exchange  
355 coefficient, which is a key parameter in simulating surface sensible heat flux, was overestimated  
356 in WRF when comparing with values calculated from observational data. Further investigations in  
357 Sun et al. [26] show that the flux-profiles adopted by Monin–Obukhov similarity theory that are  
358 widely employed in surface layer schemes deviated from the stability function curves estimated  
359 from observations. The excessive surface turbulence in the simulations transfers more heat to the  
360 boundary layer and leads to higher simulated PBL heights, and thus allows for more vertical  
361 mixing and lessens the buildup of air pollution concentrations in the model, similar to our CMAQ  
362 findings here.

363 In CMAQ, some of the meteorological fields are re-processed to generate the specific fields  
364 needed in the CTM. One important parameter is the minimum value of eddy diffusivity ( $K_{zmin}$ )  
365 which sets a lower bound for the modeled turbulent mixing in CMAQ. This value is currently not  
366 available in the WRF outputs. In this study,  $K_{zmin}$  was set to the default ‘Y’ in the CMAQ  
367 configuration, which is a function of urban area fraction in the grid [16].  $K_{zmin}$  ranges from 0.01  
368 at predominantly non-urban grids to  $1 \text{ m}^2/\text{s}$  at urban grids. The HW site is an urban area and the  
369 urban area fraction in the nearest CMAQ grid is 36%. The modeled  $K_{zmin}$  in urban areas can be  
370 larger than the actual values in meteorological models [54]. Larger  $K_{zmin}$  in CMAQ tends to  
371 smear out the stable boundary layer structure over urban areas and leads to lower simulated air  
372 pollutant concentrations under stable atmospheric conditions. A larger  $K_{zmin}$  value would also  
373 simulate mixing that brings  $\text{O}_3$  from the upper atmosphere with higher concentrations to the  
374 surface [54], which partly explains the high nighttime  $\text{O}_3$  concentrations (Figure 3c). Regardless  
375 of the WRF PBL scheme used, the vertical diffusion within CMAQ is reprocessed using the ACM2  
376 PBL scheme that adopts non-local closure method in the boundary layer. This highlights the

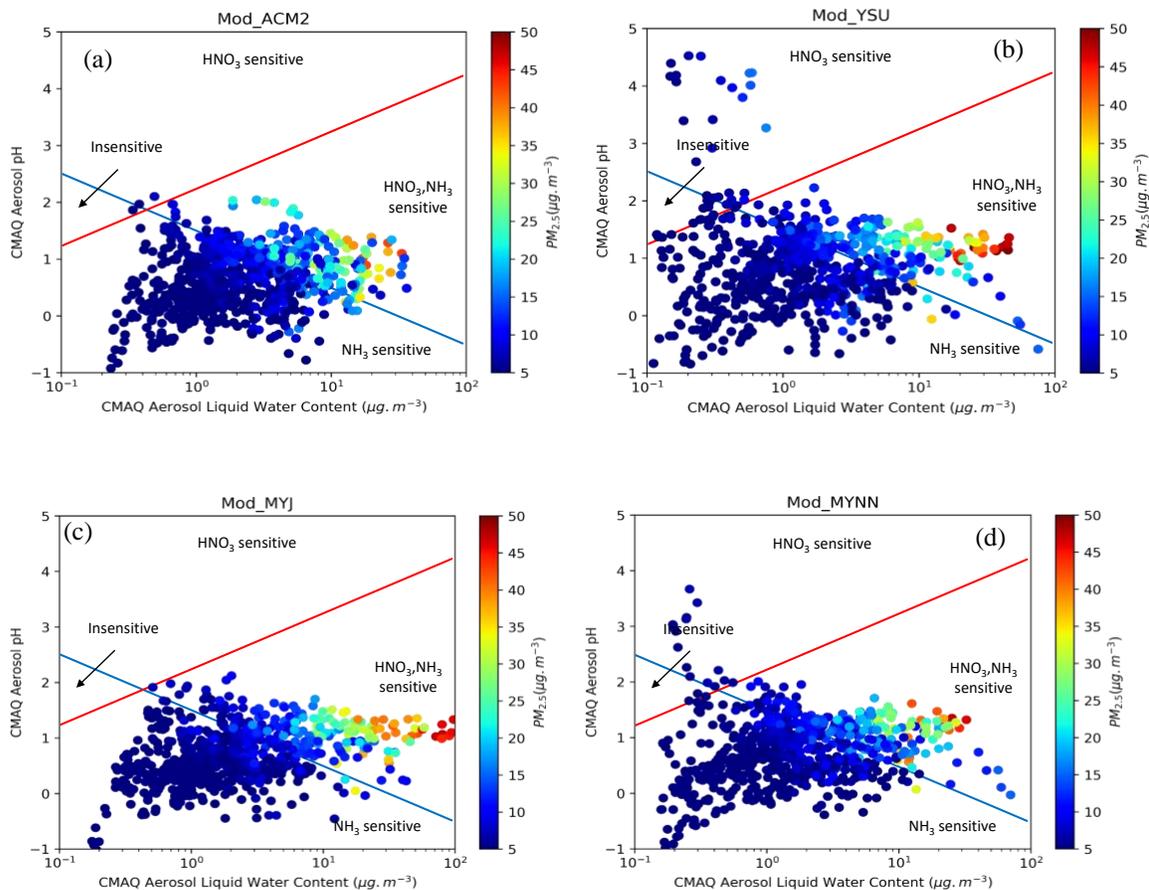
377 importance of adopting local closure PBL schemes in CTMs, which can be more suitable for stable  
378 atmospheric boundary layer conditions compared with non-local closure schemes [26, 30, 55].

379 In addition, based on previous field campaigns, the chemistry of the secondary aerosol  
380 formation that contributes to  $PM_{2.5}$  increases in the SLV is still not clear [38, 53, 56]. There have  
381 been a limited number of field campaigns aimed at determining the sources of  $PM_{2.5}$  increases  
382 during winter in the SLV. The Utah Winter Fine Particulate Study (UWFPS) [21] was conducted  
383 in the winter of 2015 to 2016 in Northern Utah. UWFPS combined ground-based observations and  
384 aircraft measurements to investigate the chemistry process and species important for  $PM_{2.5}$   
385 formation. Nocturnal production of ammonium nitrate through the heterogeneous  $N_2O_5$  uptake  
386 was found to account for 52%-85% of the morning air pollution accumulation in SLV during  
387 winter pollution events using a box model [57]. Using the UWFPS observations, Baasandorj [21]  
388 concluded that the formation of ammonium nitrate, which is the main  $PM_{2.5}$  component in SLV,  
389 was  $HNO_3$  limited using the nitrogen ratio method. However, Womack et al. [58] suggests that  
390  $NH_4NO_3$  formation is insensitive to the  $NO_x$  precursor but sensitive to VOCs that can impact  
391 oxidation cycles based on photochemical box modeling. Ivey et al. [39] used a source-oriented  
392 modeling approach to identify fossil fuel combustion and non-electric generating stationary  
393 sources as the top contributors to  $PM_{2.5}$  during PCAPs. Here we use the CMAQ model results to  
394 further discuss the potential sources contributing to the  $PM_{2.5}$  increase during wintertime in SLV.

395 Model deficiencies for  $PM_{2.5}$  stemming from emissions and chemistry are addressed using the  
396 thermodynamic ammonium nitrate regime method from Nenes et al. [42]. The CMAQ simulated  
397 aerosol pH and simulated aerosol LWC from the four model scenarios are shown in Figure 6. The  
398 simulated aerosol pH in SLV for Jan 2011 was below 3, with a few exceptions above 3 and below  
399 5 in Mod\_YSU and Mod\_MYNN. This indicates that there are acidic aerosol conditions in SLV

400 during wintertime. The pH range at the low PM<sub>2.5</sub> concentration end is higher than at the high  
401 PM<sub>2.5</sub> end. The characteristic pH and LWC curves were calculated based on the average  
402 temperature during Jan 2011 (271K) using the spreadsheet in the supplemental material from  
403 Nenes et al. [42]. Based on this aerosol pH and LWC method, most of the data points reside in the  
404 NH<sub>3</sub> sensitive region. This means that there are high enough HNO<sub>3</sub> concentrations that the aerosol  
405 formation is not limited by HNO<sub>3</sub> but by NH<sub>3</sub>, indicating that SLV is in the NH<sub>3</sub>-dominated regime.  
406 With increasing PM<sub>2.5</sub> concentration above ~15 μg m<sup>-3</sup>, the data points move to the HNO<sub>3</sub>-NH<sub>3</sub>  
407 sensitive region. The transition of the sensitivity regime from NH<sub>3</sub> to HNO<sub>3</sub>-NH<sub>3</sub> in Figure 6 is  
408 suspected to be governed by the LWC variations. High aerosol LWC promotes more PM formation  
409 because it enhances the sensitivity of aerosols to NH<sub>3</sub> and HNO<sub>3</sub> levels. Mapping the LWC and  
410 RH (Figure S10) shows that higher LWC is associated with higher RH.

411 The aerosol pH and LWC can also regulate the dry deposition of nitrogen, impacting the  
412 simulated PM<sub>2.5</sub> nitrate concentrations. Nenes et al. [59] found that conditions that favor a high  
413 partitioning fraction of nitrate (e.g., high RH) reduce the dry deposition velocity, which allows for  
414 the accumulation of nitrate aerosol. The lower simulated RH (MB= -18%) from WRF during the  
415 three PCAP events contributes less aerosol formation, as well as higher dry deposition rates. Both  
416 would lead to underestimated PM<sub>2.5</sub> in the CMAQ simulation results because of the underestimated  
417 nitrate (i.e., less nitrate formation and increased nitrogen deposition).



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Figure 6 CMAQ simulated aerosol pH variations with simulated aerosol liquid water content from (a)

Mod\_ACM2, (b) Mod\_YSU, (c) Mod\_MYJ, and (d) Mod\_MYNN. The datapoints are color-coded by  $PM_{2.5}$

concentration. The blue line and red line are the characteristic pH to define when aerosol is sensitive to changes in

available nitrate and ammonia, respectively.

424 Using the nitrogen ratio method, the simulated limiting reagents for ammonium nitrate

425 variation with  $PM_{2.5}$  are shown in Figure S11, SI. The simulated nitrogen ratio was less than 1,

426 except for five datapoints. This suggests that the  $NH_4NO_3$  formation in SLV during wintertime

427 was mainly in excess of reduced nitrogen and limited by  $HNO_3(g)$ . This was also demonstrated by

428 observations from the UWFPS [21] and measurements collected during two inversion events

429 during wintertime in 2009 [53]. The nitrogen ratio method contradicts the results based on the PM

430 sensitivity to  $\text{HNO}_3$  and  $\text{NH}_3$  discussed above. This indicates the equilibrium of ammonium nitrate  
431 is not simply expressed by a balance between  $\text{HNO}_3/\text{NO}_3^-$  and  $\text{NH}_3/\text{NH}_4^+$ .

432 The model also simulated a decreasing nitrogen ratio with increasing  $\text{PM}_{2.5}$  concentrations.  
433 This indicates that  $\text{NH}_4\text{NO}_3$  formation became more  $\text{HNO}_3(\text{g})$  limited with higher concentrations  
434 of  $\text{PM}_{2.5}$  in the simulations. However, Baasandorj [21] reported larger nitrogen ratios (close to 1)  
435 under high aerosol loadings, although with a limited number of observations. They suggested that  
436 the ammonium nitrate formation shifted to  $\text{NH}_3$ -limited with time during long PCAP episodes  
437 based on observations. This reverse behavior of the variation of nitrogen ratio with increasing  
438  $\text{PM}_{2.5}$  concentrations in CMAQ suggests that the model may underestimate nitric acid formation  
439 during pollution episodes associated with PCAP events, as ratios less than one indicate higher  
440 reduced nitrogen in the model and nitrate concentrations were greater than ammonium  
441 concentrations. This is possibly related to the nighttime nitrate formation through  $\text{N}_2\text{O}_5$   
442 heterogeneous reactions that are not well addressed in models [19, 38]. It is also important to note  
443 that the observation results in Baasandorj [21] were for  $\text{PM}_1$ , while our CMAQ simulations are  
444 for  $\text{PM}_{2.5}$ . Further inspection shows that the CMAQ simulated nitrogen ratio for  $\text{PM}_1$  exhibited  
445 similar magnitudes and trends compared to  $\text{PM}_{2.5}$  (Figure S9).

446 More effort, including both measurements and model development, is needed to understand  
447 the aerosol nitrate formation mechanism during wintertime air pollution events, particularly in  
448 mountainous regions. Future field campaigns aiming to improve the understanding of increased  
449 wintertime  $\text{PM}_{2.5}$  concentrations should be comprehensive in considering the complexity of the  
450 aerosol formation and transport. It is pivotal that a field campaign includes thorough measurements  
451 focusing on both meteorology and chemistry. Surface sensible heat fluxes, which transfer heat  
452 from the surface to the boundary layer, have been found to be overestimated during PCAPs [26].

453 Eddy covariance flux tower measurements to study the land-atmosphere exchange during the  
454 stable boundary layer events can help understand the atmospheric physics during PCAP evolution,  
455 thus contributing to improved parameterizations of land-atmosphere interactions and turbulent  
456 mixing in NWP models. In addition to the routine concentration measurements of PM<sub>2.5</sub>, high  
457 temporal resolution (hourly or shorter) of speciated PM<sub>2.5</sub> concentrations and gas phase precursors  
458 during both daytime and nighttime can provide valuable information, in particular for nighttime  
459 ammonium nitrate formation and transport. Vertical measurements of these meteorology and  
460 chemistry variables should be combined with ground-based observations to help understand the  
461 PCAP evolution and aerosol formation and transport.

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## 466 **Supporting Information**

467 The supporting information includes: WRF Model Setup (Section S1), Vertical Profiles of  
468 Temperature and Aerosol Backscatter (Section S2), SO<sub>2</sub> Simulation Analysis (Section S3), 2 tables  
469 and 11 figures.

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