



**Impact of Low-altitude Meteorological Drone Data
Assimilation on Convective-Scale Short-Term Rainfall
Forecasts: An Observing System Simulation Study**

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Abstract

25
26 This work leverages observing system simulation experiments (OSSEs) to quantify
27 the utility of low-altitude meteorological drone (MD) measurements for
28 convective-scale analyses and short-term rainfall forecasts over the
29 Beijing-Tianjin-Hebei region. Synthetic MD observations of temperature, specific
30 humidity, and horizontal wind are generated from a free-running truth simulation and
31 assimilated into the Weather Research and Forecasting (WRF) model using the
32 National Severe Storms Laboratory three-dimensional variational data assimilation
33 (DA) system. Five sets of sensitivity experiments are conducted to evaluate the
34 impacts of horizontal resolution, observation height, spatial distribution, joint
35 assimilation of thermodynamic and wind observations, and observation errors of MD
36 data, respectively. The results show that assimilation of MD temperature and humidity
37 observations improves both thermodynamic analyses and precipitation forecasts, with
38 the magnitude of benefit strongly dependent on MD network design. Denser MD
39 networks more effectively reduce thermodynamic analysis and forecast errors, leading
40 to better rainband placement, rainfall intensity, and higher quantitative precipitation
41 skill. Among the tested configurations, the 5- and 10-km networks provide the most
42 robust and consistent forecast benefits. Multi-level MD data yield the most balanced
43 improvement, while observations extending to higher levels within the planetary
44 boundary layer are generally more beneficial than those confined to the lowest level
45 alone. Restricting observations to the plain area degrades forecast performance,
46 highlighting the importance of upstream mountainous observations where convection
47 is initiated. In addition, joint assimilation of thermodynamic and wind observations
48 further improves quantitative precipitation forecasts by substantially reducing
49 lower-tropospheric wind errors. Short-term forecast skill is also sensitive to the
50 observation error standard deviations, with inflated wind observation error producing
51 a larger degradation than inflated thermodynamic errors. Overall, it is demonstrated
52 that MD observations have considerable potential to improve convective-scale
53 numerical weather prediction, particularly when the observing network is sufficiently



54 dense, vertically resolved, and capable of constraining both thermodynamic and
55 dynamical structures within the planetary boundary layer.



56 **1 Introduction**

57 Meteorological uncrewed aircraft systems (UASs), referred to here as
58 meteorological drones (MDs), have emerged as a promising observing platform for
59 reducing persistent observational gaps in the lower atmosphere, especially within the
60 planetary boundary layer (PBL) (Bell et al., 2020; Chilson et al., 2019; Pinto et al.,
61 2021; Reuder et al., 2012). Compared with conventional surface stations and
62 radiosondes, MDs can provide flexible, high-frequency, and vertically resolved in situ
63 observations of key thermodynamic and kinematic variables, including temperature,
64 humidity, and wind. For example, MD systems such as weather-observing UAS
65 (WxUAS) and Small Unmanned Meteorological Observer (SUMO) are capable of
66 providing atmospheric profiles up to approximately 1-2 km above ground level, with
67 vertical resolutions on the order of tens of meters and temporal sampling intervals of
68 several minutes (Chilson et al., 2019; Reuder et al., 2012; Sun et al., 2020). Such
69 capabilities are particularly valuable for convective-scale numerical weather
70 prediction (NWP), as the initiation and early evolution of convection are highly
71 sensitive to the distribution of temperature, moisture, and low-level airflow within the
72 PBL (Chilson et al., 2019; Crook, 1996; Weckwerth and Parsons, 2006).

73 In recent years, the World Meteorological Organization organized the Uncrewed
74 Aircraft Systems Demonstration Campaign, which investigated the applicability of
75 using MDs as a sustainable and low-cost alternative approach for collecting vertical
76 profiles of meteorological information (Inoue et al., 2025). In the United States, with
77 the rapid development of drone technology and continuing reduction in platform cost,
78 an increasing number of studies have demonstrated substantial progress in the
79 development and application of MD observations (Chilson et al., 2019; De Boer et al.,
80 2024; Jensen et al., 2021; Pinto et al., 2021; Reuder et al., 2012; Segales et al., 2020).
81 Early work established the feasibility of using both fixed-wing and rotary-wing MD
82 (e.g., CopterSonde, Meteodrone) to obtain lower-atmospheric profiles under a range
83 of environments, including complex terrain and polar regions (Reuder et al., 2012).
84 Subsequent efforts further advanced the observational capability of MDs through



85 improved platform design, sensor integration, and boundary layer profiling
86 applications (Bell et al., 2020; Segales et al., 2020). More recent studies have
87 extended these efforts toward increasingly automated and operational concepts, such
88 as coordinated profiling networks and dense lower-atmospheric observing systems
89 (Chilson et al., 2019; Jensen et al., 2021; Pinto et al., 2021). Meanwhile, MD
90 observations have been explored through data assimilation (DA) experiments for a
91 variety of applications, including fog prediction, convective storms, coastal rainfall,
92 and polar boundary layer forecasts, with generally positive impacts on
93 lower-tropospheric analyses and short-term forecasts (Jensen et al., 2021;
94 Leuenberger et al., 2020; Pinto et al., 2024).

95 In China, typhoon-oriented meteorological drone observations have expanded
96 markedly in recent years, from the first upper-air integrated unmanned aerial vehicle
97 (i.e. HAIYAN-I) typhoon sounding experiment in 2020 to coordinated maneuvering
98 observations over the South China Sea in 2023 and multi-aircraft typhoon campaigns
99 in 2024 (Wen et al., 2025). This reflects a growing capability for targeted offshore
100 profiling and dropsonde observations in tropical cyclones. Since late 2024,
101 low-altitude meteorological development agenda for China Meteorological
102 Administration has placed increasing emphasis on the deployment of low-altitude
103 observing systems, with particular focus on meteorological drones. Under this
104 framework, MDs are expected to support fixed-point profiling, route-based
105 observations, and targeted mobile observations, primarily within the low-altitude
106 atmosphere below 1000 m, with extensions up to 3000 m when needed. These
107 observations are intended to support a range of typical low-altitude economy
108 applications, including cargo logistics, passenger transport, emergency rescue and
109 disaster response, cultural and tourism activities, agricultural and forestry protection,
110 ecological conservation, and so on. In recent years, several pilot programs in China
111 have begun exploring low-altitude meteorological observation systems based on MD
112 platforms, including low-altitude meteorological observation testbeds in Shenzhen,
113 boundary-layer profiling experiments in Shanxi, and route-based MD observation



114 campaigns in Nanjing aimed at supporting low-altitude flight operations. Although
115 these developments indicate growing international interest in MD applications, there
116 is little peer-reviewed published research investigating the potential benefit of
117 low-altitude MD observations within this emerging low-altitude meteorological
118 framework, particularly from the perspective of observing network design.

119 Despite the growing availability of MD observations, their impact on
120 convective-scale NWP remains insufficiently investigated. As routine operational MD
121 observations remain quite limited in world meteorological community, observing
122 system simulation experiments (OSSEs) provide an effective framework for
123 evaluating their potential forecast value before nationwide deployment. In an OSSE,
124 synthetic observations generated from a realistic nature run are assimilated into a
125 forecast system, allowing the impacts of observation type, network configuration,
126 spatial distribution, and sampling strategy to be examined in a controlled manner
127 (Hoffman and Atlas, 2016). In mesoscale and convective-scale NWP, OSSEs have
128 been widely used to assess the potential impact of new observing systems (Hu et al.,
129 2017; Huang et al., 2022; Huo et al., 2023; Zhang and Pu, 2010; Zhao et al., 2021a,
130 2025). In the context of MD observations, OSSEs are especially useful because they
131 allow key design questions, such as network density, observation height, deployment
132 area, and observation error specification, to be tested before operational
133 implementation (Murdzek et al., 2026).

134 The main motivation of this study is therefore to explore, through an OSSE
135 framework, the potential value of MD observations for convective-scale analyses and
136 short-term precipitation forecasts over the Beijing-Tianjin-Hebei (BTH) region as an
137 example, and to assess the implications for future MD network design. The BTH
138 region is one of China's most densely populated and economically developed areas,
139 characterized by complex terrain including the Taihang and Yanshan Mountains to the
140 west and north, which strongly modulate local convective weather through influences
141 on PBL thermodynamic and dynamical structures (Jiang et al., 2021; Li et al., 2024;
142 Zhang et al., 2018). Another motivation for selecting this study region is that



143 high-impact severe weather events occur frequently, especially in summer. Several
144 related questions will also be addressed. How does the horizontal resolution of MD
145 network impact convective analyses and heavy rainfall forecast in the BTH region?
146 How sensitive is the forecast skill to observation height and deployment area within
147 the PBL? Does the joint assimilation of MD thermodynamic and wind data provide
148 added benefit over the thermodynamic observations alone? To what extent do the
149 analyses and forecasts depend on the assumed MD observation errors? Ultimately,
150 this study seeks to clarify the role of low-altitude MD observations in
151 convective-scale NWP and to provide guidance for the design of future MD observing
152 networks.

153 Following the Introduction, Section 2 introduces the forecast model and DA
154 system. Section 3 describes the truth and background simulations, synthetic MD
155 observations, and experimental design. Section 4 presents analysis and forecast results
156 from DA sensitivity experiments. Section 5 summarizes key findings and conclusions.

157 **2 Model and DA System**

158 Version 3.7.1 of the Weather Research and Forecasting (WRF) Model with the
159 Advanced Research WRF (ARW) dynamical core (Skamarock et al., 2008) is
160 employed for both DA and forecast experiments. Simulations are performed on a
161 1-km resolution domain with 630×720 horizontal grid points and 51 vertical levels,
162 extending to a model top at 50 hPa. The model domain is centered over northern
163 China, covering the BTH region (Fig. 3a). The physical parameterization suite
164 includes the National Severe Storms Laboratory (NSSL) two-moment four-ice bulk
165 microphysics scheme (Mansell et al., 2010; Mansell and Ziegler, 2013; Ziegler, 1985),
166 the Rapid Radiative Transfer Model (RRTM) longwave radiation scheme (Mlawer et
167 al., 1997), the Dudhia shortwave radiation scheme (Dudhia, 1989), the Rapid Update
168 Cycle (RUC) land surface model (Benjamin et al., 2004), and the Yonsei University
169 (YSU) planetary boundary layer scheme (Hong et al., 2006).



170 This study adopts the NSSL Experimental Warn-on-Forecast three-dimensional
171 variational DA system (NSSL3DVAR) (Gao et al., 2013, 2016; Gao and Stensrud,
172 2014; Wang et al., 2019; Zhuang et al., 2016), which is developed for
173 convective-scale NWP and severe storm forecasting (Gao et al., 2024; Heinselman et
174 al., 2024). Within the NSSL3DVAR framework, the analysis is obtained through
175 minimization of a cost function composed of the background term J_b , the observation
176 term J_o , and the constraint term J_c :

$$177 \quad J = J_b + J_o + J_c = \frac{1}{2}(\mathbf{x} - \mathbf{x}_b)^T \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}_b) + \frac{1}{2}(H(\mathbf{x}) - \mathbf{y}_o)^T \mathbf{R}^{-1}(H(\mathbf{x}) - \mathbf{y}_o) + J_c, \quad (1)$$

178 where $\mathbf{x}$ and $\mathbf{x}_b$ denote the analysis and background state vectors; $\mathbf{y}_o$ is the observation
179 vector; and H represents the observation operator that maps model variables into
180 observational space. The matrices $\mathbf{B}$ and $\mathbf{R}$ correspond to the background and
181 observation error covariance matrices, respectively. The weak constraint term J_c
182 incorporates the elastic mass continuity equation and a diagnostic pressure equation
183 constraint, which are formulated to improve dynamical consistency for
184 convective-scale DA (Gao et al., 2004; Ge et al., 2012). The control variables in the
185 analysis system include the three-dimensional wind components, pressure, potential
186 temperature, water vapor mixing ratio, and hydrometeor mixing ratios for cloud water,
187 rain, ice, snow, and graupel (Gao and Stensrud, 2012).

188 The NSSL3DVAR system is capable of efficiently assimilating a wide range of
189 high-resolution observations, including radar radial velocity and reflectivity (Gao et
190 al., 2013, 2016), radar wind profiler (Zhao et al., 2025), conventional sounding and
191 surface measurements (Hu et al., 2019), and several satellite-derived products, such as
192 cloud water path (Pan et al., 2021), total precipitable water (Jones et al., 2018; Pan et
193 al., 2018), Geostationary Lightning Mapper (GLM)-retrieved water vapor (Fierro et
194 al., 2019; Hu et al., 2020), and atmospheric motion vectors (Mallick and Jones, 2020;
195 Zhao et al., 2021b, 2022). To help address the scarcity of observations in the PBL,
196 which plays an important role in forecasting high-impact weather such as
197 thunderstorms and dense fog, a MD assimilation module is developed and
198 incorporated into the DA system. Given the operational demand for rapid updates in



199 severe weather forecasting, the computational efficiency of the 3DVAR framework
200 makes it well suited for short-cycle applications (e.g., 15-min update intervals; Hu et
201 al., 2021). As the primary objective here is to evaluate the impact of assimilating MD
202 data on convective-scale analyses and short-term forecasts, the ensemble-based
203 background error covariance option available in the DA system is not employed (Gao
204 et al., 2016; Gao and Stensrud, 2014; Wang et al., 2019). Instead, the background
205 error covariance matrix is specified using a static formulation, constructed as the
206 product of a diagonal matrix of background error standard deviations and a spatial
207 recursive filter (Gao et al., 2004, 2013). The standard deviations for control variables
208 are estimated from multi-year statistics of 3-h forecasts from the Rapid Update Cycle
209 (RUC; Benjamin et al., 2004a) system (Fierro et al., 2019; Pan et al., 2021). Spatial
210 correlations are modeled using the recursive filter approach of Purser et al. (2003a, b),
211 which can be applied in multiple passes with distinct correlation length scales to
212 represent the characteristic scales of assimilated observations. Taking the baseline
213 5-km MD data assimilation experiment (MD_H5) as an example, the horizontal
214 correlation length scales are specified as 10 km in the first pass and 5 km in the
215 second pass, while the corresponding vertical correlation length scales are set to two
216 and one grid points, respectively. The chosen correlation scales are proportional to the
217 observation spacing, reflecting the characteristic scales resolved by the MD network.

218 **3. Experimental design**

219 **3.1 Truth run and background run configuration**

220 In the OSSE framework, synthetic MD observations are produced by perturbing
221 the model “truth” with prescribed observation errors. The truth simulation is
222 generated using the WRF model initialized with the fifth-generation European Centre
223 for Medium-Range Weather Forecasts reanalysis dataset (ERA5; Hersbach et al.,
224 2020; Hoffmann et al., 2019), following the model configuration and physical
225 parameterizations described in Sect. 2. A heavy rainfall event that occurred over the
226 BTH region on 29 July 2024 is selected as the test case for constructing the OSSE and



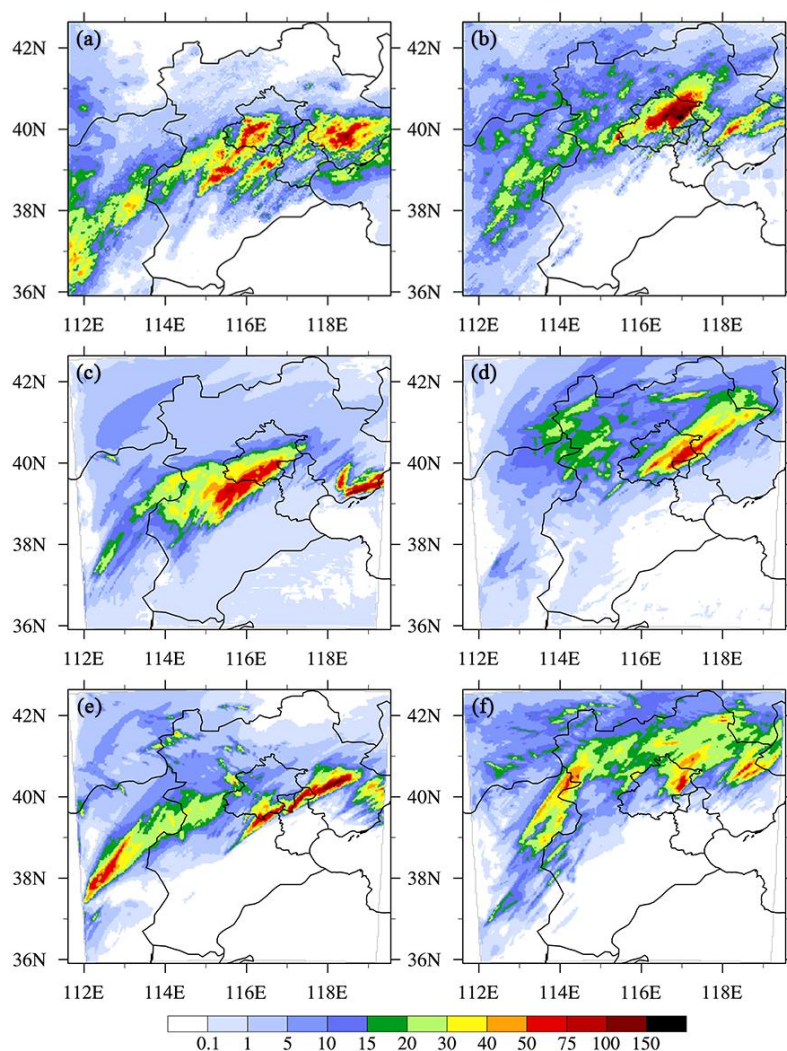
227 examining the influence of different MD network configurations on short-term
228 convective precipitation forecasts. This event occurred in a favorable synoptic
229 environment characterized by the periphery of the subtropical high, an
230 eastward-propagating upper-level trough, and a low-level jet, which together provided
231 abundant moisture and strong vertical wind shear conducive to organized convection.
232 For the truth run, the WRF model is initialized with ERA5 and integrated forward for
233 18 h, with lateral boundary conditions updated hourly from the ERA5 data.

234 This study adopts an OSSE framework based on an identical-twin design, in
235 which the same numerical model is used for both the truth simulation and the forecast
236 system. Consequently, the results should be interpreted with the limitation that such
237 configuration may lead to overly optimistic estimates of observational impacts
238 (Hoffman and Atlas, 2016). To partially alleviate this issue, the first-guess
239 background simulation (NoDA) is initialized and forced with forecasts from the
240 National Centers for Environmental Prediction (NCEP) Global Forecast System
241 (GFS), which differ from those used in the truth simulation.

242 The 6-h accumulated precipitation forecasts from both the truth and background
243 runs are evaluated against rainfall estimates from the China Meteorological
244 Administration Multisource Precipitation Analysis System (CMPAS), a
245 gauge-radar-satellite merged precipitation product (Pang et al., 2021) with a spatial
246 resolution of $0.01^\circ \times 0.01^\circ$ and an hourly temporal resolution (Fig. 1). The CMPAS
247 estimates (Fig. 1a and b) reveal a well-organized southwest-northeast-oriented
248 precipitation band extending across the BTH region, with several embedded
249 precipitation cores exceeding 50-100 mm. The most intense rainfall is mainly located
250 over Beijing and eastern Hebei Province, indicating a typical organized convective
251 precipitation system. The truth simulation (Fig. 1c and d) reproduces the primary
252 precipitation structure reasonably well, including the orientation and spatial extent of
253 the main rainband, and also captures its overall propagation tendency. The dominant
254 rainfall centers are generally well reproduced, although the simulated field appears
255 somewhat smoother and shows slight spatial displacement relative to the CMPAS



256 estimates. Despite these differences, the rainfall distribution and intensity are broadly
257 consistent with the CMPAS product, indicating that the truth run provides a
258 physically realistic representation of the convective system for the OSSE framework.
259 In contrast, the NoDA forecasts (Fig. 1 e and f) show larger departures from the
260 CMPAS product. Although a precipitation band is still evident, its position and
261 structure differ more substantially from the observed rainfall pattern, and the localized
262 heavy-rainfall cores are less well captured. These deficiencies indicate considerable
263 errors in the background forecast prior to DA. The discrepancies among the
264 background forecast, the truth simulation, and the multi-source precipitation product
265 provide a meaningful testbed for evaluating the potential benefits of assimilating
266 additional observations. In particular, given that convective precipitation systems are
267 highly sensitive to thermodynamic and kinematic conditions in the PBL, this case
268 offers a suitable scenario for assessing the potential contribution of MD observations
269 to improving convective-scale analyses and short-term precipitation forecasts.



270

271 **Figure 1. Comparison of precipitation forecasts from Truth and NoDA**
272 **experiments with multi-source merged precipitation product.**

273 The 6-h accumulated precipitation fields (mm, shaded) from 1800 UTC 29 July to
274 0000 UTC 30 July (left), and from 0000 UTC 30 July to 0600 UTC 30 July, 2024
275 (right) from (a)–(b) the China Meteorological Administration Multisource
276 Precipitation Analysis System (CMPAS) rainfall estimates, (c)–(d) Truth simulations,
277 and (e)–(f) NoDA experiments.



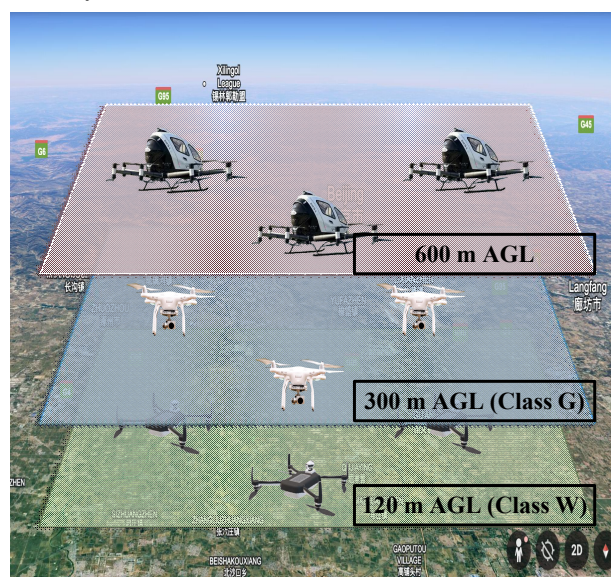
278 **3.2 Synthetic meteorological drone observations**

279 Meteorological drones have been increasingly developed to address
280 observational gaps in the PBL by providing high-resolution measurements of key
281 thermodynamic and kinematic variables, including temperature, humidity, and wind
282 (Houston et al., 2020; Inoue et al., 2025; Pinto et al., 2021). MD observations are
283 typically conducted within the lowest 1-3 km of the atmosphere, where many
284 weather-sensitive processes relevant to short-term forecasting occur, and commonly
285 involve vertical profiling or targeted flight operations with temporal resolutions of
286 seconds and vertical resolutions on the order of tens of meters (Bell et al., 2020;
287 Houston et al., 2020). Currently, MDs in China employ both multirotor and
288 fixed-wing platforms to provide vertical profiling and targeted mobile data. The
289 observations are also characterized by high temporal and vertical resolutions, with
290 various horizontal resolutions depending on flight mode, ranging from point-based
291 profiling to kilometer-scale transects. Future MD development plans are expected to
292 focus primarily on the low-altitude airspace below 1 km, including targeted
293 observations within representative operating layers such as about 120 m (referred to
294 as Class W airspace), 300 m (referred to as Class G airspace), and 600 m for urban
295 and general aviation applications.

296 In this study, the synthetic profiles of temperature (T), specific humidity (Q_v),
297 zonal and meridional wind components (U and V) are specified at 120-, 300-, and
298 600-m altitudes to represent realistic MD deployment in China (Fig. 2). These
299 variables are extracted from the truth thermodynamic and kinematic fields using linear
300 interpolation in the vertical. Simulated MD observations are then synthesized by
301 averaging the truth fields onto coarser grids. Horizontal resolutions of 5, 10, 20, and
302 40 km are adopted to mimic the spatial representativeness of real MD observations
303 (Fig. 3). It is noted that Fig. 3b displays only a subset of the full model domain (black
304 box in Fig. 3a) to more clearly illustrate the distribution of observational grids at
305 different resolutions. The synthetic observations are generated at 15-min intervals. To
306 account for measurement uncertainty, Gaussian random errors with a mean of zero are

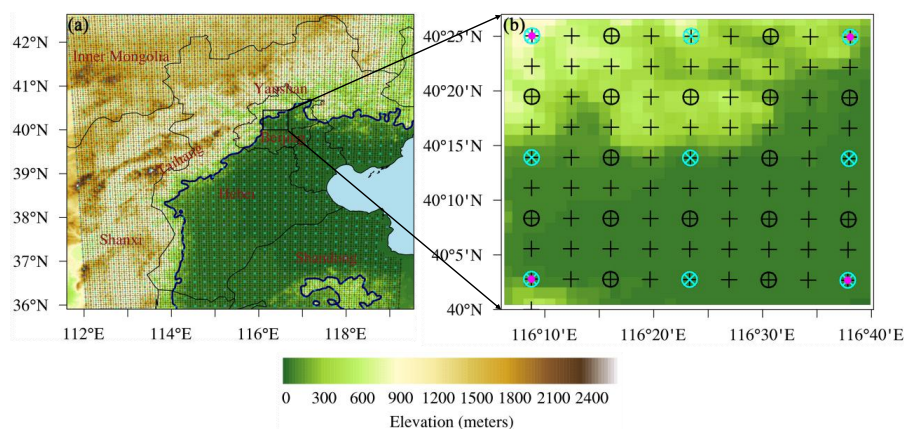


307 added to the synthetic observations. The standard deviations are set to 1 K for
308 temperature, 1 g kg^{-1} for specific humidity, and 1 m s^{-1} for wind, which are broadly
309 consistent with the range of observational uncertainties reported in previous studies
310 (Bell et al., 2020; Kay et al., 2025; Murdzek et al., 2026; Pinto et al., 2021).



311
312 **Figure 2. Schematic configuration of multi-layer meteorological drone (MD)**
313 **observational framework.**

314 Three tiers of MD sampling heights are illustrated: low-level observations at 120 m
315 above ground level (AGL, Class W airspace), mid-level observations at 300 m AGL
316 (Class G airspace), and upper-level observations at 600 m AGL. Base terrain imagery
317 modified from Google Earth.



318

319 **Figure 3. Overview of the numerical simulation domain and spatial layout of MD**
320 **observation grids with four distinct horizontal resolutions.**

321 (a) Full modeling domain overlaid on shaded terrain elevation; color bar denotes
322 elevation in meters, ocean regions are shaded light blue. The simulated MD networks
323 with horizontal spacings of 5 km (black crosses), 10 km (black circles), 20 km (cyan
324 circles), and 40 km (magenta dots) are also shown. The thick blue contours mark the
325 300-m elevation boundary separating mountain and plain terrain. Red text labels the
326 major administrative regions (Beijing, Hebei, Shanxi, Shandong, and Inner Mongolia)
327 as well as the Taihang and Yanshan Mountains. The black rectangular box outlines
328 the subdomain magnified in panel (b). (b) Magnified subdomain showing MD
329 sampling points at four horizontal grids.



330 As our primary objective is to quantify the effects of assimilating
331 thermodynamic and kinematic observations from different MD networks on
332 convective-scale analyses and short-term severe weather forecasts, only synthetic MD
333 data are assimilated in this study. Conventional observations, including radiosondes
334 and surface stations, as well as satellite and radar measurements, are excluded. This
335 experimental design allows a more direct attribution of forecast impacts to the
336 simulated MD observations, although it may also overstate their relative contribution
337 (Hoffman and Atlas, 2016). As a result, the DA experiments are designed to evaluate
338 the upper bound of the information content provided by MD observations, rather than
339 their marginal impact when added to an operational DA system that already
340 assimilates a broad range of conventional and remote-sensing observations.

341 **3.3 DA experiment setup**

342 To emulate an operational rapid-update forecasting environment, the OSSE is
343 configured with a 6-h cycling framework with analyses updated every 15 min, broadly
344 following the real-time Warn-on-Forecast System (WoFS) Spring Forecast
345 Experiment workflow (Heinselman et al., 2024; Hu et al., 2021; Jones et al., 2018).
346 GFS forecasts are used to provide both the initial and lateral boundary conditions for
347 all simulations. To serve as a reference, an experiment without assimilating any
348 observations is carried out and referred to as NoDA. To assess the impact of different
349 MD network configurations on convective-scale NWP, five sets of DA sensitivity
350 experiments are conducted:

- 351 1. The first set of experiments examines the impact of MD observations with
352 different horizontal resolutions (5, 10, 20, and 40 km) in order to assess how
353 observation density influences analyses and forecasts. Among these
354 experiments, MD_H5, in which synthetic observations with 5-km grid
355 spacing are assimilated, is selected as the baseline reference for subsequent
356 sensitivity tests.
- 357 2. The second set investigates the sensitivity to observation height by
358 separately assimilating MD observations at 120, 300, and 600 m,



359 respectively, while keeping the horizontal resolution fixed at 5 km. These
360 experiments are designed to examine the relative contribution of
361 observations collected at different altitudes of the PBL.

362 3. For the third set, assimilated MD observations are distributed only over the
363 plain area, defined here as regions with terrain elevation below 300 m (thick
364 blue contours in Fig. 3a). This design tests whether the forecast impact
365 depends on the spatial deployment of the MD network.

366 4. The fourth set evaluates the added value of MD wind observations. Whereas
367 only temperature and humidity observations are assimilated in the first three
368 sets, this set of experiment assimilates thermodynamic data together with
369 horizontal wind observations, thereby quantifying the contribution of
370 kinematic information to the analyses and forecasts.

371 5. The fifth set explores the sensitivity of the analyses and forecasts to
372 prescribed observation errors. Separate experiments are conducted by
373 inflating the observation error assigned to temperature, humidity, and wind,
374 respectively, in order to assess how the assumed uncertainty of each variable
375 affects the analyses and subsequent forecasts.

376 Basic configurations for each set of sensitivity experiments implemented in the
377 variational system are listed in Table 1. In addition to assessing the impact of
378 synthetic MD observations on convective-scale DA and NWP, sensitivity experiments
379 in each set are compared with the baseline experiment (MD_H5) to isolate the effects
380 of horizontal resolution, observation height, spatial distribution, joint assimilation of
381 thermodynamic and wind observations, and prescribed observation errors,
382 respectively.



Table 1. List of DA sensitivity experiments based on various configurations of the meteorological drone (MD) network over the Beijing-Tianjin-Hebei region.

Experiment		Horizontal resolution (km)	Detection height (m)	Observation variables	Observation error (standard deviations)
Set 1	MD_H40	40	120/300/600	T, Q _v	1 K, 1 g kg ⁻¹
	MD_H20	20			
	MD_H10	10			
	MD_H5	5			
Set 2	MD_H5_Z120	5	120	T, Q _v	1 K, 1 g kg ⁻¹
	MD_H5_Z300		300		
	MD_H5_Z600		600		
Set 3	MD_H5_Plain	5	120/300/600	T, Q _v	1 K, 1 g kg ⁻¹
Set 4	MD_H5_UV	5	120/300/600	T, Q _v , U, V	1 K, 1.0 g kg ⁻¹ , 1 m s ⁻¹
Set 5	MD_H5_ERR_T	5	120/300/600	T, Q _v , U, V	3 K, 1 g kg ⁻¹ , 1 m s ⁻¹
	MD_H5_ERR_Q				1 K, 3 g kg ⁻¹ , 1 m s ⁻¹
	MD_H5_ERR_UV				1 K, 1 g kg ⁻¹ , 3 m s ⁻¹

4 Results and discussion

The impact of assimilating synthetic MD observations on convective-scale NWP is assessed from the perspectives of initial field structure, evolution of analysis and forecast errors, and precipitation forecast skill. First, the influence of MD DA on the model initial conditions is diagnosed through detailed analyses of the spatial structures of temperature, humidity, and wind fields. Additionally, time series and vertical profiles of root-mean-square errors (RMSEs) for thermodynamic and



kinematic variables are computed throughout the DA cycles and subsequent 6-h free forecasts for each experimental configuration. Finally, the influence on short-term precipitation forecast is examined through both qualitative inspection and quantitative verification of accumulated rainfall against the truth simulation. Quantitative precipitation forecast skill is evaluated using a neighborhood-based approach with a 12-km radius across multiple accumulated precipitation thresholds, including the equitable threat score (ETS, Clark et al., 2010) and contingency-table metrics such as probability of detection (POD), false alarm ratio (FAR), success ratio (SR), frequency bias (BIAS), and critical success index (CSI).

4.1 Sensitivity to horizontal resolution

4.1.1 Impact on thermodynamic analyses and forecasts

To illustrate how the assimilation of MD observations with different horizontal resolutions modifies the thermodynamic analyses, Figures 4 and 5 present the 850-hPa temperature and 925-hPa specific humidity fields, respectively, together with the corresponding wind vectors from the truth run and the differences between each experiment and the truth simulation at the end of analysis cycles. Figures 4b–f and 5b–f show the temperature and specific humidity departures of NoDA, MD_H40, MD_H20, MD_H10, and MD_H5 relative to the truth run, respectively; these departures are interpreted here as analysis errors. Positive (negative) values indicate a warm (cold) bias relative to the truth in Fig. 4, whereas in Fig. 5 they indicate a moist (dry) bias. In the truth simulation, a pronounced northwest–southeast temperature gradient is evident over the BTH region, with relatively cool air over the northern and northwestern mountainous areas and warmer conditions over the southeastern plains (Fig. 4a). The NoDA experiment exhibits widespread warm biases over much of western and northern domain, especially near the Yanshan and Taihang Mountains, while weak cold biases are found over northeastern Hebei, northern Shandong, and the adjacent coastal waters (Fig. 4b). This indicates that the background run does not adequately represent the mesoscale thermal structure. Assimilation of MD data clearly reduces these temperature errors, although the magnitude of improvement depends on



the horizontal resolution of MD observation network. The MD_H40 experiment still retains relatively large warm and cold bias patches, particularly in the Taihang Mountains upstream of Beijing (Fig. 4c). Sequential refinement of horizontal sampling grid spacing from 40 to 20, 10, and 5 km produces steady reductions in both the spatial extent and amplitude of the temperature bias (Fig. 4d-f).

Among all experiments, MD_H5 produces the smallest and smoothest temperature departures from the truth run over most of the domain (Fig. 4f), which suggests that the densest MD network most effectively constrains the lower-tropospheric thermal analysis. Nevertheless, some residual errors remain, especially near the northern mountainous region, implying that thermodynamic structures in terrain-influenced areas are still difficult to fully recover even with relatively dense MD observations. For all DA experiments, the wind analysis errors are only marginally reduced, as assimilating thermodynamic observations alone provides only limited adjustment to the flow field.

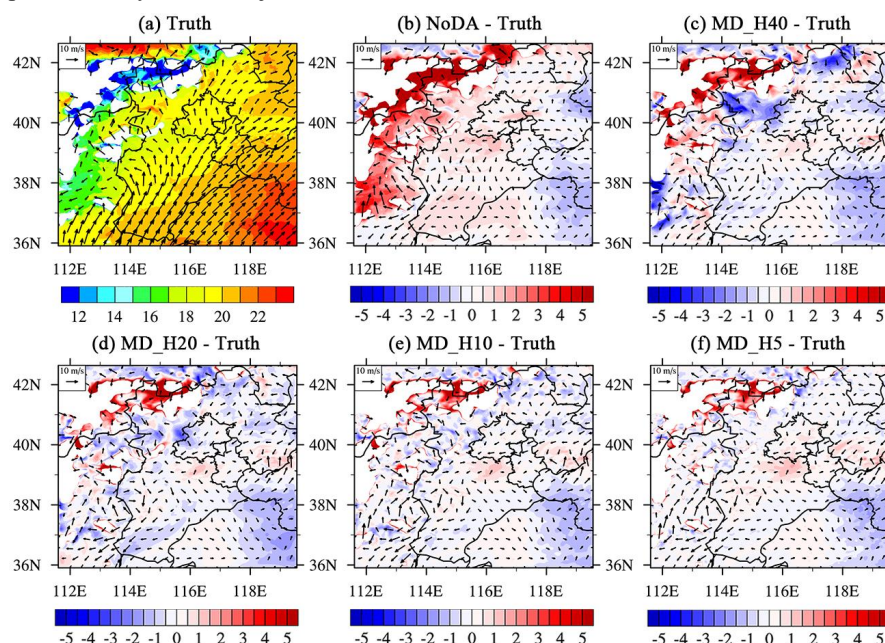
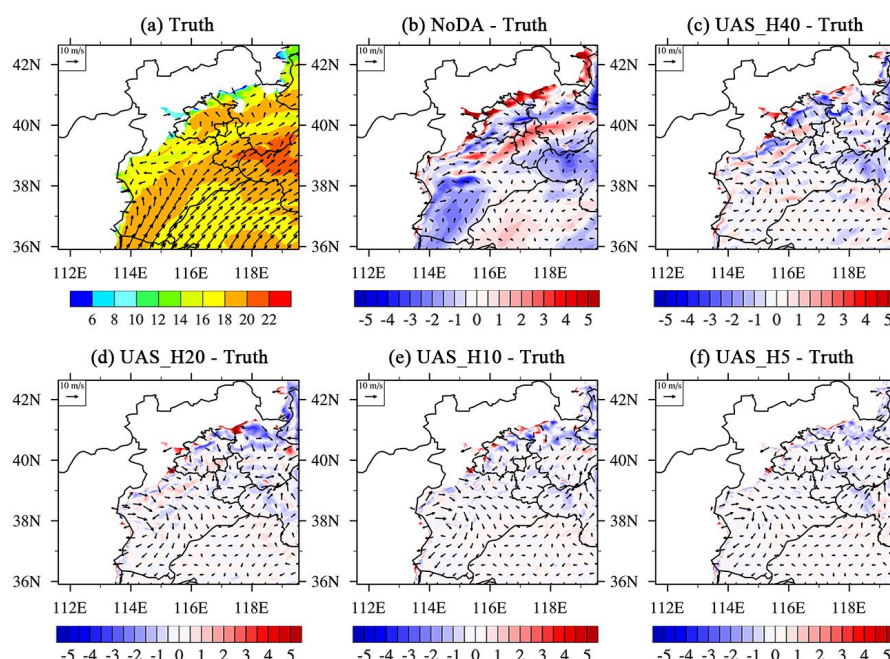


Figure 4. Horizontal resolution sensitivity of 850-hPa temperature analysis bias at 1800 UTC on 29 July 2024, the final time step of the data assimilation cycling.
(a) Shaded 850-hPa temperature ($^{\circ}\text{C}$) and horizontal wind vectors from the truth run.



439 Panels (b)–(f) show 850-hPa temperature and wind vector bias (experiment minus
440 truth): (b) NoDA, (c) MD_H40, (d) MD_H20, (e) MD_H10, and (f) MD_H5
441 experiments. Red shading denotes positive temperature bias relative to the truth run,
442 while blue shading denotes negative bias.

443 Figure 5 further shows that the impact of MD horizontal resolution on the
444 humidity field is broadly consistent with that found for the temperature analysis. In
445 the truth simulation, the low-level jet transports the moist and unstable airmass across
446 the southeastern plains and Bohai coastal area (Fig. 5a). The NoDA experiment
447 produces substantial dry biases over Beijing and central-southern Hebei, together with
448 moist biases along the northern belt near the Yanshan Mountains and along a second
449 southwest-northeast-oriented belt southeast of Beijing (Fig. 5b). Generally,
450 assimilation of MD observations substantially reduces these errors in the background
451 moisture structure, and the improvement becomes more evident as the horizontal
452 resolution of simulated MD observations increases (Fig. 5c-f). In particular, large dry
453 biases over Beijing and central-southern Hebei are progressively weakened, and the
454 two parallel southwest-northeast-oriented moist bias bands are also reduced. Among
455 all experiments, MD_H5 yields the smallest humidity departures from the truth and
456 provides the best overall recovery of the mesoscale moisture pattern (Fig. 5f). Only
457 minor residual humidity errors remain, mainly near the northern mountainous region
458 and over offshore areas where no MD observations are available. This indicates that
459 the moisture field is generally well adjusted after assimilation of MD data, although
460 terrain-influenced regions remain more difficult to constrain than the plains.



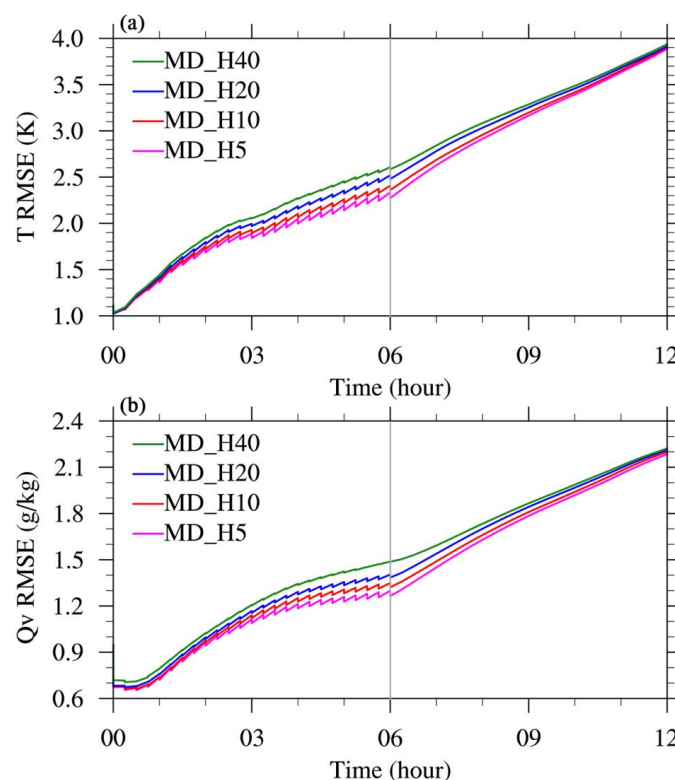
461

462 **Figure 5. Same as Fig. 4, but the 925-hPa specific humidity (g kg^{-1}) and wind**
463 **vectors.**

464 The influence of the horizontal resolution of MD observations on the
465 thermodynamic analyses and forecasts can also be directly assessed by examining the
466 RMSEs of temperature and humidity fields during the 6-h assimilation cycles and
467 subsequent 6-h free forecasts. Time series of domain-averaged RMSEs from the
468 MD_H40, MD_H20, MD_H10, and MD_H5 experiments are compared in Fig. 6.
469 During the 6-h cycling period, RMSEs of both temperature and specific humidity
470 increase in all experiments; however, a clear dependence on observation density is
471 evident. Finer MD networks consistently produce smaller errors, with MD_H5 giving
472 the lowest RMSEs, followed by MD_H10, MD_H20, and MD_H40. This ordering
473 agrees well with the diagnostic results shown in Fig. 4 and 5. Moreover, the same
474 ranking is retained in the subsequent 6-h free forecasts, indicating that the improved
475 thermodynamic fields are carried forward into the prediction. The benefits of a denser
476 MD network are most evident during the cycling period and early forecast hours.
477 With increasing forecast lead time, however, RMSEs continue to grow and the



478 differences among sensitivity experiments gradually diminish. Overall, assimilation of
479 MD observations with higher horizontal resolution improves both temperature and
480 moisture analyses and leads to corresponding gains in short-term forecasts.



481
482 **Figure 6. Impact of horizontal resolution on RMSEs of thermodynamic analyses**
483 **and forecasts.**

484 Time series of domain-averaged root-mean-square errors (RMSEs) for (a) temperature
485 (K), and (b) specific humidity (g kg^{-1}) analyses and forecasts from the MD_H40
486 (green), MD_H20 (blue), MD_H10 (red), and MD_H5 (magenta) experiments. The
487 thin grey line separates analysis cycling and 6-h free forecasts.

488 4.1.2 Impact on precipitation forecasts

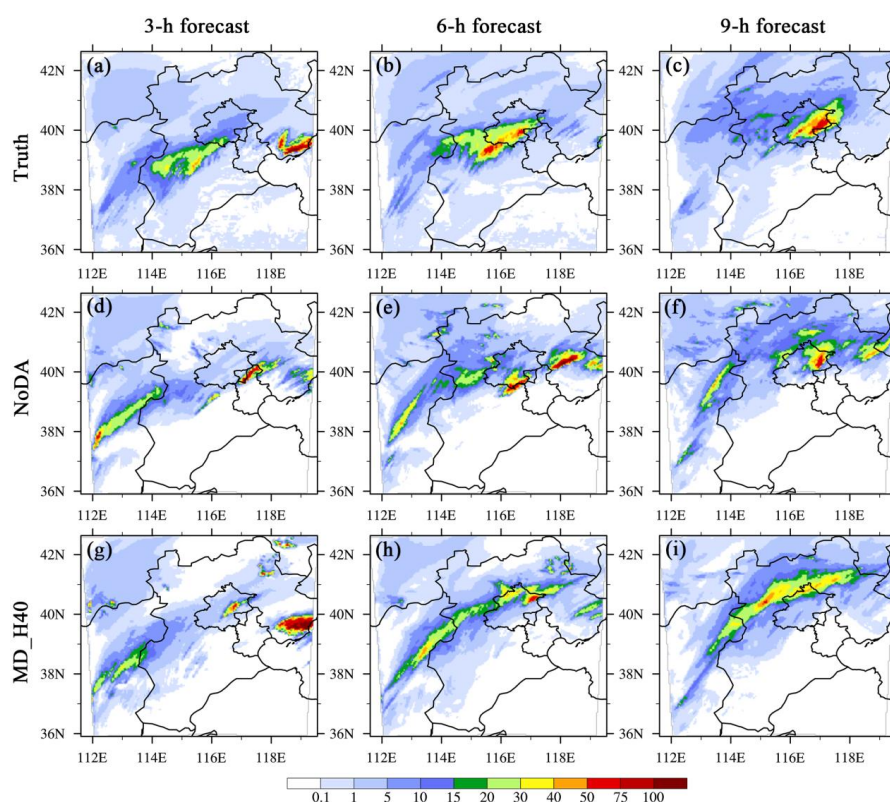
489 The 3-, 6-, and 9-h accumulated precipitation forecasts from NoDA and the first
490 set of DA experiments, are compared with the truth simulation in Fig. 7 and 8. All DA
491 forecasts are initialized from the final analysis at the end of assimilation cycles. For



492 the truth simulation, the rainfall system evolves from a relatively compact
493 southwest-northeast-oriented band at 3 h into a more organized mesoscale rainband
494 extending across central Hebei and southern Beijing at 6 h, followed by a
495 concentrated heavy rain center over the central and eastern parts of Beijing at 9 h (Fig.
496 7a-c). In contrast, the NoDA experiment exhibits substantial precipitation forecast
497 errors, characterized by markedly weaker precipitation over Beijing and central Hebei
498 province, and overpredicted rainfall in Shanxi province, resulting in a less coherent
499 representation of the primary rainband, especially at 3- and 6-h forecast lead times
500 (Fig. 7 d-f). In addition, NoDA fails to reproduce the narrow heavy-rain band over
501 eastern Hebei near the coast seen in the truth simulation. Assimilation of MD
502 observations overall improves the location, continuity, and orientation of the forecast
503 rainband. Relative to NoDA, the DA experiments better reproduce the northeastward
504 extension of the rainfall system and reduce the separation between the western and
505 eastern precipitation cores, while also capturing the narrow coastal heavy-rain band
506 over eastern Hebei province, albeit with slightly overpredicted intensity. The
507 improvement becomes generally more evident as the observation density increases
508 from 40 to 5 km (Fig. 7g-i, Fig. 8), indicating that denser MD networks provide more
509 effective constraints on the mesoscale thermodynamic structure relevant to
510 precipitation evolution. Among the DA experiments, MD_H10 and MD_H5 show the
511 closest agreement with the truth, with a better-defined central rainband and reduced
512 spatial displacement. In particular, MD_H5 gives the closest placement of the primary
513 heavy-rain band, whereas coarser networks, especially MD_H40, tend to place the
514 rainband too far north and overestimate the areal coverage of precipitation.
515 Nevertheless, all experiments still retain some deficiencies in the location and
516 intensity of the heavy precipitation forecasts, with the rainband displaced to the north
517 to varying degrees in all DA experiments. This likely reflects the fact that the
518 assimilated MD observations are limited to below 1 km and thus can only partially
519 constrain the thermodynamic structure of a deep convective system, while the
520 associated adjustment to the dynamical field through assimilation of thermodynamic



521 observations alone remains relatively weak.



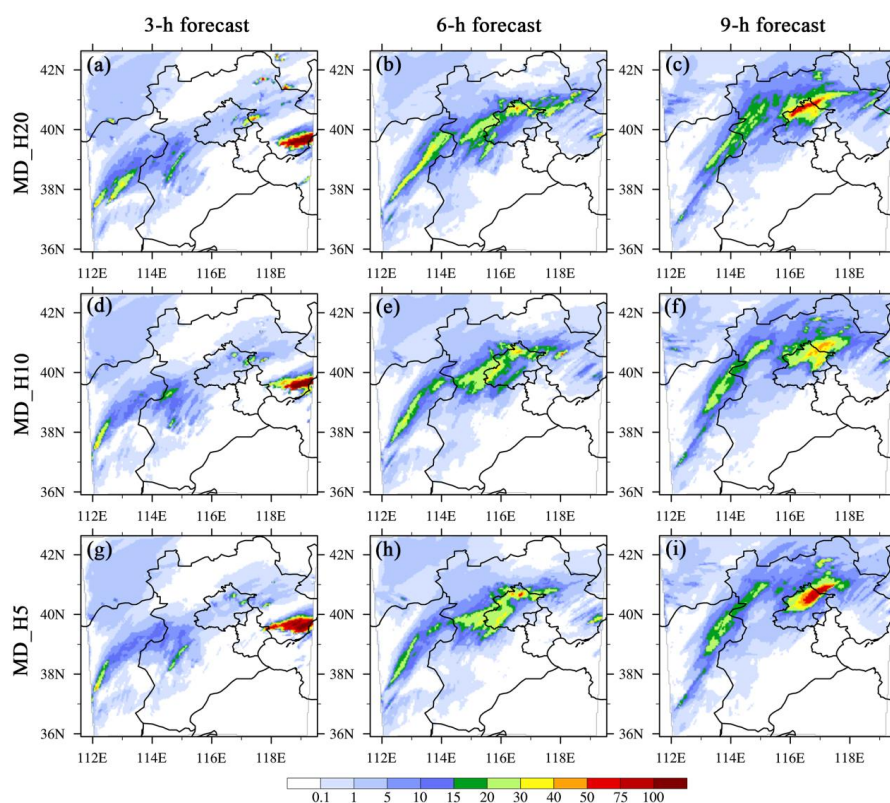
522

523 **Figure 7. Impact of horizontal resolution on precipitation forecasts.**

524 The 3-hourly accumulated precipitation forecasts (mm, shaded) for (a)-(c) Truth,

525 (d)-(f) NoDA, and (g)-(i) MD_H40 experiments initiated at 1800 UTC 29 July 2024.

526 The (left) 3-, (middle) 6-, and (right) 9-h forecasts are shown.



527

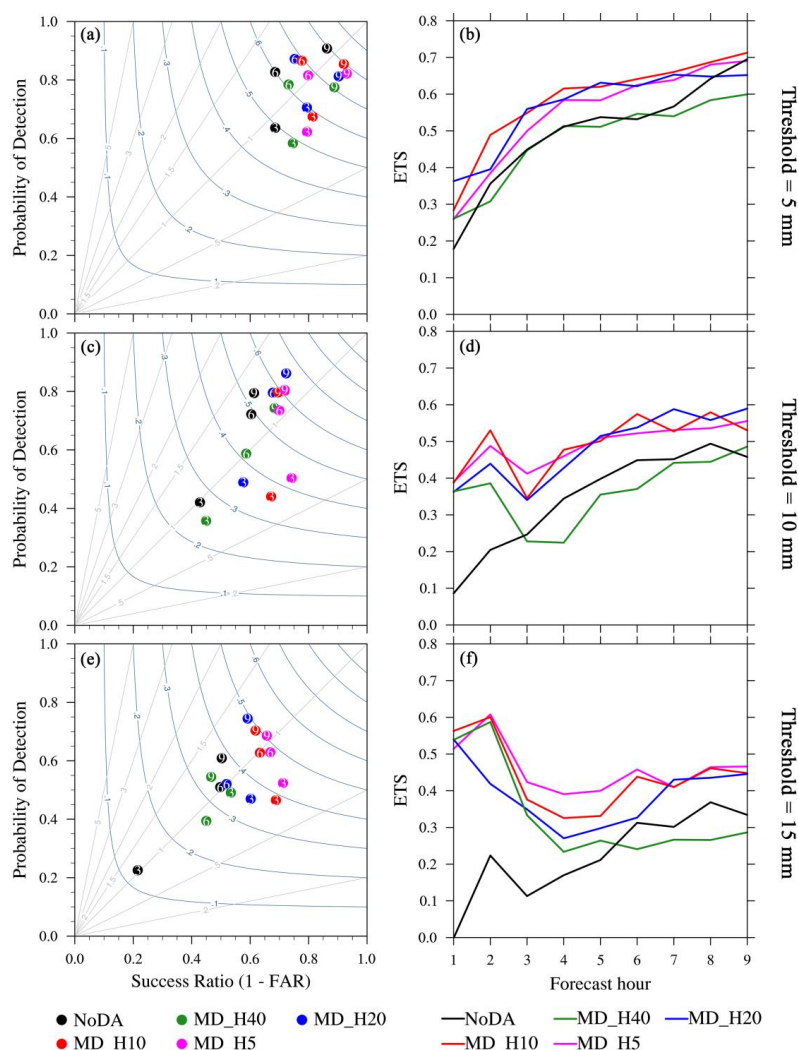
528 **Figure 8. Continued from Fig. 7.**

529 Same as in Fig. 7, but for the accumulated precipitation forecasts (mm, shaded) from

530 (a)–(c) MD_H20, (d)–(f) MD_H10, and (g)–(i) MD_H5 experiments.



531 To quantify the performance of precipitation forecasts by assimilating MD data
532 with different horizontal resolutions, neighborhood-based ETS and categorical
533 performance diagrams are derived for the 1-9 h hourly precipitation amount (HPRCP)
534 forecasts initialized at the end of the DA cycles (Fig. 9). All metrics are evaluated
535 using a 12-km neighborhood radius. In the performance diagrams, higher forecast
536 skill is associated with larger POD, SR, and CSI values and therefore points closer to
537 the upper-right corner, while BIAS values larger (smaller) than 1.0 indicate
538 overprediction (underprediction). Consistent with the spatial distribution of
539 precipitation forecasts shown in Fig. 7 and 8, all DA experiments, except MD_H40,
540 generally outperform NoDA throughout 1-9 h forecast period, indicating an overall
541 positive impact of MD DA on short-term precipitation forecasts. However, MD_H40
542 shows slightly degraded forecast skill at some forecast lead times, which may be
543 partly attributed to the fact that the 40-km MD network is too coarse to adequately
544 represent mesoscale and smaller-scale thermodynamic structures, as evidenced by the
545 residual temperature and moisture biases over Beijing and the upstream mountainous
546 region (Fig. 4c and Fig. 5c). MD_H5 and MD_H10 remain closest to the upper-right
547 portion of the performance diagrams and retain the largest ETS values for most
548 forecast lead times, followed by MD_H20, while MD_H40 has the poorest forecast
549 skills among all DA experiments. As the rainfall threshold increases from 5 to 15 mm,
550 forecast skill decreases in all experiments, as reflected by lower POD, SR, CSI, and
551 ETS values, but the relative ranking remains broadly similar. It is worth noting that
552 the skill advantage of MD_H5 is most pronounced at the 15-mm threshold.
553 Collectively, these score metrics support the visual impression from Fig. 7 and 8 that
554 denser MD networks, especially those with 10- and 5-km grid spacing, more
555 effectively predict the precipitation evolution and yield more accurate quantitative
556 precipitation forecasts.



557

558 **Figure 9. Impact of horizontal resolution on score metrics of precipitation**
559 **forecast.**

560 Score metrics of 1-9 h hourly precipitation amount (HPRCP) forecasts for the NoDA
561 (black), MD_H40 (green), MD_H20 (blue), MD_H10 (red), and MD_H5 (magenta)
562 experiments. (left) The performance diagrams, and (right) the equitable threat score
563 (ETS) for (a)–(b) 5 mm, (c)–(d) 10 mm, and (e)–(f) 15 mm thresholds, respectively.
564 Results are shown for a neighborhood radius of 12-km. The numbers within the
565 colored dots in the performance diagrams denote the forecast hour (i.e., 3-, 6-, and 9-h
566 forecasts).



Overall, the results in this section indicate that increasing the horizontal resolution of MD observations improves the representation of the lower-tropospheric thermodynamic structure, as reflected by reduced temperature and humidity analysis and forecast errors. The thermodynamic improvements contribute to more accurate precipitation forecasts, including better rainband placement, a more realistic representation of rainfall intensity, and higher quantitative precipitation forecast skill. Among the tested configurations, the 5- and 10-km MD observation networks show the most consistent benefits, suggesting that relatively dense MD observations are more effective for improving convective-scale short-term precipitation forecasts.

4.2 Sensitivity to observation height and spatial distribution

Given the generally positive impact of dense MD observations shown above, a natural next question is how the analysis and forecast sensitivity depends on the vertical placement and spatial deployment of the MD network. To address this issue, the experiments in this section compare three single-level MD assimilation configurations (i.e. the MD_H5_Z120, MD_H5_Z300, and MD_H5_Z600 experiments), in which observations are sampled at 120, 300, and 600 m, respectively, along with an additional experiment (MD_H5_Plain) in which the MD network is restricted to the plain area with terrain elevation below 300 m. These representative observation heights are chosen to reflect realistic low-altitude MD operations in China and are broadly consistent with typical operating levels within the PBL (Fig. 2). As the MD_H5 experiment shows the superior performance in Sect. 4.1, all sensitivity experiments in this section are performed using the 5-km MD network as the reference configuration.

Figure 10 compares the vertical profiles of domain-averaged RMSEs for temperature and specific humidity analyses from the second and third sets of DA experiment and the baseline experiment. As illustrated in Fig. 10a, the temperature RMSE profiles are broadly similar among the experiments in the middle and upper troposphere, and the primary differences are evident in the lower troposphere (below 700 hPa). The strongest sensitivity is found below about 800 hPa, where the analysis

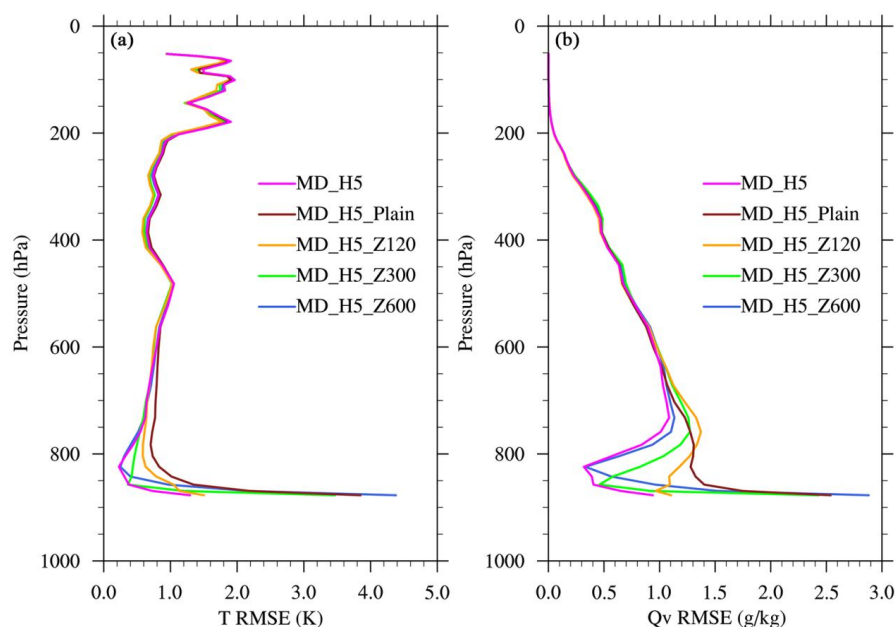


596 is most directly constrained by the assimilated MD observations. Within this layer, the
597 baseline experiment MD_H5 yields the smallest temperature RMSEs, whereas the
598 single-level DA experiments show varying degrees of degradation, with the
599 magnitude and vertical distribution of the errors depending on the observation height.
600 This indicates that observations distributed over multiple levels provide better
601 adjustments on the lower-tropospheric thermal structure than observations limited to a
602 single height. Among the three single-level experiments, MD_H5_Z600 and
603 MD_H5_Z300 generally outperform MD_H5_Z120 throughout most levels. It is also
604 noticed that the level where each single-level RMSE profile most closely matches that
605 of MD_H5 shifts upward with increasing observation height, consistent with the
606 vertical placement of the assimilated observations. On the other hand, the near-surface
607 temperature RMSE becomes larger as the observation height rises. By contrast,
608 MD_H5_Plain exhibits the largest temperature RMSEs through most levels, except
609 near the lowest level, where its analysis error is slightly smaller than that of
610 MD_H5_Z600. This suggests that restricting the MD network to the plain area
611 degrades the temperature analysis relative to the full-network configuration, likely
612 because the largest temperature errors are mainly located over the mountainous region
613 (Fig. 4b).

614 The humidity RMSE profiles exhibit a vertical dependence similar to that of
615 temperature, with relatively small differences among the experiments in the middle
616 and upper troposphere and stronger sensitivity in the lower troposphere (Fig. 10b).
617 Compared with the temperature analysis, however, the inter-experiment spread is
618 significantly larger below 700 hPa, indicating a stronger sensitivity of the moisture
619 analysis to MD observation height and network deployment. MD_H5 again yields the
620 smallest humidity RMSEs overall. And the single-level experiments show larger
621 errors, with MD_H5_Z120 performing the worst and the level of closest agreement
622 with MD_H5 shifting upward as the observation height increases. As in the
623 temperature field, restricting the network to the plain area similarly degrades the
624 humidity analysis, and MD_H5_Plain exhibits relatively larger RMSEs across much



625 of the lower troposphere. Overall, the moisture analysis is more sensitive than
626 temperature to both observation height and spatial distribution of MD data, while the
627 assimilation of multi-level MD observations provides the greatest improvement in the
628 lower-tropospheric moisture structure.

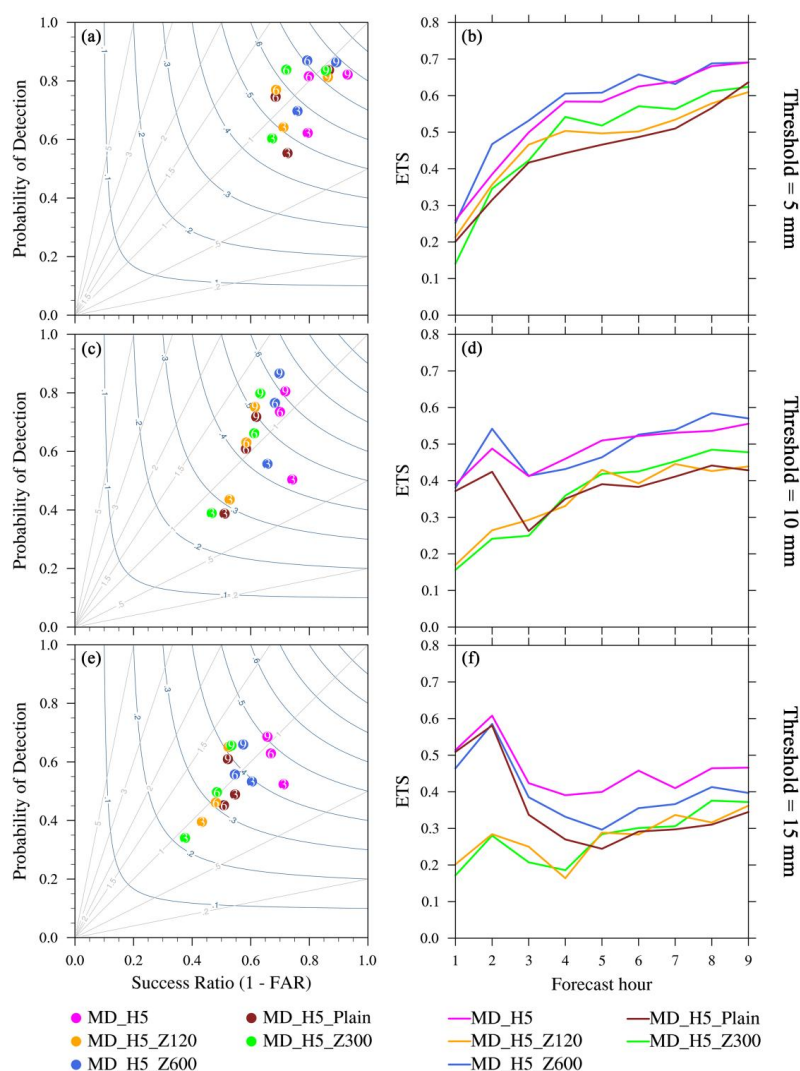


629 **Figure 10. Impact of observation height and spatial distribution on RMSE**
630 **profiles of temperature and humidity analyses.**

632 Vertical profiles of domain-averaged RMSEs for (a) temperature (K), and (b) specific
633 humidity (g kg^{-1}) analyses at 1800 UTC 29 July 2024 (end of the assimilation cycles)
634 from the MD_H5 (magenta), MD_H5_Plain (brown), MD_H5_Z120 (orange),
635 MD_H5_Z300 (green), and MD_H5_Z600 (blue) experiments.



636 To assess the impact of different observation heights and spatial distributions of
637 MD data on precipitation forecasts, neighborhood-based ETS and performance
638 diagrams for the sensitivity and baseline experiments are compared in Fig. 11. At the
639 5-mm threshold, all experiments show generally good forecast skill, but
640 MD_H5_Z600 exhibits superior performance throughout most forecast lead times,
641 with the highest ETS, CSI, POD, and SR values and a BIAS closest to 1, followed
642 closely by the baseline experiment MD_H5 (Fig. 11a and b). Among the remaining
643 sensitivity experiments, MD_H5_Z120 performs slightly better during the 1-3 h
644 forecast period, whereas MD_H5_Z300 becomes more skillful at later forecast lead
645 times. By contrast, the MD_H5_Plain experiment tends to show inferior performance
646 throughout most of the forecast period at the threshold of 5 mm. As the threshold
647 increases to 10 and 15 mm, the differences among the experiments become more
648 pronounced. For the 10-mm threshold, MD_H5 and MD_H5_Z600 show comparable
649 performance and remain the most skillful experiments (Fig. 11 c and d). Unlike the
650 5-mm threshold, MD_H5_Plain performs much better than MD_H5_Z300 and
651 MD_H5_Z120 during the first 3 h, while these three experiments exhibit similar
652 forecast skill thereafter. At the 15-mm threshold, the baseline experiment MD_H5
653 shows overwhelming superiority over the other DA experiments, followed by
654 MD_H5_Z600, whereas the plain-only and lower-level configurations remain less
655 skillful (Fig. 11 e and f). These results suggest that, within the tested height range,
656 MD observations extending to higher levels are generally more beneficial for
657 precipitation forecasts than those confined to the lowest level alone, while the
658 multi-level MD DA still provides the most robust overall improvement. In addition,
659 the degraded performance of the plain-only experiment highlights the importance of
660 MD thermodynamic observations over the upstream mountainous regions, where the
661 temperature and humidity errors are relatively large and where convection is initiated
662 before moving downstream into the plains.



663

664 **Figure 11. Impact of observation height and spatial distribution on precipitation**
665 **forecasts.**

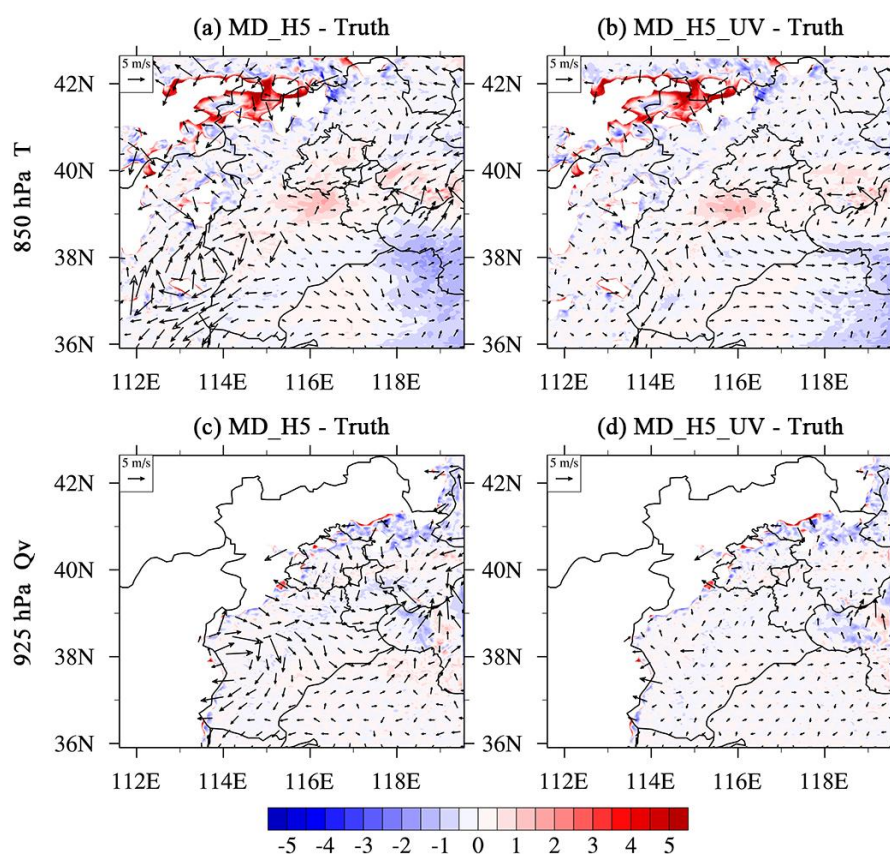
666 Same as Fig. 9, but for the MD_H5 (magenta), MD_H5_Plain (brown),
667 MD_H5_Z120 (orange), MD_H5_Z300 (green), and MD_H5_Z600 (blue)
668 experiments.



669 **4.3 Sensitivity to joint thermodynamic-wind assimilation and observation error**

670 The results above indicate assimilation of synthetic MD thermodynamic
671 observations can benefit convective-scale precipitation forecasts. Since the evolution
672 of convection also depends strongly on the dynamical environment, it is further
673 examined here whether the assimilation of MD wind observations together with
674 temperature and humidity data provides additional forecast skill. A related issue is
675 how sensitive is the assimilation performance to the assumed quality of the MD
676 observations. To address these questions, the experiments in this section investigate
677 the added value of jointly assimilating thermodynamic and wind observations, as well
678 as the sensitivity of the analyses and forecasts to prescribed observation errors in
679 temperature, humidity, and wind, respectively.

680 The influence of jointly assimilating MD wind observations with temperature
681 and humidity can be straightforwardly assessed by examining the temperature,
682 specific humidity, and wind departures from the truth (Fig. 12). The overall
683 temperature error pattern at 850 hPa remains similar between MD_H5 and
684 MD_H5_UV, with residual warm biases along the northern mountainous region and
685 weak cold biases over offshore area (Fig. 12a and b). For the humidity analysis, the
686 error patterns in MD_H5 and MD_H5_UV are also broadly similar (Fig. 12c and d),
687 indicating that the additional assimilation of wind observations has only a limited
688 effect on the thermodynamic analyses. In Contrast, the MD_H5_UV experiment
689 substantially reduces the wind errors relative to MD_H5, particularly along the
690 Taihang Mountains and the coastal area, where the lower-tropospheric flow structure
691 is remarkably better captured. This suggests that assimilating MD wind data together
692 with temperature and humidity observations not only improves the thermodynamic
693 analyses, but also yields a more pronounced additional benefit in optimizing the
694 lower-tropospheric dynamical field.



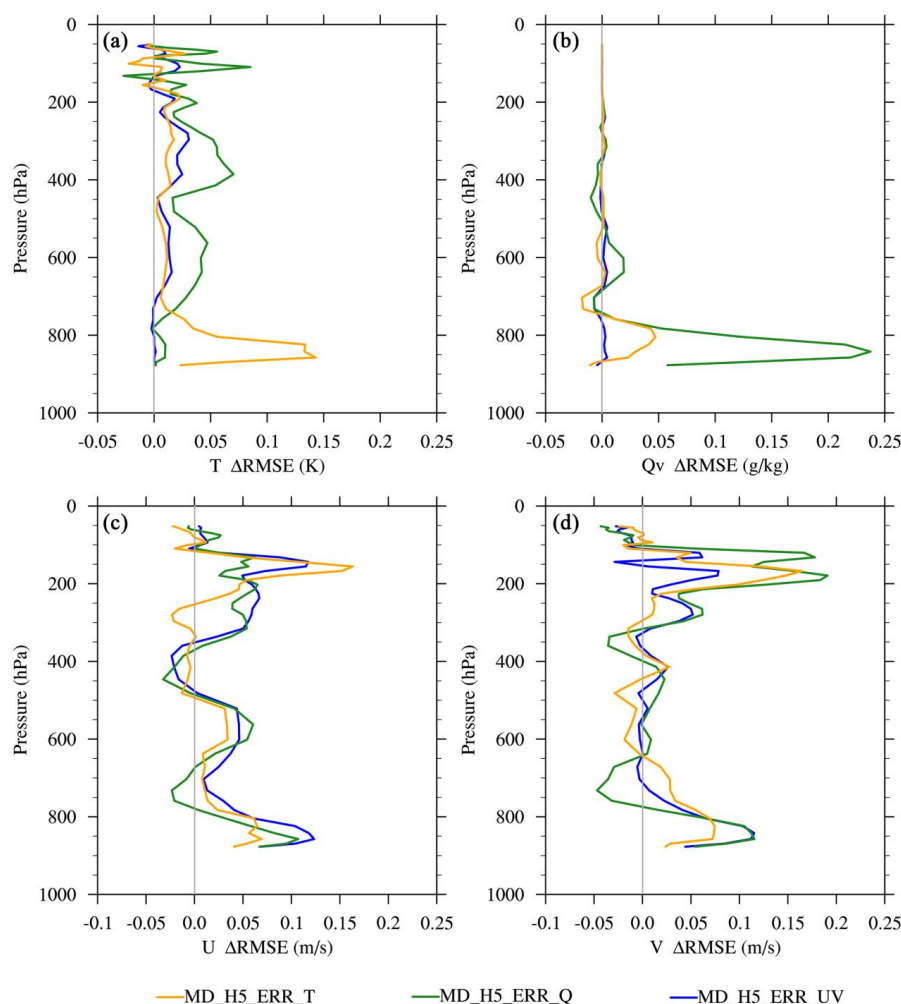
695

696 **Figure 12. Impact of joint assimilation of thermodynamic and wind observations**
697 **on analyses.**

698 (a) Differences in 850-hPa temperature ($^{\circ}\text{C}$, shaded) and wind (vectors) between the
699 MD_H5 experiment and the truth run at 1800 UTC 29 July 2024 (end of the
700 assimilation cycles). (b) As in (a), but for the MD_H5_UV experiment. (c)
701 Differences in 925-hPa specific humidity (g kg^{-1} , shaded) and wind (vectors) between
702 the MD_H5 experiment and the truth run. (d) As in (c), but for MD_H5_UV.



703 Figure 13 illustrates the sensitivity of the analyses to inflated observation errors
704 for temperature, humidity, and wind observations, respectively. To highlight the
705 differences among the sensitivity experiments, this figure shows the vertical profiles
706 of RMSE differences relative to the MD_H5_UV experiment, such that positive
707 values (to the right of the gray line in Fig. 13) represent degraded analyses under
708 inflated observation errors. The response is clearly variable dependent, with the most
709 pronounced degradations generally occurring in the lower troposphere, where the MD
710 observations provide the strongest constraint. As expected, increasing the temperature
711 (humidity) observation error mainly degrades the temperature (humidity) analysis,
712 especially below about 700 hPa, while its impact on the humidity (temperature)
713 analysis remains comparatively limited (Fig. 13a and b). Moreover, inflated
714 temperature or humidity observation error also increases the wind RMSEs in both the
715 upper and lower troposphere (Fig. 13c and d). This behavior suggests that, although
716 the thermodynamic analyses are adjusted primarily by their respective observations,
717 the resulting thermal perturbations can still affect the wind analysis through
718 hydrostatic and mass-wind balance relationships embedded in the variational system.
719 By contrast, increasing the wind observation error produces the largest degradations
720 in both the u and v analyses, whereas its impact on the thermodynamic analyses
721 remains relatively small, which agrees well with the earlier finding that the additional
722 assimilation of wind observation exerts only a limited influence on the
723 thermodynamic analyses (Fig. 12). Overall, the analysis is controlled primarily by the
724 observation error standard deviations of the directly assimilated variables, while
725 cross-variable correlations allow part of the observational information, and its
726 associated error, to be distributed to related fields. These results emphasize that the
727 quality of MD observations is critical for obtaining an accurate lower-tropospheric
728 analysis, and that consistency between thermodynamic and wind observations is also
729 important for maintaining a balanced and dynamically coherent analysis.



730

731 **Figure 13. Impact of inflated observation errors on analysis RMSEs.**

732 Vertical profiles of (a) temperature (K), (b) specific humidity (g kg^{-1}), (c) u (m s^{-1}),
 733 and (d) v (m s^{-1}) analysis RMSE differences for the MD_H5_ERR_T (orange),
 734 MD_H5_ERR_Q (green), and MD_H5_ERR_UV (blue) experiments relative to the
 735 MD_H5_UV experiment at 1800 UTC 29 July 2024. The gray vertical line denotes
 736 zero RMSE difference; positive values to the right of the line indicate degraded
 737 analysis.

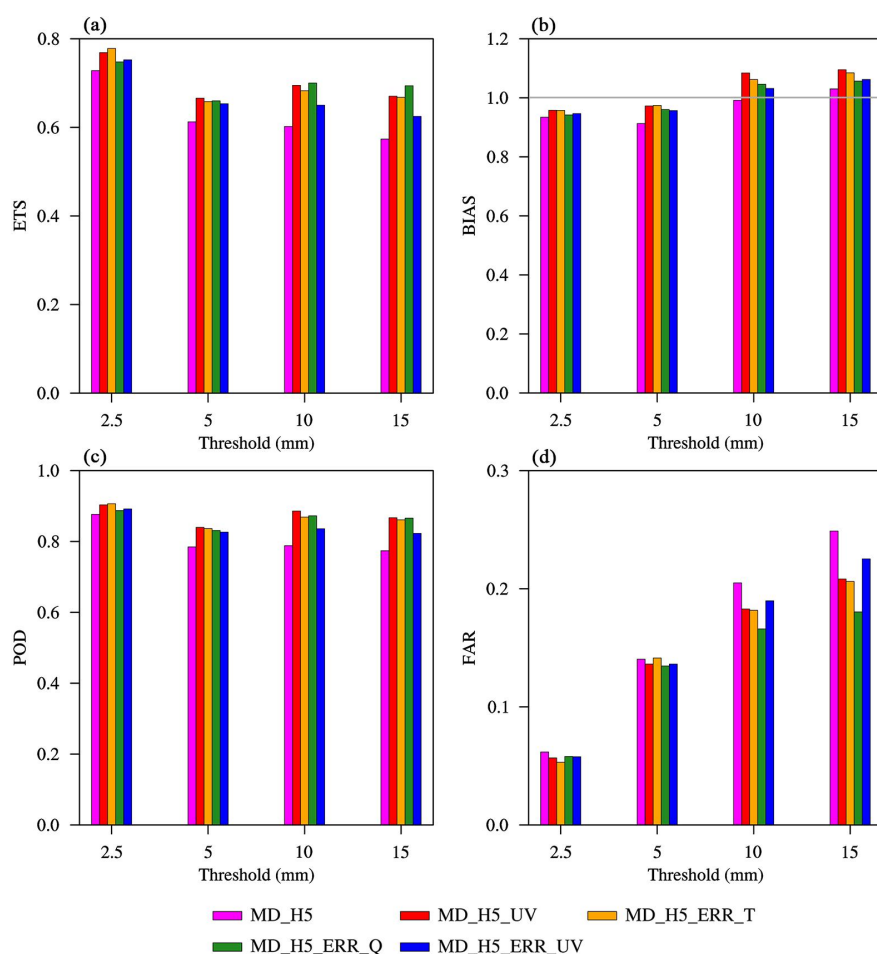
738 To provide an overall assessment of the effects of joint thermodynamic-wind
 739 assimilation and observation error on precipitation forecasts, quantitative verification



740 metrics including ETS, BIAS, POD, and FAR for the 6-h accumulated precipitation
741 forecast are compared among the MD_H5, MD_H5_UV, MD_H5_ERR_T,
742 MD_H5_ERR_Q, and MD_H5_ERR_UV experiments (Fig. 14). Compared with the
743 thermodynamic-only baseline experiment MD_H5, the joint assimilation experiment
744 MD_H5_UV consistently yields higher ETS and POD values, and lower FARs at all
745 thresholds, together with a modest increase in BIAS. This indicates that incorporating
746 wind observations improves precipitation forecasts without substantially increasing
747 overprediction. This is mainly attributed to improvements in the lower-tropospheric
748 wind analyses by joint thermodynamic-wind assimilation (Fig. 12), underscoring the
749 importance of PBL flow field in the convective-scale precipitation forecast.
750 Additionally, the sensitivity to prescribed observation error is also evident in Fig. 14.
751 At the lower thresholds of 2.5 and 5 mm, the differences among the DA experiments
752 are relatively small, suggesting that light-to-moderate rainfall forecasts are less
753 sensitive to the assumed MD observation quality (Fig. 14a and b). At the 10- and
754 15-mm thresholds, however, the contrasts become more pronounced (Fig. 14c and d).
755 Although the ETS and POD (FAR) scores from the three inflated-error joint
756 assimilation experiments are lower (higher) than those of MD_H5_UV, they still
757 generally outperform MD_H5 across most thresholds. Regarding BIAS, a slight
758 underprediction (overprediction) bias is observed for all DA experiments at the 2.5
759 and 5 mm (10 and 15 mm) thresholds. Among the three error-inflation experiments,
760 MD_H5_ERR_UV shows the most evident reduction in forecast skill overall,
761 indicating that rainfall prediction is especially sensitive to the wind observation errors.
762 By contrast, MD_H5_ERR_Q exhibits a somewhat different behavior from
763 MD_H5_ERR_T and MD_H5_ERR_UV, with ETS slightly higher than that of
764 MD_H5_UV and FAR occasionally lower at some thresholds (e.g. 10 and 15 mm).
765 Several factors may contribute to this result. First, the precipitation forecast in this
766 case appears to be more sensitive to the retained wind and temperature constraints
767 than to a moderate degradation of the humidity analysis. Second, inflating the
768 humidity observation error may weaken the direct moisture adjustment and thus



769 reduce localized moisture overcorrection, which can in turn suppress overpredicted
770 precipitation in northern Beijing. Third, as the variational assimilation system
771 distributes observational information through coupled thermodynamic and dynamical
772 balance relationships, and the model forecast between assimilation cycles further
773 enforces consistency among variables, part of the loss of humidity information may be
774 compensated for by the remaining temperature and wind observations.



775

776 **Figure 14. Impact of joint assimilation and observational error on precipitation**
777 **forecasts.**

778 (a) The equitable threat score (ETS) , (b) bias, (c) probability of detection (POD), and
779 (d) false alarm ratio (FAR) of 6-hourly accumulated precipitation forecasts from the



MD_H5 (magenta), MD_H5_UV (red), MD_H5_ERR_T (orange), MD_H5_ERR_Q (green), and MD_H5_ERR_UV (blue) experiments at 2.5-, 5-, 10-, and 15-mm thresholds, respectively.

In summary, jointly assimilating wind observations with temperature and humidity provides clear additional benefits over the thermodynamic DA alone. Although the thermodynamic analysis fields are only slightly modified by wind DA, the lower-tropospheric flow is significantly improved, and this dynamical improvement leads to more skillful 6-h precipitation forecasts. The observation-error sensitivity experiments further show that the forecast benefit is also sensitive to the assumed quality of MD data, with the most pronounced degradation in forecast skill occurring when the wind observation error is inflated. These findings highlight the importance of both accurately representing the PBL airflow and maintaining high-quality, internally consistent thermodynamic and wind observations for improving convective-scale analyses and precipitation forecasts.

5. Summary and conclusions

This research investigates the potential impact of MD observations on convective-scale analyses and short-term precipitation forecasts through an OSSE framework. Synthetic MD observations of temperature, specific humidity, and horizontal winds are generated from the free-running truth simulation and assimilated into the convective-scale DA system NSSL3DVAR. A series of sensitivity experiments is conducted to examine how MD network horizontal resolution, observation height, spatial distribution, joint thermodynamic-wind assimilation, and observation errors affect the analyses and forecasts.

The results indicate that the horizontal resolution of the MD network has a pronounced impact on both thermodynamic analyses and precipitation forecasts. Assimilating higher-horizontal-resolution MD data yields smaller temperature and humidity errors during the assimilation cycles and subsequent short-term forecasts, as well as improved precipitation forecasts in terms of rainband placement, rainfall



808 intensity, and quantitative score metrics. Among the tested configurations, the 5- and
809 10-km networks provide the most consistent benefits, whereas the 40-km network is
810 too coarse to adequately resolve the mesoscale and smaller-scale thermodynamic
811 structures relevant to convective precipitation evolution.

812 Sensitivity experiments on observation height reveal that the impact of MD
813 observations also depends on their vertical placement within the PBL. Multi-level MD
814 DA provides the most balanced improvements in both temperature and humidity
815 analyses, while single-level observations confined to the lower levels are less
816 effective. In general, assimilation of observations extending to higher levels (i.e. 600
817 m) is more beneficial for precipitation forecasts than those limited to the lowest level
818 alone. In addition, the inferior forecast performance in the plain-only DA experiment
819 also underscores the value of MD observations over the upstream mountainous areas,
820 where larger thermodynamic errors persist and where the convection system in this
821 case is initiated and intensifies before propagating into the downstream plains.

822 The joint assimilation of MD wind observations with thermodynamic data
823 further improves the analyses and forecasts. The additional assimilation of wind
824 observations substantially reduces wind analysis errors, especially over the Taihang
825 Mountains and the coastal areas, although it produces only very small additional
826 adjustments to the temperature and humidity analyses beyond those already achieved
827 by thermodynamic observations. This dynamical improvement leads to more skillful
828 precipitation forecasts, indicating that an accurate representation of the PBL flow is
829 important for convective-scale precipitation prediction. The observation-error
830 sensitivity experiments further demonstrate that forecast skill is also influenced by the
831 assumed quality of MD observations, with inflated wind observation error producing
832 the most pronounced degradation in precipitation forecast performance. These results
833 indicate that the impact of MD observations depends not only on the availability of
834 both thermodynamic and wind measurements, but also on their resolution, vertical
835 distribution, and accuracy and mutual dynamical and thermodynamic consistency.



836 Overall, the OSSE results consistently demonstrate that MD observations have
837 considerable potential to improve convective-scale analyses and short-term
838 precipitation forecasts. The greatest forecast benefits are achieved when the MD
839 network is sufficiently dense, spans multiple levels within the PBL, incorporates wind
840 observations, and samples the upstream mountainous region where convection is
841 initiated. Meanwhile, the results also suggest that the forecast impact remains
842 sensitive to the observation error standard deviations and to the limited vertical extent
843 of low-altitude MD measurements. The insights gained from this OSSE study can
844 help guide the optimal design of MD observation networks over the BTH region.

845 Although this study shows encouraging results of assimilating simulated MD
846 data into a convective-scale model, several limitations should be noted. First, only
847 synthetic MD observations are assimilated, while conventional observations (e. g.,
848 radiosonde and surface data) as well as radar and satellite observations are excluded.
849 This experimental design facilitates a clearer attribution of forecast impacts to MD
850 observations, while the forecast improvements reported here should therefore be
851 interpreted as an estimate of the maximum potential impact of MD observations. In
852 operational applications, where conventional observations are already assimilated, the
853 incremental benefit of MD observations may be smaller and warrants further
854 investigation. Second, the MD observations are confined to the lower troposphere
855 (below 1 km), consistent with current low-altitude MD deployment strategies in China,
856 so their ability to constrain the full-depth thermodynamic structure of deep convection
857 remains limited. Third, the conclusions are based on a heavy rainfall event occurred
858 over the Beijing-Tianjin-Hebei region. Additional cases covering different synoptic
859 and convective environments and regions are needed to assess the robustness and
860 generality of these findings. Future work should therefore extend the present
861 framework to multiple cases, incorporate MD observations together with other dense
862 observations, and further evaluate optimal strategies for network density, observation
863 height, and adaptive deployment. Moreover, the benefits of assimilating real MD
864 observations for convective-scale NWP can be investigated once operational MD



865 networks become available. Such efforts will provide a more comprehensive
866 assessment of the practical value of MD observations for convective-scale NWP and
867 short-term high-impact weather forecasting.

868

869 **Code and data availability**

870 The ERA5 reanalysis and GFS forecast data are accessible from ECMWF
871 (<https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5/>, Hersbach et al.,
872 2020) and National Centers for Environmental Prediction, National Weather Service,
873 NOAA, US Department of Commerce (<https://doi.org/10.5065/D65D8PWK>, National
874 Centers for Environmental Prediction et al., 2015), respectively. The source code for
875 WRF model version 3.7.1 and the input ERA5 and GFS data used in this study have
876 been archived on Zenodo at <https://doi.org/10.5281/zenodo.19691512> (Zhao, 2026a).
877 The namelist files for WRF and the assimilation system used in this study are
878 accessible online (<https://doi.org/10.5281/zenodo.19691638>, Zhao, 2026b).

879

880 **Author contributions**

881 JZ and JPG conceptualized this study. JZ executed the experiments, analyzed the
882 results, and wrote the original draft. JPG supervised the project, delivered key
883 suggestions during experiments, and participated in manuscript revision. JDG
884 provided guidance for the DA method and contributed to the revision of the
885 manuscript. HLY provided guidance on the design of the MD observation networks.

886

887 **Competing interests**

888 The contact author has declared that none of the authors has any competing interests.

889

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