

ESSD-2021-217

Response to RC1 (Referee 1)

The authors thank referee 1 for a thoughtful review of the manuscript. We agree with many of the referee's points and have made the necessary changes. The responses for the referee's specific comments are as follows.

Overall comments:

The authors generated the East Asia Regional Reanalysis (EARR) using Weather Research and Forecasting (WRF, v3.7.1) during the ten-year period 2010-2019, based on the advanced hybrid gain data assimilation method (AdvHG). The new advanced hybrid gain (AdvHG) data assimilation method combining E3DVAR and ERA5 based on WRF model is newly proposed and investigated in this study. The manuscript verified the EARR for two-year period 2017-2018 by comparing EARR against ERA-Interim, ERA5 and observations.

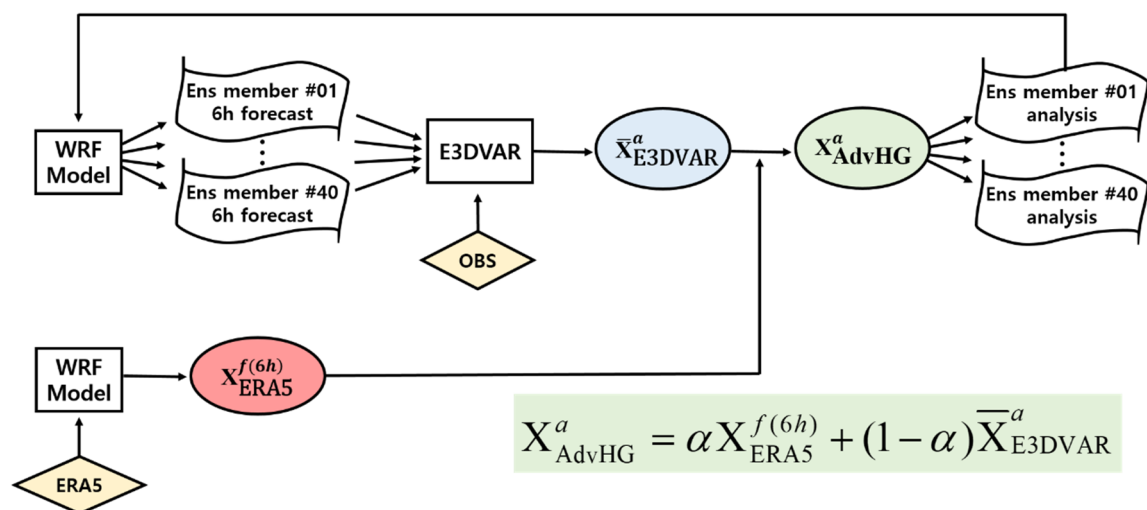
I think a lot of work behind this manuscript is worth publishing. However, there are some details and the underlying physics processes were not well discussed.

The detailed comments are listed as below.

Major comments:

1-A. It is not easy to understand the regional reanalysis method used in this paper. I'd suggest the authors use schematic diagram to clearly describe the regional reanalysis method.

Authors' response: Following the referee's suggestion, a schematic diagram for the advanced hybrid gain method is added to the revised manuscript as Fig. 2 (Figure_rev1. below).



Figure_rev1. The schematic diagram of the advanced hybrid gain data assimilation method in the East Asia regional reanalysis system.

1-B. What does “forecast fields are integrated up to 36h” mean? Is reinitialization used? What does “6h forecast of ERA5 reanalysis based on WRF model” mean? Does it mean WRF simulations using ERA5 as LBC forcing?

Authors' response: “Forecast fields are integrated up to 36 h” implies that forecast fields are produced using WRF model for 36 h. Thus, 24 and 36 h forecast fields are evaluated in this study (Figs. 4, 5, and 7 in the revised manuscript).

Reinitialization is not used in this study. For the experiments using data assimilation methods based on WRF model (E3DVAR, AdvHG), analysis fields are produced every 6 h (00, 06, 12, 18 UTC) via 6-h assimilation cycle, so forecast fields are generated from these cycled analysis fields used as initial conditions. For (WRF-based) ERA5 and ERA-I experiments, 36 h forecast fields are generated using WRF model with ERA5 and ERA-I reanalysis fields used as initial conditions, so reinitialization is not required in this study.

“6 h forecast of ERA5 reanalysis based on WRF model” means that 6 h forecast fields are produced using WRF model with ERA5 reanalysis as the initial condition. For WRF-based

ERA5 experiment, ERA5 is used as the lateral boundary condition as well as the initial condition in WRF model.

1-C. How many experiments are used in this manuscript? What experiments do “E3DVAR”, “AdvHG”, “WRF-ERA5” and “WRF-ERAIN” refer to respectively? These details should be more clarified.

Authors’ response: In this study, E3DVAR and AdvHG imply analysis or forecast fields of experiments based on WRF model using E3DVAR and AdvHG data assimilation methods, respectively. Regarding reanalysis and (re)forecast fields of ECMWF, reanalysis fields (ERA5 and ERA-I) downloaded from ECMWF are evaluated (Figs. 3 and 6 in the revised manuscript). There are two different (re)forecast fields (e.g., ERA5_fromECMWF, WRF-based ERA5) used in this study, as mentioned in section 2.4. WRF-based ERA5 and ERA-I are forecast fields based on WRF model where ERA5 and ERA-I are used as initial conditions, respectively. In contrast, ERA5_fromECMWF and ERA-I_fromECMWF are reforecast fields based on ECMWF model not WRF model, and these reforecast fields are only evaluated for precipitation (Figs. 8 and 9 in the revised manuscript). Following the referee’s suggestion, detailed information on each experiment is added to section 2.4 and Table 3 in the revised manuscript (L210-219) as follows (underlined).

(L210-219) “In this study, (re)forecast as well as reanalysis fields need to be verified. Regarding reanalysis and (re)forecast fields of ECMWF, reanalysis fields (i.e., ERA5 and ERA-I) downloaded from ECMWF are evaluated (Figs. 3 and 6). There are two different (re)forecast fields (e.g., ERA5_fromECMWF, WRF-based ERA5) used in this study. WRF-based ERA5 and ERA-I are forecast fields based on WRF model with 12 km horizontal resolution where ERA5 and ERA-I are used as initial conditions, respectively. In contrast, ERA5_fromECMWF and ERA-I_fromECMWF are reforecast fields based on ECMWF model not WRF model, so the reforecast fields of ERA5 and ERA-I are provided and downloaded from ECMWF. These reforecast fields are only used for evaluation of precipitation (Figs. 8 and 9). The (re)analysis and (re)forecast fields and corresponding experiments are explained in Table 3”

2. The newly advanced hybrid gain (AdvHG) data assimilation method uses 6h forecast ERA5 instead of deterministic analysis, and uses ERA5 instead of producing their own analysis fields from a variational DA method. The method is expected to save time and computing cost compared to traditional data assimilation framework. Why does the author use the 6h forecast of ERA5 reanalysis based on WRF instead of the deterministic analysis in AdvHG? Will the regional reanalysis be more accurate if using ERA5 deterministic analysis in AdvHG?

Authors’ response: In this study, 6 h forecast of ERA5 based on WRF model is used instead of ERA5 reanalysis fields to maintain the consistency between different modeling systems as well as different resolutions. ERA5 reanalysis fields are generated based on the Integrated Forecasting System (IFS) of ECMWF with approximately 30 km horizontal

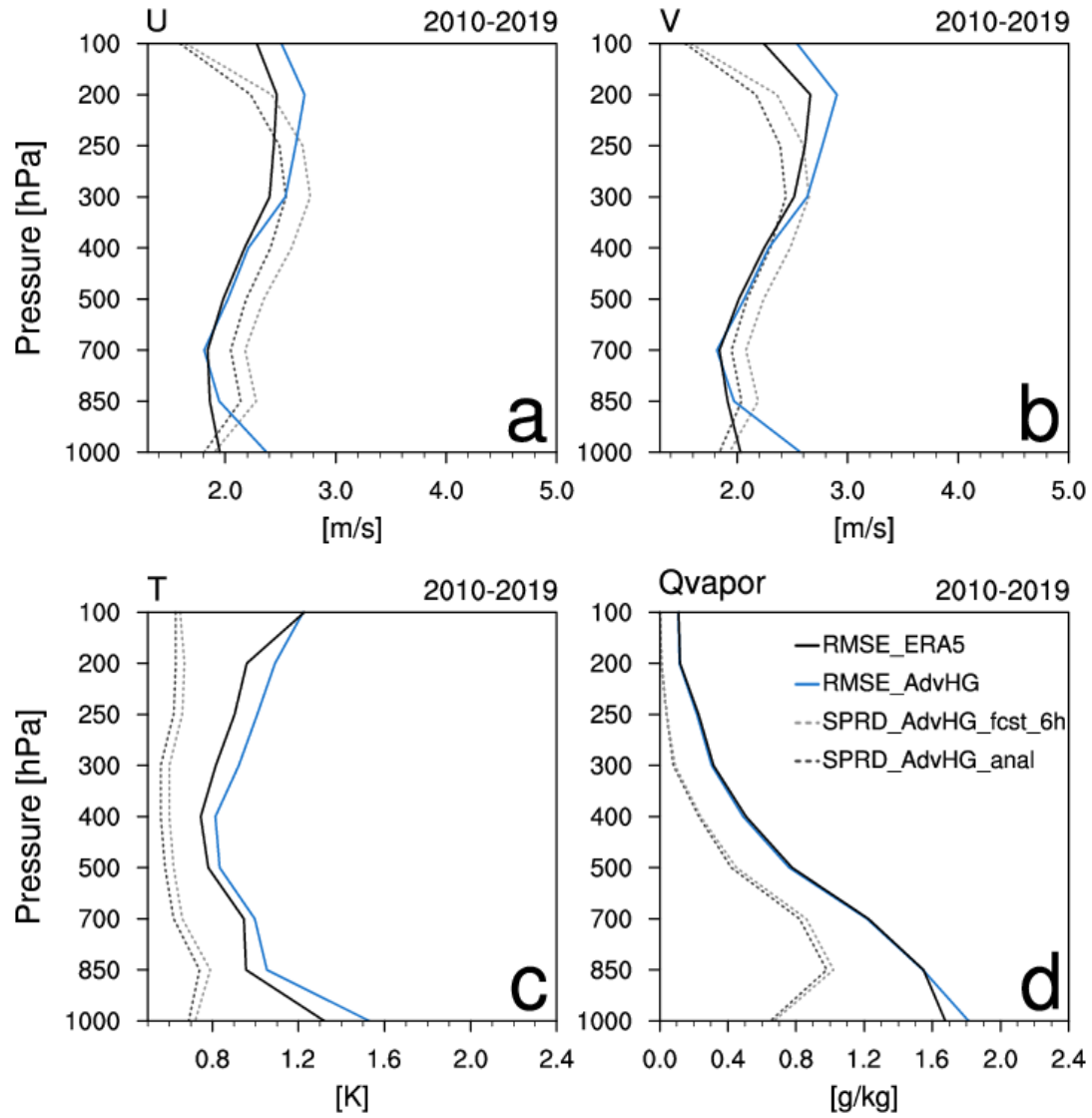
resolution. If ERA5 reanalysis is directly used to combine with E3DVAR analysis based on WRF model whose horizontal resolution is 12 km, there could be some imbalance occurred in meteorological fields resulting from two different modeling systems. Thus, to reduce the imbalance and ensure the stability and consistency during analysis process, 6 h forecast of ERA5 is used instead of ERA5 deterministic reanalysis in Advanced Hybrid Gain method.

3. EARR is developed during the ten-year period 2010-2019, while in the manuscript, the authors only verified the product for two-year period 2017-2018. Why is this two-year period instead of the entire ten-year period chosen to be verified? I would like to see how the EARR product performs compared to the other two ECMWF global reanalysis in a longer time period, and whether EARR is suitable for application in long-term climatology research. If so, the influence of this product will be greatly increased.

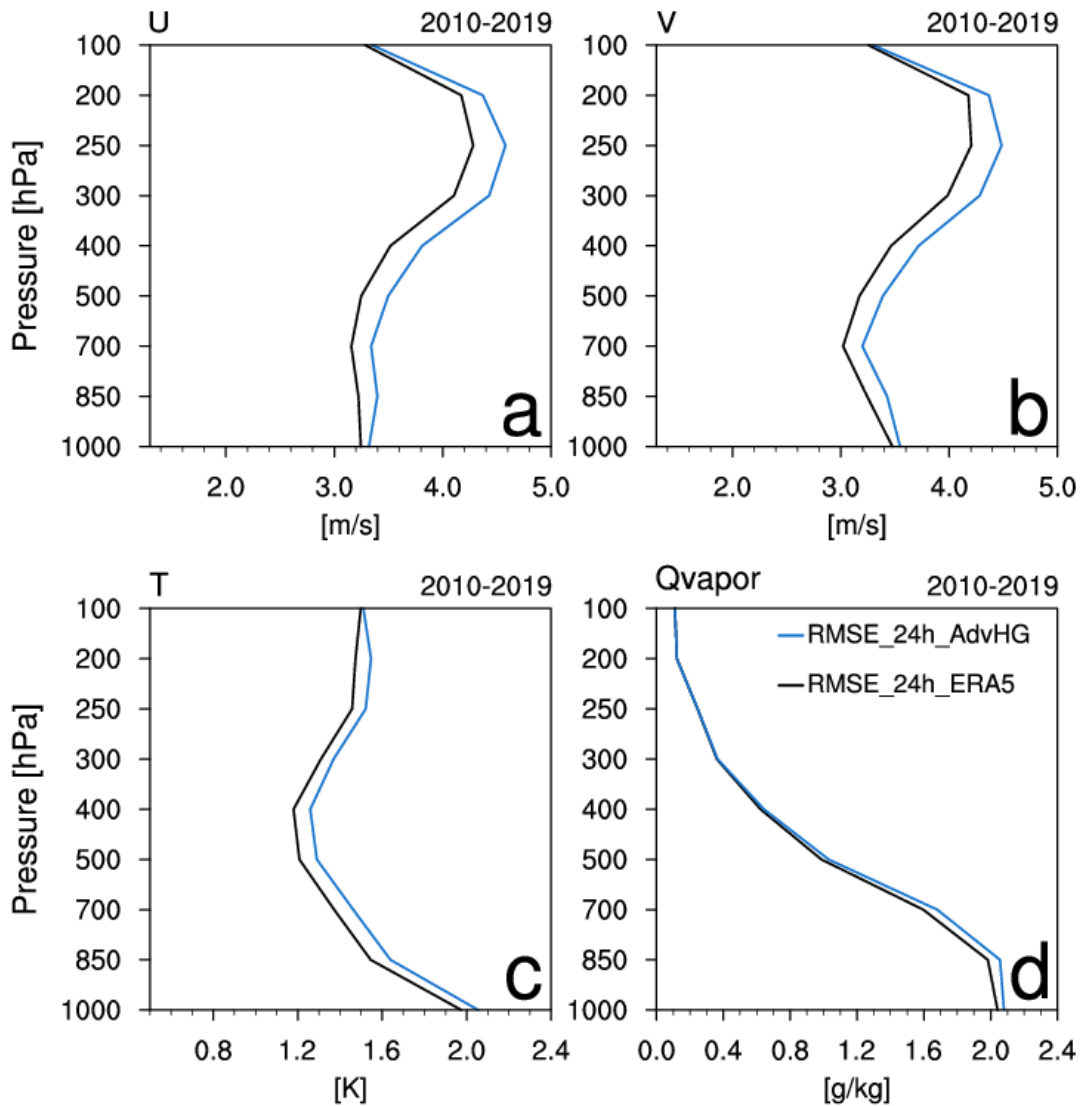
Authors' response: One of the reasons for verifying only for two-year period in this study is that producing 36 h forecast fields of ERA5 using WRF model for 10-year period is too computationally expensive. In this study, (re)forecast as well as (re)analysis fields are verified. As mentioned in the section 2.4, for (re)forecast fields, two different forecast fields from ECMWF (i.e., forecast based on WRF model and reforecast based on ECMWF model) are used for comparison. In particular, 24 h forecast fields of ERA5 using WRF model are evaluated, as shown in Figs. 4 and 7 in the revised manuscript. While 24 h reforecast fields of EARR (AdvHG) for 10-year period have been generated during production process for the whole period, producing 24 h forecast for ERA5 is not necessary. Hence, two-year period was originally chosen for the purpose of evaluation. Furthermore, we consider it more valuable to make our dataset open to the public at the earliest possible time, so that it could benefit more people using this dataset. For these reasons, two-year period was originally verified in this study.

Nevertheless, as the referee pointed out, more investigation for longer-term period would be necessary. Therefore, as the referee proposed, we have evaluated longer-term datasets of EARR and ERA5 that are able to be verified for the whole 10-year period and replaced the results of two-year period with those of ten-year period (Figs. 6 and 7 in the revised manuscript) (Please see Figs_rev2 and rev3 below). Because the aim of our study is to investigate EARR (AdvHG) performance with ERA5, it is worth evaluating reanalysis and (re)forecast fields of EARR and ERA5 for 10-year period, as referee pointed out. However, it seems unfeasible to compare EARR performance with various experiments (e.g., E3DVAR, ERA-Interim) for the whole period due to the high computational costs producing those datasets, especially ensemble-based one (i.e. E3DVAR). The updated results for the period of 2010-2019 (Figs_rev2 and rev3) are almost the same as the previous results with two-year period, except for the water vapor mixing ratio (Qvapor). Although Qvapor RMSEs of reanalysis and (re)forecast of EARR and ERA5 for ten-year period are greater than those for two-year period, both of EARR and ERA5 Qvapor RMSEs increase and the RMSE differences between EARR and ERA5 for ten-year period are

similar to those for two-year period. Thus, the longer-term evaluation reveals a large variability of atmospheric humidity and consequent predictability variability over East Asia for ten-year period of 2010-2019. We have revised the manuscript accordingly.



Figure_rev2. RMSEs of analysis of (a) zonal wind, (b) meridional wind, (c) temperature, and (d) Qvapor (water vapor mixing ratio) from ERA5 (black solid) and AdvHG (blue solid) and spreads of analysis (black dashed) and 6 h forecast (gray dashed) of AdvHG depending on pressure levels averaged over the ten-year period of 2010–2019.

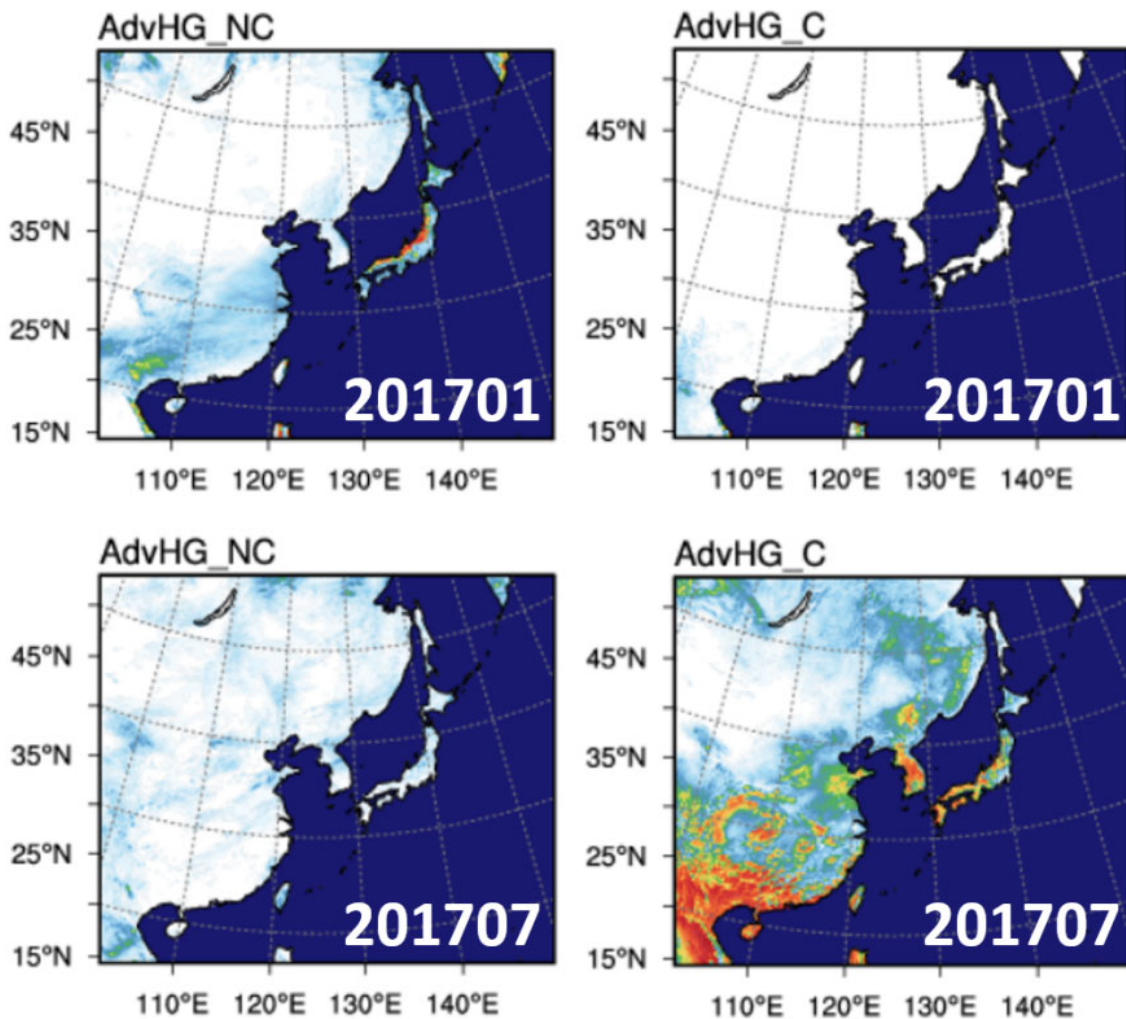


Figure_rev3. Same as Fig_rev2 except for RMSE of 24 h forecast.

4. The precipitation of AdvHG in winter (January) is the most accurate among other results, while E3DVAR (ERA5) performs better for weak (strong) thresholds in summer (July). The assimilation method tends to have positive effects on the simulated winter rainfall while brings limited improvement on summer rainfall. The possible underlying physics have not been well understood. Which physical process could be mostly possible affected leading to such positive effects?

Authors' response: As the referee pointed out, AdvHG shows the most accurate performance of precipitation in winter. In contrast, it shows limited improvement for summer. For summer season, ETS differences between the different results are not significant and the values of ETS are approximately 2 times smaller than those for the winter season (Fig. 8 in the revised manuscript). Hence, the overall predictability of precipitation for winter season for all results is higher than that for summer season.

To elucidate which physical process is responsible for more accurate simulation of precipitation, non-convective and convective precipitation fields of AdvHG are investigated respectively. The precipitation fields from microphysics (AdvHG_NC) and cumulus (AdvHG_C) parameterization schemes in WRF model for January and July 2017 are shown in Figure_rev4, and two seasons have different features in precipitation. While the majority of precipitation in January 2017 is represented by the large-scale (non-convective) precipitation, the simulation of precipitation in July 2017 depends mostly on the convective precipitation. Because convective scheme is more likely to have larger sub-grid variability, the predictability of precipitation in winter where large-scale precipitation can represent most of the total precipitation fields tends to be higher than that in summer.



Figure_rev4. The spatial distribution of the monthly accumulated precipitation of AdvHG from microphysics (AdvHG_NC) and cumulus (AdvHG_C) schemes for January and July 2017.

Furthermore, although large-scale variables of ERA5 forecast based on WRF (wind, temperature, specific humidity) have the lowest RMSEs among other results both for winter and summer seasons, the differences of forecast RMSEs between ERA5 and AdvHG for winter are much smaller than those for summer (Figs. 4 and 5 in the revised manuscript). The more accurate large-scale variables of AdvHG in winter could lead to higher AdvHG ETS in winter. Although AdvHG forecasts have less accurate large-scale variables than ERA5 forecasts, AdvHG ETS is higher than ERA ETS in winter implying that the precipitation could be a combination of small and large-scale processes in winter. In addition, it seems that producing analysis and forecast in the same system (WRF in AdvHG) could lead positive effects. Therefore, the consistency of modeling system for producing analysis and forecast could be fundamentally important.

5. Figure 2, it is clear that E3DVAR has the lowest RMSE for up-level variables, so what are the advantages of AdvHG? Does ERA5 in Fig. 2 mean WRF results forcing by ERA5?

Authors' response: As mentioned in the original manuscript L251-254 (in the revised manuscript L288-291), lower RMSEs of analysis fields do not guarantee the higher accuracy of analysis fields. Instead, RMSE of analysis indicates how much analysis fields are fitted to observations. Thus, not only those of analysis fields but also those of forecast fields need to be evaluated and compared to each other. As the referee pointed out in Fig. 2 in the original manuscript (Fig. 3 in the revised manuscript), the RMSEs of analysis fields of E3DVAR are lower than those of AdvHG. However, in Figs. 3 and 4 in the original manuscript (Figs 4 and 5 in the revised manuscript), RMSEs of 24 h and 36 h forecast fields of AdvHG are lower than those of E3DVAR. This is why AdvHG is used as a data assimilation method for East Asia Regional Reanalysis system in this study.

In addition, the ERA RMSEs in Fig. 2 in the original manuscript (Fig. 3 in the revised manuscript) are calculated based on ERA reanalysis fields downloaded from ECMWF. In contrast, ERA5 in Figs. 3, 4, and 6 in the original manuscript (Figs. 4, 5, and 7 in the revised manuscript) indicates forecast fields using WRF model, where ERA5 is used as the initial and lateral boundary conditions.

Minor comments:

1. The meaning of variables in Eq. (3)-(6) should be clarified.

Authors' response: Following the referee's suggestion, the explanation of variables in Eqs. (3)-(6) are added to the revised manuscript L141-143 as follows (underlined).

(L141-143) "**H** is an observation operator mapping the model state vector to observation space and **R** is the observation error covariance matrix. The matrices **P^f** and **B** indicate the ensemble-based and the static climatological BEC, respectively."

The authors thank referee 2 for a thoughtful review of the manuscript. We agree with many of the referee’s points and have made the necessary changes. The responses for the referee’s specific comments are as follows.

1. Title. Suggest the authors change it. If it is the development of EARR, the information of input observations data quality or evaluations of more variables/indexes during the whole 10 years 2010-2019 should be included in the figures, but not only 201701 and 201707 mainly in Fig 2-4, 7-13 and only 2017-2018 in Fig 4-5. If it is the development of AdvHG, the innovation contents from your own group should be included in 2.2.2 (page5-8), otherwise, they are all the approaches you could adopt, but not develop. The main contents of the paper are evaluation in 2017-2018, including the method, results and usage in EARR, so maybe it is more suitable to call the title like “Evaluation of EARR based on AdvHG”, for your reference. If more figures of longer time series results could be replaced here, it is better. Anyway, the results are not enough, the period is short. The representativeness of the result is limited, comparing with the ERA (2010-2019).

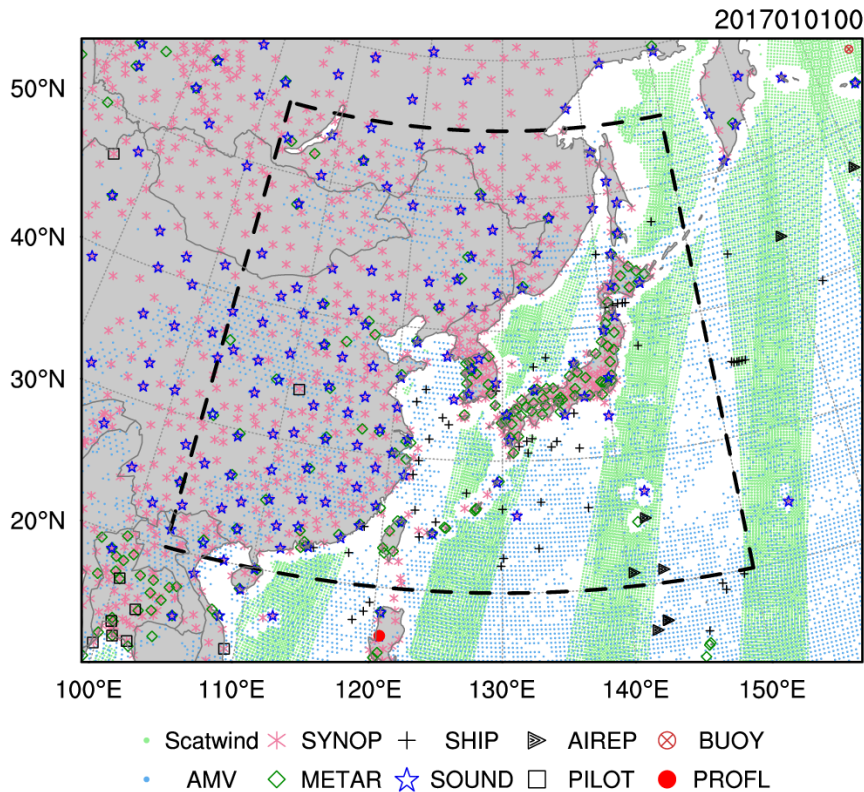
Authors’ response: We agree with the referee’s point, so we have added or changed the contents according to the referee’s suggestions in order to keep the original title for this manuscript.

Firstly, as the referee recommended, we have added the information on observations data quality to the revised manuscript as Table 2 (Table_rev1 below). Figure 1 is also modified to show spatial distributions of observations used in this study in the revised manuscript (Figure_rev1 below). Furthermore, the explanation of observation quality control procedure applied to this study is added to section 2.3 in the revised manuscript (underlined below).

Table_rev1. Summary of observations used in this study. The default observation error statistics provided in WRFDA system are used for assimilation in this study. The variables u, v, T, RH, Ps, and TPW denote zonal wind, meridional wind, temperature, relative humidity, surface pressure, and total precipitable water, respectively.

Observations	Descriptions	Variables	Observation errors (depending on vertical levels)
SOUND	Upper-air observation from radiosonde	u, v	1.1-3.3 m/s
		T	1 K
		RH	10-15%
PROFILER	Upper-air wind profile from wind profiler	u, v	2.2-3.2 m/s
PILOT	Upper-air wind profile from pilot balloon	u, v	2.2-3.2 m/s

	or radiosonde		
AIREP	Upper-air wind and temperature from aircraft	u, v	3.6 m/s
		T	1 K
Scatwind	Scatterometer oceanic surface winds	u, v	2.5-3.8 m/s
SHIPS	Surface synoptic observation from ship	u, v	1.1 m/s
		T	2 K
		Ps	1.6 hPa
		RH	10%
SYNOP	Surface synoptic observation from land station	u, v	1.1 m/s
		T	2 K
		Ps	1 hPa
		RH	10%
BUOY	Surface synoptic observation from buoy	u, v	1.4-1.6 m/s
		T	2 K
		Ps	0.9-1 hPa
		RH	10%
GPSPW	Precipitable water vapor from global positioning system (GPS)	TPW	0.2 mm
METAR	Aviation routine weather report from automatic weather station (AWS)	u, v	1.1 m/s
		T	2 K
		Ps	1 hPa
		RH	10%
AMV	Conventional atmospheric motion vector data from geostationary satellite	u, v	2.5-4.5 m/s

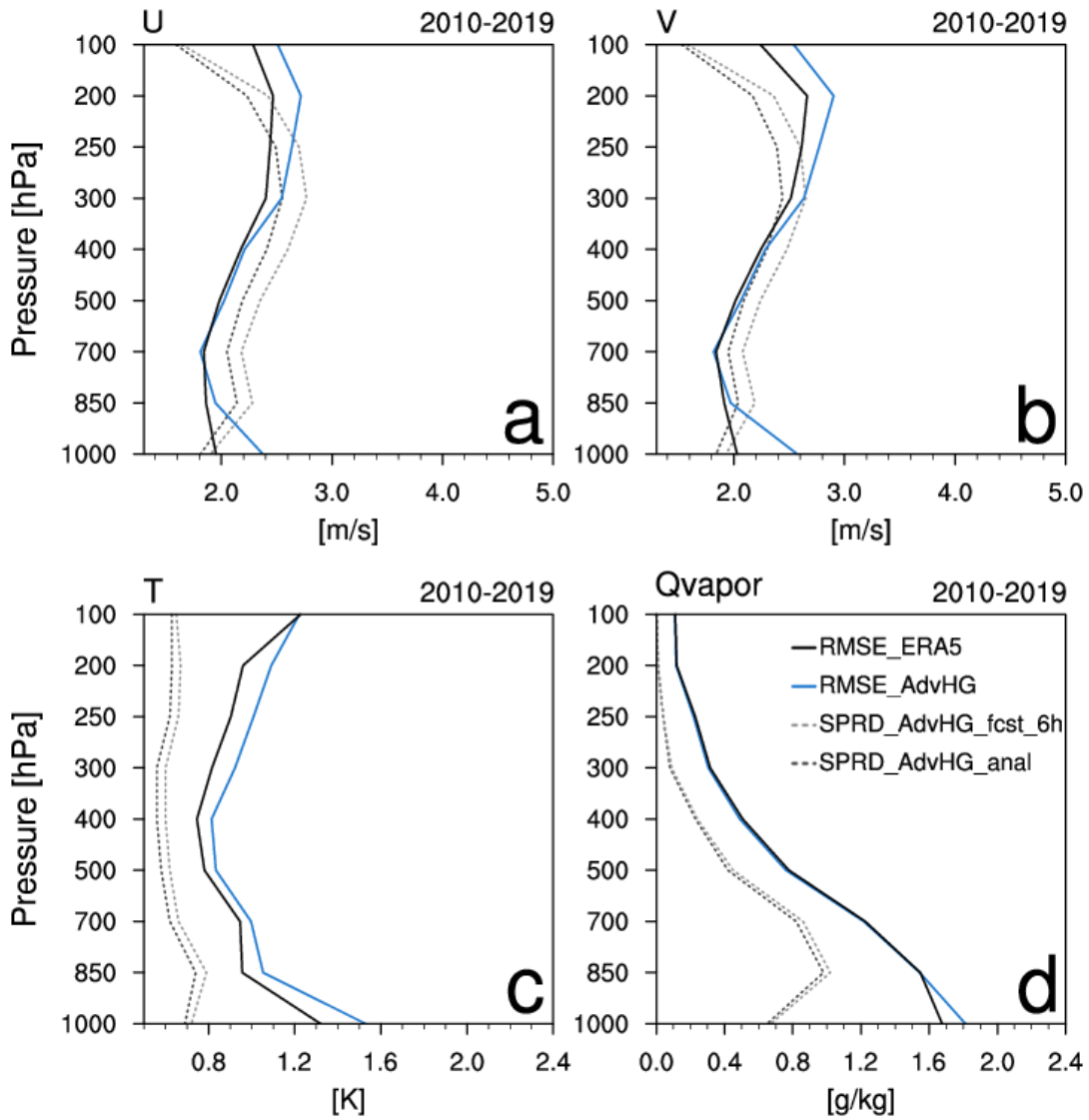


Figure_rev1. The East Asia Regional Reanalysis domain with different types of NCEP PrepBUFR observations available for assimilation at 00 UTC on 1st of January in 2017. The black dashed box denotes a verification area.

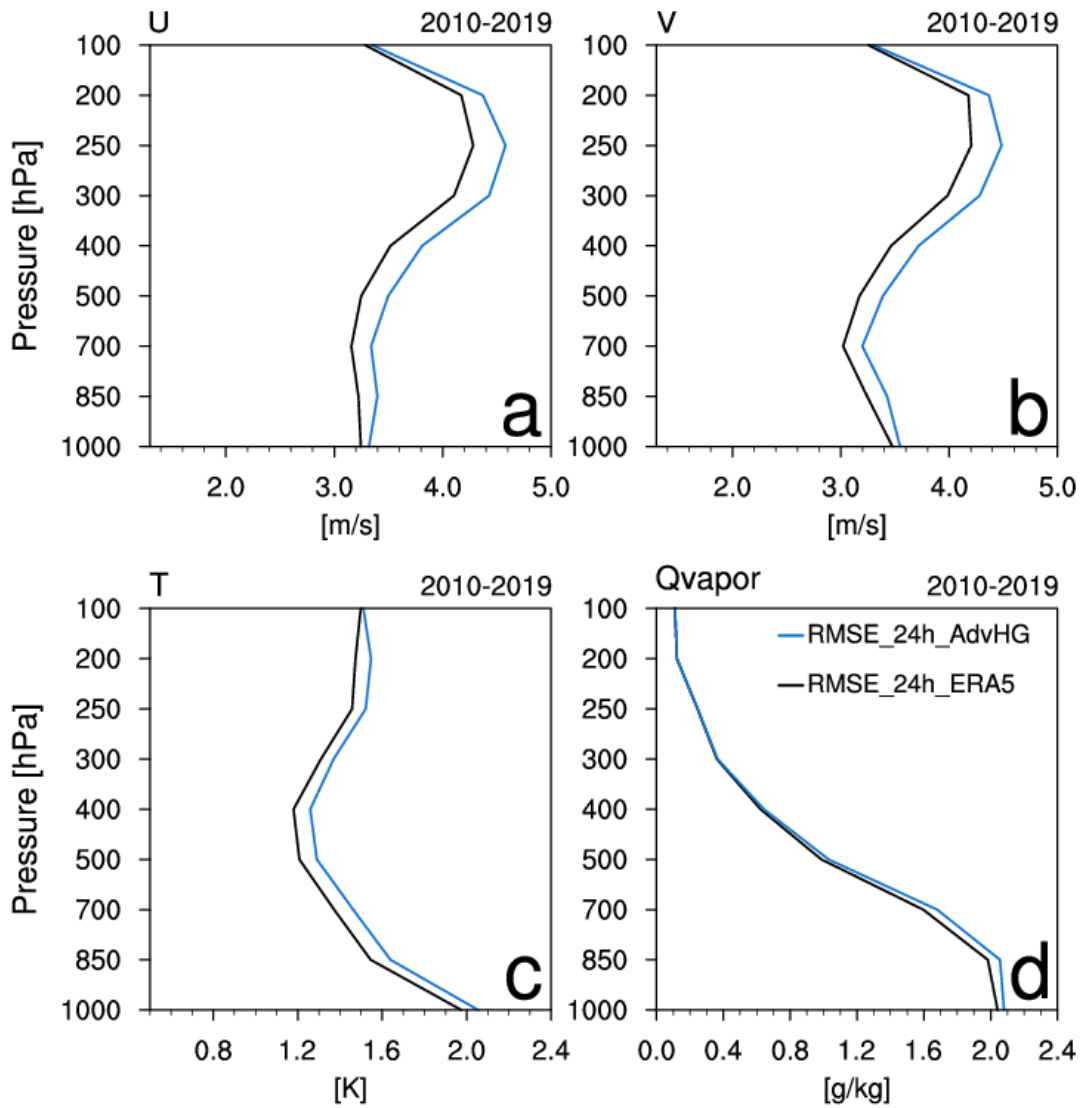
(L178-196) “The NCEP PrepBUFR [Prepared or QC’d data in BUFR (Binary Universal Form for the Representation of meteorological data) format] conventional observations (global upper air and surface weather observations, NCEP/NWS/NOAA/U.S.DOC 2008) are used every 6 h (00, 06, 12, and 18 UTC) for an assimilation by E3DVAR and AdvHG methods (Fig. 1). The PrepBUFR is the output of the final process for preparing the observations to be assimilated in the different NCEP analyses. For observations, rudimentary multi-platform quality control (QC) and more complex platform-specific QC were conducted (e.g., surface pressure, rawinsonde heights and temperature, wind profiler, aircraft wind and temperature) in NCEP (Keyser 2013). Furthermore, if the innovations (i.e., observation minus background) of some observations are greater than 5 times the observational error, then that observation is rejected during assimilation procedure in this study.”

The assimilated observations are as follows: the surface observations (SYNOP, METAR, Ship, and Buoy), radiosonde observation (SOUND), upper-wind report (PILOT), wind profiler, aircraft, atmospheric motion vector (AMV) wind from a geostationary satellite (GEOAMV), scatterometer oceanic surface winds (Scatwind), and precipitable water vapor from global positioning system (GPSW). The observation errors depending on each observation platform, variable, and vertical levels are assigned based on the default observation error statistics provided in WRFDA system (Table 2). All observations are spatially thinned by 20 km except for AMV thinned by 200 km as done by Warrick (2015), Cotton et al. (2016), and Shin (2016).”

Secondly, as referee proposed, we have evaluated longer-term datasets of EARR and ERA5 that are able to be verified for the whole 10-year period and replaced the results of two-year period with those of ten-year period (Figs. 6 and 7 in the revised manuscript) (Please see Figs_rev2 and 3 below). Because the aim of our study is to investigate EARR (AdvHG) performance with ERA5, it is worth evaluating reanalysis and (re)forecast fields of EARR and ERA5 for 10-year period, as referee pointed out. However, it seems unfeasible to compare EARR performance with various experiments (e.g., E3DVAR, ERA-Interim) for the whole period due to the high computational costs producing those datasets, especially ensemble-based one (i.e. E3DVAR). The updated results for the period of 2010-2019 (Figs_rev2 and 3) are almost the same as the previous results with two-year period, except for the water vapor mixing ratio (Qvapor). Although Qvapor RMSEs of reanalysis and (re)forecast of EARR and ERA5 for ten-year period are greater than those for two-year period, both of EARR and ERA5 Qvapor RMSEs increase and the RMSE differences between EARR and ERA5 for ten-year period are similar to those for two-year period. Thus, the longer-term evaluation reveals a large variability of atmospheric humidity and consequent predictability variability over East Asia for ten-year period of 2010-2019. We have revised the manuscript accordingly.

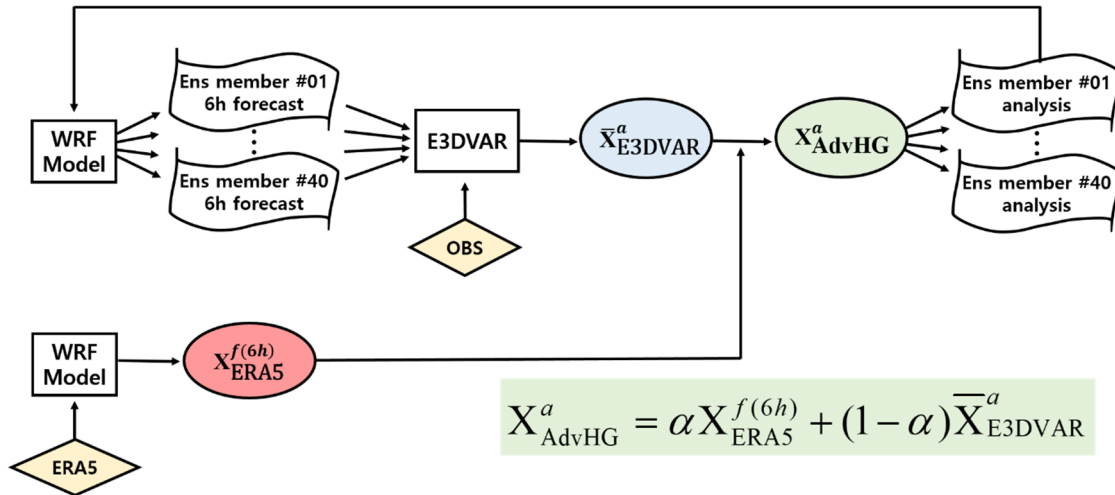


Figure_rev2. RMSEs of analysis of (a) zonal wind, (b) meridional wind, (c) temperature, and (d) Qvapor (water vapor mixing ratio) from ERA5 (black solid) and AdvHG (blue solid) and spreads of analysis (black dashed) and 6 h forecast (gray dashed) of AdvHG depending on pressure levels averaged over the ten-year period of 2010–2019.



Figure_rev3. Same as Fig_rev2 except for RMSE of 24 h forecast.

Lastly, we have added a new content from our group which is a schematic diagram of Advanced Hybrid Gain (AdvHG) method as Fig. 2 in the revised manuscript (Fig_rev4 below). And the section 2.2.2 for an explanation of AdvHG method is divided into two sections 2.2.2 and 2.2.3 to differentiate AdvHG method we newly developed in this study from the existing Hybrid Gain (HG) method.



Figure_rev4. The schematic diagram of the advanced hybrid gain data assimilation method in the East Asia regional reanalysis system.

2. Horizontal resolution, 12km. It is suggested to mention the raw description of model/DA like other reanalysis, for it is not the same resolution anywhere in the global. Add the information only once in 2.1, like in line 84 (540*432 grid points), it is suggested.

Authors' response: The model used in this study is the WRF model, which is a regional model based on a grid-point model not a spectral model. Thus, 12-km horizontal resolution for the WRF model is a reasonable way to express a horizontal grid spacing of a model. Meanwhile, for ERA-Interim and ERA5 models' resolution, as the referee suggested, we have added the information on spectral truncation (underlined) to the revised manuscript as follows.

(L205-206) "The horizontal resolutions of ERA-I and ERA5 are approximately 79 km (TL255) and 31 km (TL639), respectively."

3. 1. introduction. The motivation is described well enough here, like a full story, while the scientific background introduction is not enough, not like an excellent scientific introduction in a paper.

Authors' response: As the referee suggested, we have revised introduction to have the scientific background (underlined) in the revised manuscript.

(L50-63) "The long-term high-resolution datasets are essential to investigate the past extreme weather events which might be associated with mesoscale features such as heavy rainfall events with high spatial and temporal variability which coarser-resolution model cannot represent. The dynamical downscaling approaches can be a solution for generating high-resolution dataset, but they have some issues with insufficient spin-up (Kayaba et al. 2016). Moreover, Fukui et al. (2018) demonstrated that regional reanalysis over Japan assimilating only the conventional observations had the potential to reproduce precipitation fields better

than the dynamical downscaling approaches. Ashrit et al. (2020) also found that the high-resolution regional reanalysis over India showed substantial improvements of regional hydroclimatic features during summer monsoon for the period of 1979-1993 compared to the global reanalysis ERA-Interim (ERA-I, Dee et al. 2011) from ECMWF. Furthermore, He et al. (2019) revealed that the pilot regional reanalysis over the Tibetan Plateau was able to represent more accurate precipitation features as well as atmospheric humidity than the global reanalyses of ECMWF (i.e., ECMWF’s fifth-generation reanalysis (ERA5, Hersbach et al. 2020) and ERA-I).”

4. 2. system. Line 83-85, the sentence is not right, Fig 1 is the domain.

Authors’ response: As the referee pointed out, we have revised the sentence (underlined) in the revised manuscript as follows.

(L101-103) “In this study, the Advanced Research Weather Research and Forecasting (WRF, v3.7.1) model is used with 12-km horizontal resolution (540 x 432 grid points) and 50 vertical levels (up to 5 hPa) for East Asia domain shown in Fig. 1.”

5. Line 134-140, what is alpha in EQ 7?

Authors’ response: Alpha in Eq. (7) is a tunable parameter the same as in Eq. (2). To elucidate it, we have added a sentence (underlined) in the revised manuscript as follows.

(L156-158) “where $X_{\text{ERA5}}^{f(6h)}$ denotes the 6 h forecast of ERA5 reanalysis based on WRF model and $\overline{X}_{\text{E3DVAR}}^a$ denotes the analysis of E3DVAR (Fig. 2). In Eq. (7), α is a tunable parameter and is assigned to be 0.5 in this study.”

6. The authors make great effort in the DA approach, while what is the characteristics in East Asia of the EARR, comparing with other regional reanalysis, considering of the terrain, climate state like monsoon. In this scope, 50% is cover by the ocean, how is the ocean-land-atmospheric coupled here or just simply depends on all in WRF?

Authors’ response: There are a variety of regional reanalysis datasets particularly focusing on the impact of terrain like the Tibetan Plateau (He et al. 2019) and regional hydroclimatic features during monsoon over India (Ashrit et al. 2020). However, the main aim of this stage of this study is to develop a regional reanalysis over East Asia with newly proposed DA method and investigate the uncertainties and characteristics of general meteorological variables of the reanalysis such as temperature and precipitation with existing global reanalysis. Furthermore, we consider it more valuable to make our dataset open to the public at the earliest possible time, so that it could benefit more people using this dataset. As the referee pointed out, more investigation from different perspectives would be conducted in the future.

Ocean, land, and atmosphere are not coupled in WRF model, because WRF model is an atmospheric model producing atmospheric simulations. In this study, sea surface temperature (SST) obtained from ERA5 is used to be updated in WRF model and Unified Noah Land Surface Model (Tewari et al. 2004) is used as a land surface model.

7. Line 160, it is wrong here to mention *QuikSCAT* which is 199907-200911, it is not in 2010-2019. For your reference: (1) *Coriolis/WindSAT* (20070813-20120804) from CFSR prepbufr, (2) *Oceansat-2/OSCAT* (20091215-20140220) KNMI reprocessed but not in CFSR, (3) *MetOp-A/ASCAT* (20070101-20140331 KNMI reprocessed, GTS data till present in GDAS), (4) *MetOp-B/ASCAT* (20140408-present in GDAS). You may not use reprocessed ASCAT wind, but it is used in ERA5.

Authors' response: We appreciate the referee's correction. Even though QuikSCAT no longer collects ocean wind data, the convention of naming the scatterometer oceanic surface winds as a group of "QSCAT" still remains in WRFDA system, which made us mistaken. Because the scatterometer oceanic surface winds (Scatwind) are assimilated in EARR, we have rectified the error in the original manuscript by revising the sentence (underlined).

(L189-193) "The assimilated observations are as follows: the surface observations (SYNOP, METAR, Ship, and Buoy), radiosonde observation (SOUND), upper-wind report (PILOT), wind profiler, aircraft, atmospheric motion vector (AMV) wind from a geostationary satellite (GEOAMV), scatterometer oceanic surface winds (Scatwind), and precipitable water vapor from global positioning system (GPSPW)."

8. 4. Result, it is suggest to shorten the results to 60%. The emphasis is how good is EARR but not ERA5. There are many sentences/paragraphs with the subject of ERA5 but not your reanalysis. Like line 235-256, 260-262, 290-291, 328-331, 410-412, 449-452, 520-521. And the difference between ERA5 and ERA-I could be shorten like line 265-270. Pay more attention in how good EARR but not how is ERA5 like line 357-363. The order of the results from different reanalysis is also important. Line 312-314 is good in expression.

Authors' response: Following the referee's suggestion, we have shortened the results and revised the manuscript to pay more attention to EARR rather than ERA5.

9. Line 324, except for strong thresholds, how is strong? >4 mm/6h? how is week?

Authors' response: As the referee pointed out, we have revised sentences (underlined) in the revised manuscript as follows. For a more objective and specific description, the adjectives for threshold such as 'strong' and 'weak' are replaced by 'high' and 'low' and specific threshold values are presented in the revised manuscript.

(L353-356) "For January 2017 (Fig. 8a), ETS of ERA5 (i.e., WRF-based ERA5) is higher than that of ERA5_fromECMWF for all thresholds, whereas ETS of ERA-I (i.e., WRF-based

ERA-I) is lower than that of ERA-I_fromECMWF except for high thresholds (8 and 16 mm (6 h)⁻¹).”

(L360-362) “Regarding FBI in winter (Fig. 8b), for 4, 8, and 16 mm (6 h)⁻¹ thresholds, all the results show the FBI smaller than 1, implying the underestimation of frequency of precipitation for high-threshold events.”

(L374-376) “With respect to FBI in July 2017, the WRF-based results show the FBIs greater than 1, whereas reforecast from ECMWF show the FBIs greater than 1 for 0.5, 1, and 4 mm (6 h)⁻¹ thresholds and smaller than 1 for higher thresholds (8 and 16 mm (6 h)⁻¹) (Fig. 8d).”

(L417-420) “At 0.5, 1, and 4 mm (6 h)⁻¹ thresholds, E3DVAR BSS is the greatest, which is similar to ETS. At 8 and 16 mm (6 h)⁻¹ thresholds, ERA5 ETS is the highest, followed by AdvHG and E3DVAR, whereas overall E3DVAR BSS is the highest, followed by AdvHG and ERA5.”

(L440-442) “During July in 2017, ERA5 and ERA-I simulate heavier precipitation than AdvHG (not shown), which is consistent with larger FBI of ERA5 and ERA-I at higher thresholds.”

(L456-460) “Moreover, although all the results similarly represent overall features of precipitation in January (Fig. 13), ERA5_fromECMWF (Fig. 13g) simulates the overestimated precipitation over South China, which is consistent with the results in the previous section as well as its larger FBI at lower thresholds (0.5 and 1 mm (6 h)⁻¹) shown in Fig. 8b.”

(L468-470) “This is consistent with the result in Fig. 8d, in which FBIs from WRF-based results are generally greater than 1 for higher thresholds (8 and 16 mm (6 h)⁻¹), whereas those from ECMWF are smaller than 1.”

(L538-542) “In addition, the ETS differences between the results are not distinctive in July. For higher thresholds (8 and 16 mm (6 h)⁻¹) in July, AdvHG ETS is greater than E3DVAR ETS and smaller than ERA5 ETS, whereas E3DVAR ETS is the greatest followed by ERA5 and AdvHG for lower thresholds (0.5 and 1 mm (6 h)⁻¹).”

10. Fig 7, Line 346-348, results of AdvHG in Jan is better than in Jul, FBI closer to 1. Different FBI results in Jul are larger than 1 (over-forecast) more than in Jan, more difficult to improve for summer than winter. Index ETS and FBI are more difficult to handle and analysis than POD and FAR which is better when it is larger and smaller, separately.

Authors’ response: POD and FAR seem to be straightforward to deal with. However, as mentioned in section 3.2, POD can be artificially improved by systematically over-forecasting the events (Wilson 2010), so FAR should be used with POD. Moreover, ETS is a more balanced score than POD and FAR, because it is sensitive to both false alarms and

misses (Wilson 2010). To elucidate this, we have added the explanation (underlined) about ETS in the revised manuscript.

(L223-225) “The ETS range is from -1/3 to 1 and the value 1 for ETS is a perfect score. ETS is a more balanced score than Probability of Detection (POD) and False Alarm Ratio (FAR), because it is sensitive to both false alarms and misses (Wilson 2010).”

11. Line 354, (Figs. 8a and b), is it right? 8b is FAR.

Authors’ response: As the referee pointed out, we have revised the sentence (underlined) in the revised manuscript as follows.

(L383-384) “For January in 2017, AdvHG POD is the greatest among the WRF-based results, followed by E3DVAR, ERA5, and ERA-I (Fig. 9a).”

12. 6. Summary, it is not concise in this paragraph.

Authors’ response: As the referee pointed out, we have revised the summary in the revised manuscript to make it concise.

13. Reference, line 608-614, it is repeated, please delete. Line 621-622 seems with larger font size.

Authors’ response: As the referee suggested, we have deleted the repeated reference and reduced the font size of the reference the referee pointed out in the revised manuscript.

14. Fig 2, is it the result of all EARR domain? Jan and Jul shown in Fig 2-6 while YYYYMM or YYYYMMDD shown in Fig 7-11, it is suggested to use unified expression. Fig 6, Temp revised to T like Fig 2.

Authors’ response: Figure 2 in the original manuscript (Fig. 3 in the revised manuscript) is the result of verification domain (dashed box in Fig. 1), not all EARR domain. To make it clearer, we have added the explanation about verification domain in the revised manuscript as follows (underlined).

(L272-276) “The analysis and forecast RMSEs of E3DVAR, AdvHG, the WRF-based ERA-I, and WRF-based ERA5 are calculated for zonal wind, meridional wind, temperature, and Qvapor (water vapor mixing ratio in WRF) variables against sonde observations at 00 and 12 UTC in verification domain (dashed box in Fig. 1) for January and July in 2017 and averaged over each month (Figs. 3, 4, and 5).”

Furthermore, as the referee suggested, we have modified Figs 3-7 to use unified expression (e.g., YYYYMM) and have changed ‘Temp’ to ‘T’ in Fig. 7 in the revised manuscript.

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1 **Development of East Asia Regional**
2 **Reanalysis based on advanced hybrid gain**
3 **data assimilation method and evaluation**
4 **with E3DVAR, ERA-5, and ERA-Interim**
5 **reanalysis**

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7
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ABSTRACT

The East Asia Regional Reanalysis (EARR) system is developed based on the advanced hybrid gain data assimilation method (AdvHG) using Weather Research and Forecasting (WRF) model and conventional observations. Based on EARR, the high-resolution regional reanalysis and reforecast fields are produced with 12 km horizontal resolution over East Asia for 2010–2019. The newly proposed AdvHG is based on the hybrid gain approach, weighting two different analysis for an optimal analysis. The AdvHG is different from the hybrid gain in that 1) E3DVAR is used instead of EnKF, 2) 6 h forecast of ERA5 is used to be more consistent with WRF, and 3) the pre-existing, state-of-the-art reanalysis is used. Thus, the AdvHG can be regarded as an efficient approach to generate regional reanalysis dataset due to cost savings as well as the use of the state-of-the-art reanalysis. The upper air variables of EARR are verified with those of ERA5 for January and July 2017 and ~~the two-year period of 2017–2018~~ the ten-year period of 2010–2019. For upper air variables, ERA5 outperforms EARR over two years, whereas EARR outperforms (shows comparable performance to) ERA-I and E3DVAR for January in 2017 (July in 2017). EARR better represents precipitation than ERA5 for January and July in 2017. Therefore, though the uncertainties of upper air variables of EARR need to be considered when analyzing them, the precipitation of EARR is more accurate than that of ERA5 for both two seasons. The EARR data presented here can be downloaded from <https://doi.org/10.7910/DVN/7P8MZT> for data on pressure levels and <https://doi.org/10.7910/DVN/Q07VRC> for precipitation.

40 **1. Introduction**

41 Reanalysis datasets have been widely used in the socio-economical field as well as
42 meteorological and climate research areas all over the world. Most of reanalysis datasets
43 consist of global reanalysis whose spatial and temporal resolutions are relatively coarse (e.g.,
44 Schubert et al. 1993; Kalnay et al. 1996; Gibson et al. 1997; Kistler et al. 2001; Kanamitsu et
45 al. 2002; Uppala et al. 2005; Onogi et al. 2007; Bosilovich 2008; Saha et al. 2010; Dee et al.
46 2011; Rienecker et al. 2011; Bosilovich 2015; Kobayashi et al. 2015; Hersbach et al. 2020). As
47 the importance of regional reanalysis dataset emerged, many operational centers and research
48 institutes around the world have been producing the dataset in their own areas (Mesinger et al.
49 2006; Renshaw et al. 2013; Borsche et al. 2015; Bromwich et al. 2016; Jerney and Renshaw
50 2016; Zhang et al. 2017; Bromwich et al. 2018; Fukui et al. 2018; He et al. 2019; Ashrit et al.
51 2020).

52 The long-term high-resolution datasets are essential to investigate the past extreme
53 weather events which might be associated with mesoscale features such as heavy rainfall events
54 with high spatial and temporal variability which coarser-resolution model cannot represent.
55 The dynamical downscaling approaches can be a solution for generating high-resolution dataset,
56 but they have some issues with insufficient spin-up (Kayaba et al. 2016). Moreover, Fukui et
57 al. (2018) demonstrated that regional reanalysis over Japan assimilating only the conventional
58 observations had the potential to reproduce precipitation fields better than the dynamical
59 downscaling approaches. Ashrit et al. (2020) also found that the high-resolution regional
60 reanalysis over India showed substantial improvements of regional hydroclimatic features
61 during summer monsoon for the period of 1979-1993 compared to the global reanalysis ERA-
62 Interim (ERA-I, Dee et al. 2011) from ECMWF. Furthermore, He et al. (2019) revealed that
63 the pilot regional reanalysis over the Tibetan Plateau was able to represent more accurate

64 precipitation features as well as atmospheric humidity than the global reanalyses of ECMWF
65 (i.e., ECMWF's fifth-generation reanalysis (ERA5, Hersbach et al. 2020) and ERA-I).

66 As part of this effort, regional reanalysis over East Asia were produced based on the
67 Unified Model for the two-year period of 2013-2014 and it was confirmed that regional
68 reanalysis over East Asia is beneficial (Yang and Kim 2017; Yang and Kim 2019). However,
69 because UM was no longer available for generating regional reanalysis over East Asia, another
70 numerical weather prediction (NWP) model and its data assimilation (DA) method are required.

71 To find the most appropriate and cost-efficient DA method for a regional reanalysis over
72 East Asia, several DA methods were compared. Yang and Kim (2021) demonstrated that the
73 hybrid ensemble-variational data assimilation method (E3DVAR) shows the better
74 performance compared to three-dimensional variational data assimilation (3DVAR) and
75 ensemble Kalman filter (EnKF) over East Asia for January and July in 2016. However, it is
76 essential to confirm if this hybrid method is accurate enough to be used for a regional reanalysis
77 over East Asia. Thus, E3DVAR was compared with the latest and the previous reanalysis data
78 ~~from ECMWF (i.e., ECMWF's fifth-generation reanalysis (ERA5, Hersbach et al. 2020) and~~
79 ~~ERA-Interim (ERA-I, Dee et al. 2011))~~—from ECMWF (ERA5 and ERA-I) for (re)analysis
80 and (re)forecast variables and it was found that a performance for a regional reanalysis needs
81 to be further improved.

82 For this reason, a new advanced hybrid gain (AdvHG) data assimilation method, which
83 combines E3DVAR and ERA5 based on WRF model, is newly proposed and investigated in
84 this study. A hybrid gain data assimilation method has been developed as a new kind of hybrid
85 methods (Penny 2014). Based on this method, an advanced data assimilation method is newly
86 developed in this study. Finally, using this newly proposed DA method (AdvHG), East Asia
87 regional reanalysis (EARR) system is developed based on WRF model. ~~EARR datasets have~~
88 ~~been produced for ten-year period of 2010-2019 and are verified for two-year period of 2017-~~

89 ~~2018.~~ EARR datasets have been produced for ten-year period of 2010-2019 and are publicly
90 available (<https://dataverse.harvard.edu/dataverse/EARR>).

91 To investigate the accuracy and uncertainty of the state-of-the-art AdvHG DA algorithm
92 developed in this study, analysis and forecast atmospheric variables of E3DVAR, AdvHG,
93 WRF-based ERA-I, and WRF-based ERA5 are evaluated for January and July in 2017,
94 respectively. In addition, reforecast precipitation fields of ERA-I and ERA5 from ECMWF are
95 also verified and compared. In this study, the datasets are evaluated for two-month period
96 (January and July in 2017) or ten-year period (2010-2019) depending on the availability of
97 datasets. The reanalysis and (re)forecast fields of the EARR based on AdvHG and ERA5 are
98 verified for ten-year period (2010-2019). In section 2, the EARR system including model, data
99 assimilation method, and observations are explained. In section 3, the evaluation methods are
100 presented. The verification results of (re)analysis and (re)forecast variables are presented in
101 section 4. Section 4.1 presents evaluation results for wind, temperature, and humidity variables,
102 and section 4.2 presents those for precipitation (re)forecast. Section 5 presents data availability.
103 Lastly, summary and conclusions are presented in section 6.

104 **2. Reanalysis system**

105 *2.1. Model*

106 In this study, the Advanced Research Weather Research and Forecasting (WRF, v3.7.1)
107 model is used with 12-km horizontal resolution (540 x 432 grid points) and 50 vertical levels
108 (up to 5 hPa) ~~as shown in Fig. 1.~~ for East Asia domain shown in Fig. 1. The model settings and
109 physics scheme are summarized in Table 1. Analysis fields are obtained every 6 h (00, 06, 12,
110 and 18 UTC) via assimilation of conventional observations with a 6 h assimilation window,
111 and forecast fields are integrated up to 36 h. The ERA5 reanalysis (Hersbach et al. 2020) is
112 used as the first initial condition before the cycling, and as boundary conditions every 6 h.

113 2.2. Data assimilation methods

114 2.2.1. E3DVAR

115 The E3DVAR method is one of hybrid data assimilation methods, which use a static
116 climatological background error covariance (BEC) and ensemble-based flow-dependent BEC,
117 and couples the EnKF and 3DVAR (Zhang et al. 2013). E3DVAR is based on a cost function
118 of 3DVAR. In E3DVAR, EnKF provides flow-dependent BEC as well as updates perturbations
119 for ensemble members. Following Zhang et al. (2013),

$$J^b = J_s^b + J_e^b = \frac{1}{2} \delta \mathbf{x}^T \left[(1 - \beta) \mathbf{B} + \beta \mathbf{P}^f \circ \mathbf{C} \right]^{-1} \delta \mathbf{x} , \quad (1)$$

120 where J_s^b is a traditional cost function based on a static climatological BEC \mathbf{B} and J_e^b is an
121 additional cost function based on ensemble-based BEC \mathbf{P}^f . \mathbf{C} is a correlation matrix for
122 localization of the ensemble covariance \mathbf{P}^f . The weighting coefficient β between static and
123 ensemble-based BEC is set to 0.8 in this study. To account for model error for E3DVAR, multi-
124 physics scheme is applied to 40-member ensembles. Yang and Kim (2021) found that E3DVAR
125 is the most appropriate DA method among 3DVAR, EnKF, and E3DVAR methods over East
126 Asia. More detailed information on E3DVAR implemented in this study can be found in Yang
127 and Kim (2021).

128 2.2.2. ~~Advanced hybrid gain data assimilation method~~ Hybrid gain data assimilation method

129 In the last decade, the traditional hybrid methods have been widely used for many
130 operational centers and research institutes. Recently, Penny (2014) has proposed a new class
131 of hybrid gain methods combining desirable aspects of both variational and EnKF families of
132 algorithms by weighting analyses from 3DVAR and LETKF for an optimal analysis in the
133 Lorenz 40-component model. Since then, this algorithm has been implemented at ECMWF
134 (Bonavita et al. 2015) and at a hybrid global ocean DA system in National Centers for
135 Environmental Prediction (NCEP) (Penny et al. 2015).

136 The hybrid gain algorithm can be described with the following equations:

$$\mathbf{x}_{Hyb}^a = \alpha \mathbf{x}_{det}^a + (1 - \alpha) \overline{\mathbf{x}}^a, \quad (2)$$

137 where \mathbf{x}_{Hyb}^a , \mathbf{x}_{det}^a , and $\overline{\mathbf{x}}^a$ denote the hybrid analysis, deterministic analysis, and the ensemble
 138 mean analysis from the ensemble-based assimilation method, and α is a tunable parameter
 139 (Penny 2014, Houtekamer and Zhang 2016).

140 The hybrid gain method is different from traditional hybrid methods, in that a hybrid gain
 141 approach linearly combines analysis fields from EnKF and variational DA method to produce
 142 a hybrid gain analysis rather than linearly combining respective BECs (Penny 2014). Basically,
 143 the hybrid gain method is to hybridize two different Kalman gain matrices of ensemble-based
 144 [Eq. (4)] and variational data assimilation system [Eq. (5)] as in Eq. (3).

$$\hat{\mathbf{K}} = \beta_1 \mathbf{K}^f + \beta_2 \mathbf{K}^B + \beta_3 \mathbf{K}^B \mathbf{H} \mathbf{K}^f, \quad (3)$$

145 where

$$\mathbf{K}^f = \mathbf{P}^f \mathbf{H}^T (\mathbf{H} \mathbf{P}^f \mathbf{H}^T + \mathbf{R})^{-1}, \quad (4)$$

$$\mathbf{K}^B = \mathbf{B} \mathbf{H}^T (\mathbf{H} \mathbf{B} \mathbf{H}^T + \mathbf{R})^{-1}. \quad (5)$$

146 \mathbf{H} is an observation operator mapping the model state vector to observation space and \mathbf{R} is the
 147 observation error covariance matrix. The matrices \mathbf{P}^f and \mathbf{B} indicate the ensemble-based and
 148 the static climatological BEC, respectively. By choosing the specific coefficients ($\beta_1=1$, $\beta_2 =$
 149 α , $\beta_3 = -\alpha$), it can be written as in Eq. (6) and it can give an algebraically equivalent result
 150 with Eq. (2) (Penny 2014).

$$\hat{\mathbf{K}} = \mathbf{K}^f + \alpha \mathbf{K}^B (\mathbf{I} - \mathbf{H} \mathbf{K}^f). \quad (6)$$

151 One of advantages of the hybrid gain algorithm with respect to its development is that pre-
 152 existing operational systems can be used without significant modification for a hybrid analysis

153 (Penny 2014) and independent parallel development of respective methods is allowed
 154 (Houtekamer and Zhang 2016). Furthermore, the hybrid gain approach can be considered as a
 155 practical and straightforward method in the foreseeable future to combine advantageous
 156 features of both ensemble- and variational-based DA algorithms (Houtekamer and Zhang 2016).
 157 More detailed information on this algorithm can be found in Penny (2014).

158 2.2.3. Advanced hybrid gain data assimilation method

159 In this study, based on the hybrid gain approach, an advanced hybrid gain data assimilation
 160 method (AdvHG) is newly proposed as follows:

$$X_{AdvHG}^a = \alpha X_{ERA5}^{f(6h)} + (1 - \alpha) \bar{X}_{E3DVAR}^a, \quad (7)$$

161 where $X_{ERA5}^{f(6h)}$ denotes the 6 h forecast of ERA5 reanalysis based on WRF model and \bar{X}_{E3DVAR}^a
 162 denotes the analysis of E3DVAR (Fig. 2). In Eq. (7), α is a tunable parameter and is assigned
 163 to be 0.5 in this study. This advanced hybrid gain approach is different from the hybrid gain
 164 approach in that 1) E3DVAR analysis is used instead of EnKF, 2) 6 h forecast of ERA5 is used
 165 instead of deterministic analysis from variational DA method, and 3) the pre-existing and state-
 166 of-the-art reanalysis data (i.e., ERA5) is simply used instead of producing deterministic
 167 analysis by assimilation. The reasons for these different approaches proposed in this study are
 168 as follows:

169 1) E3DVAR is used instead of EnKF because Yang and Kim (2021) confirmed that
 170 E3DVAR outperforms EnKF for winter and summer seasons over East Asia.

171 2) Instead of deterministic analysis, the 6 h forecast of ERA5 based on WRF model is
 172 used to make the hybrid analysis more balanced and consistent with WRF model, because
 173 ERA5 reanalysis fields are based on its own modeling system with coarser resolution, which
 174 is different from that of this study.

175 3) European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis (ERA5)

176 is used instead of producing our own analysis fields from a variational DA method. This is a
177 very efficient approach because of the cost savings as well as the use of the high-quality latest
178 reanalysis from ECMWF assimilating all currently available observations with the state-of-the-
179 art and advanced technology.

180 Therefore, the approach proposed in this study is called as “advanced hybrid gain method”
181 (denoted as “AdvHG”).

182 2.3. Observations

183 The NCEP PrepBUFR [Prepared or QC'd data in BUFR (Binary Universal Form for the
184 Representation of meteorological data) format] conventional observations (global upper air and
185 surface weather observations, NCEP/NWS/NOAA/U.S.DOC 2008) are used every 6 h (00, 06,
186 12, and 18 UTC) for an assimilation by E3DVAR and AdvHG methods (Fig. 1). The PrepBUFR
187 is the output of the final process for preparing the observations to be assimilated in the different
188 NCEP analyses. For observations, rudimentary multi-platform quality control (QC) and more
189 complex platform-specific QC were conducted (e.g., surface pressure, rawinsonde heights and
190 temperature, wind profiler, aircraft wind and temperature) in NCEP (Keyser 2013).
191 Furthermore, if the innovations (i.e., observation minus background) of some observations are
192 greater than 5 times the observational error, then that observation is rejected during assimilation
193 procedure in this study.

194 The assimilated observations are as follows: the surface observations (SYNOP, METAR,
195 Ship, and Buoy), radiosonde observation (SOUND), upper-wind report (PILOT), wind profiler,
196 aircraft, atmospheric motion vector (AMV) wind from a geostationary satellite (GEOAMV),
197 and Scatterometer oceanic surface winds (Scatwind), and precipitable water vapor from global
198 positioning system (GPSPW). The observation errors depending on each observation platform,
199 variable, and vertical levels are assigned based on the default observation error statistics
200 provided in WRFDA system (Table 2). All observations are spatially thinned by 20 km except

201 for AMV thinned by 200 km as done by Warrick (2015), Cotton et al. (2016), and Shin [et al.](#)
202 (2016).

203 To evaluate 6 h accumulated precipitation simulated by E3DVAR, AdvHG, ERA-I, and
204 ERA5 over East Asia, global surface weather observations (NCEP PrepBUFR,
205 NCEP/NWS/NOAA/U.S.DOC 2008) are used every 6 h (00, 06, 12, and 18 UTC). For an
206 evaluation of the monthly precipitation fields, the world monthly surface station climatology
207 (NCDC/NESDIS/NOAA/U.S.DOC et al. 1981) over 4700 different stations (2600 in more
208 recent years) is used.

209 *2.4. Global reanalysis datasets*

210 To compare EARR generated with other reanalysis datasets, ERA5 (Hersbach et al. 2020)
211 and ERA-I (Dee et al. 2011) reanalysis are chosen. The horizontal resolutions of ERA-I and
212 ERA5 are approximately 79 km ([TL255](#)) and 31 km ([TL639](#)), respectively. Because ERA5 is
213 based on the operational system in 2016, improvements in model physics, numerics, data
214 assimilation, and additional observations over the last decade are the advantages of ERA5
215 (Hersbach et al. 2018).

216 ~~Because reforecast as well as reanalysis fields are verified in this study, for forecast fields,~~
217 ~~two different forecast fields from ECMWF (i.e., forecast based on WRF model and reforecast~~
218 ~~based on ECMWF model) are used. The WRF forecast fields (i.e., WRF-based ERA5, WRF-~~
219 ~~based ERA-I) using ERA5 and ERA-I as initial conditions are integrated with 12 km resolution.~~
220 ~~Secondly, reforecast fields based on ECMWF model (i.e., ERA5_fromECMWF, ERA-~~
221 ~~I_fromECMWF), provided and downloaded from ECMWF, are used. In this study, (re)forecast~~
222 ~~as well as reanalysis fields need to be verified. Regarding reanalysis and (re)forecast fields of~~
223 ~~ECMWF, reanalysis fields (i.e., ERA5 and ERA-I) downloaded from ECMWF are evaluated~~
224 ~~(Figs. 3 and 6). There are two different (re)forecast fields (e.g., ERA5_fromECMWF, WRF-~~
225 ~~based ERA5) used in this study. WRF-based ERA5 and ERA-I are forecast fields based on~~

WRF model with 12 km horizontal resolution where ERA5 and ERA-I are used as initial conditions, respectively. In contrast, ERA5 from ECMWF and ERA-I from ECMWF are reforecast fields based on ECMWF model not WRF model, so the reforecast fields of ERA5 and ERA-I are provided and downloaded from ECMWF. These reforecast fields are only used for evaluation of precipitation (Figs. 8 and 9). The (re)analysis and (re)forecast fields and corresponding experiments are explained in Table 3.

3. Evaluation method

3.1. Equitable threat score and Frequency bias index

Based on the contingency table (Table 24), ETS is defined as

$$ETS = \frac{A - A_r}{A + B + C - A_r}, \text{ where } A_r = \frac{(A + B)(A + C)}{A + B + C + D}. \quad (8)$$

The ETS range is from -1/3 to 1 and the value 1 for ETS is a perfect score. ETS is a more balanced score than Probability of Detection (POD) and False Alarm Ratio (FAR), because it is sensitive to both false alarms and misses (Wilson 2010).

FBI is defined as

$$FBI = \text{Bias} = \frac{A + B}{A + C}. \quad (9)$$

The FBI indicates whether the model tends to over-forecast (too frequently, FBI > 1) or under-forecast (not frequent enough, FBI < 1) events with respect to frequency of occurrence.

3.2 Probability of detection and False alarm ratio

Based on the contingency table (Table 24), POD is defined as

$$POD = \frac{A}{A + C} = \frac{\text{Hits}}{\text{Hits} + \text{Misses}}. \quad (10)$$

The POD range is from 0 to 1. POD is required to be used with FAR, because POD can be artificially improved by systematically over-forecasting the events (Wilson 2010).

245 FAR is defined as

$$\text{FAR} = \frac{B}{A+B} = \frac{\text{False alarms}}{\text{Hits} + \text{False alarms}}. \quad (11)$$

246 The range of FAR is from 0 to 1 and its lower score implies a higher accuracy.

247 3.3 Brier skill score

248 Verification of the performance of high-resolution forecast with the traditional verification
249 metrics (e.g., ETS, FBI) can be misleading due to double penalty, particularly for highly
250 variable fields (e.g., precipitation). Therefore, as one of spatial verification approaches that do
251 not require forecast to match point observation spatially, neighborhood (fuzzy) verification
252 method, which assumes that slightly displaced forecast can be acceptable and a local
253 neighborhood can define the degree of allowable displacement (Ebert 2008; Kim et al. 2015;
254 On et al. 2018), is used in this section. According to Ebert (2008), depending on the matching
255 strategy, neighborhood verifications can be categorized into two frameworks: ‘single
256 observation-neighborhood forecast (SO-NF)’ where neighborhood forecasts surrounding
257 observations are considered, and ‘neighborhood observation-neighborhood forecast (NO-NF)’
258 strategies where not only neighborhood forecasts but also neighborhood observations
259 surrounding observations are considered. Due to the absence of high-resolution gridded
260 precipitation observation data in East Asia, various verification scores widely used as
261 ‘neighborhood observation-neighborhood forecast (NO-NF)’ strategy are not available in this
262 study. Thus, in this section, Brier skill score as one of ‘single observation-neighborhood
263 forecast (SO-NF)’ strategy is introduced.

264 The Brier score (BS) is similar to the mean-squared error (MSE) and is defined as (Wilks
265 2006):

$$\text{BS} = \frac{1}{N} \sum_{i=1}^N (p_i - o_i)^2. \quad (12)$$

266 where p_i denotes the probability forecast, and o_i denotes the binary observation which is either
 267 0 or 1, and N is the total number of observations during the given period. Generally, Brier skill
 268 score (or Brier score) is used to verify ensemble forecasts which are able to calculate
 269 probabilistic forecasts (Kay et al. 2013; Kim and Kim 2017). However, Brier skill score can
 270 also be used for deterministic forecasts using a pragmatic post-processing procedure (Theis et
 271 al., 2005; Mittermaier ~~et al.~~ 2014), which derives probabilistic forecasts from deterministic
 272 forecasts at every model grid point by considering neighborhood forecast as *pseudo ensemble*.

$$\text{BSS} = 1 - \frac{\text{BS}}{\text{BS}_{\text{ref}}}, \quad (13)$$

273 where BS_{ref} is Brier score of reference. Brier skill score is skill score with respect to Brier score
 274 as in Eq. (13). For reference, a climatology or other forecast can be used either. In this study,
 275 the WRF-based ERA-I is considered as a reference.

276 3.4 Pattern correlation coefficient

277 The pattern correlation coefficient (PCC) is defined as Eq. (14) (Shiferaw et al. 2018; Yoo
 278 and Cho 2018; Park and Kim 2020).

$$\text{PCC} = \frac{\sum_{i=1}^N (x_i - \bar{x})(o_i - \bar{o})}{\left[\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (o_i - \bar{o})^2 \right]^{1/2}}, \quad (14)$$

279 where x_i and o_i are (re)forecast and observed precipitation at i th observation location and the
 280 over-bar indicates the averaged variables over N observed stations in the verification area.

281 4. Results

282 4.1 Evaluation of wind, temperature, and humidity variables

283 4.1.1 RMSE for January and July 2017

284 The analysis and forecast RMSEs of E3DVAR, AdvHG, the WRF-based ERA-I, and

285 WRF-based ERA5 are calculated for zonal wind, meridional wind, temperature, and Qvapor
286 (water vapor mixing ratio in WRF) variables against sonde observations at 00 and 12 UTC in
287 verification domain (dashed box in Fig. 1) for January and July in 2017 and averaged over each
288 month (Figs. ~~2, 3, and 4~~—3, 4, and 5).

289 ~~For analysis RMSE (Fig. 2), ERA5 is smaller than ERA-I for all levels and variables. In~~
290 ~~particular, the analysis RMSE difference between ERA5 and ERA-I is distinctive for wind. The~~
291 ~~vertically averaged wind RMSE of ERA5 for January (2.22 m s⁻¹) and July (1.98 m s⁻¹) in~~
292 ~~2017 is smaller by approximately 0.23 and 0.3 m s⁻¹ than that of ERA-I for January (2.45 m s⁻¹)~~
293 ~~and July (2.28 m s⁻¹) in 2017. The analysis RMSE of E3DVAR is smaller than that of~~
294 ~~AdvHG for all pressure levels and variables, except for temperature in July at 1000 hPa and~~
295 ~~Qvapor in January and July at 1000 hPa. In general, the analysis RMSE of AdvHG for all~~
296 ~~variables is comparable to or greater than that of ERA5.~~ For analysis RMSE (Fig. 23), E3DVAR
297 is smaller than AdvHG for all pressure levels and variables, except for temperature in July at
298 1000 hPa and Qvapor in January and July at 1000 hPa. In general, the analysis RMSE of
299 AdvHG for all variables is comparable to or greater than that of ERA5. The analysis RMSE of
300 ERA5 is smaller than that of ERA-I for all levels and variables; in particular, the analysis
301 RMSE difference between ERA5 and ERA-I is distinctive for wind.

302 Regarding wind variables of analysis (Figs. ~~2a, b, c, and d~~3a, b, c, and d), E3DVAR is the
303 most closely fitted to observations except for the wind in upper troposphere in January,
304 followed by ERA5, AdvHG, and ERA-I. For temperature RMSE (Figs. ~~2e and f~~3e and f),
305 ~~E3DVAR is smaller than AdvHG and ERA5 is smaller than ERA-I. However, in January (Fig.~~
306 ~~2e), ERA5 RMSE is the smallest for upper troposphere and RMSEs of ERA5 and E3DVAR~~
307 ~~are similar to each other for lower troposphere. In July (Fig. 2f), overall E3DVAR RMSE is the~~
308 ~~smallest except for 1000 hPa.~~ E3DVAR is smaller than AdvHG. For Qvapor, RMSE in July is
309 much larger than that in January due to a monsoonal flow carrying moist air to East Asia. In

310 general, Qvapor RMSE of E3DVAR is the smallest, followed by ERA5, AdvHG, and ERA-I.
311 Therefore, for all variables, generally E3DVAR analysis fields are the most closely fitted to
312 observations. Since the analysis RMSE implies how much analysis fields are fitted to
313 observations rather than the accuracy of analysis itself, not only analysis RMSE but also
314 forecast RMSE should be considered

315 ~~For 24 h forecast RMSEs (Fig. 3), ERA5 RMSE is the smallest for all levels and variables~~
316 ~~for January and July in 2017. In January (Figs. 3a, c, e, and g), overall, the 24 h forecast RMSE~~
317 ~~of ERA5 is the smallest and that of ERA-I is the largest for all variables, and RMSEs of AdvHG~~
318 ~~and E3DVAR are greater than those of ERA5 and smaller than those of ERA-I. Regarding~~
319 ~~AdvHG and E3DVAR, in general, AdvHG is smaller than E3DVAR for all levels and variables.~~
320 ~~Thus, in January, ERA5 is the most accurate, followed by AdvHG, E3DVAR, and ERA-I.~~
321 ~~Meanwhile, for July (Figs. 3b, d, f, and h), ERA5 shows the smallest RMSE, and AdvHG and~~
322 ~~E3DVAR show comparable RMSE to ERA-I. For 24 h forecast fields in January (Figs. 4a, c,~~
323 ~~e, and g), overall, RMSEs of AdvHG and E3DVAR are greater than those of ERA5 and smaller~~
324 ~~than those of ERA-I, and AdvHG RMSE is smaller than E3DVAR RMSE for all levels and~~
325 ~~variables. Meanwhile, for July (Figs. 4b, d, f, and h), AdvHG and E3DVAR show comparable~~
326 ~~RMSE to ERA-I.~~

327 Furthermore, general features of 36 h forecast RMSE (Fig. 45) are similar to the 24 h
328 forecast RMSE (Fig. 34). However, particularly in January, the 36 h forecast RMSE differences
329 between ERA5 and ERA-I are more distinctive compared to those of 24 h forecast. In January,
330 the vertically averaged 36 h forecast RMSE differences of ERA5 and ERA-I are 0.52 m s^{-1} for
331 wind, 0.16 K for temperature, and 0.08 g kg^{-1} for Qvapor, whereas those of 24 h forecast are
332 0.4 m s^{-1} for wind, 0.11 K for temperature, and 0.06 g kg^{-1} for Qvapor. In addition, the 36 h
333 forecast RMSE differences between ERA5 and AdvHG for January are on average 0.1 m s^{-1}
334 for wind, 0.05 K for temperature, and 0.02 g kg^{-1} for Qvapor, which are even smaller compared

335 to those of 24 h forecast, implying that AdvHG is a lot more accurate than ERA-I for January
336 in 2017. For July, 36 h forecast RMSE of ERA5 is the smallest and RMSEs of AdvHG and
337 E3DVAR are similar to those of ERA-I.

338 4.1.2 RMSE and spread for the period of ~~2017-18-2010-2019~~

339 In this section, EARR produced in this study is verified for a longer period with WRF-
340 based ERA5. RMSE and spread of reanalyses and reforecasts based on AdvHG method are
341 calculated and averaged over the period of ~~2017-2018-2010-2019~~. The reanalyses and
342 (re)forecast fields are evaluated by calculating RMSE valid at 00 and 12 UTC and spread at 00,
343 06, 12, and 18 UTC.

344 The averaged RMSEs of reanalysis for ERA5 and EARR (denoted as AdvHG in Fig. ~~56~~)
345 and spread of analysis and 6 h forecast fields of EARR (AdvHG) are shown in Fig. ~~56~~. With
346 respect to spread, the ensemble spreads of analysis fields are smaller than those of 6 h forecast
347 fields, on average, by ~~0.16~~0.15 m s⁻¹ for wind, 0.04 K for temperature, and 0.02 g kg⁻¹ for
348 Qvapor, which is the well-known characteristics of ensemble-based data assimilation methods.
349 To be specific, the wind spread (Figs. ~~56a~~ and b) is similar to or greater than the wind RMSE
350 except for the upper troposphere above 200 hPa, implying ensemble spread for wind is well
351 represented below 200 hPa. ~~Even if the ensembles for temperature (Fig. 5e) are underdispersive~~
352 ~~compared to RMSE of temperature, overall Qvapor spread (Fig. 5d) is well represented except~~
353 ~~for 1000 hPa and above 200 hPa. On the contrary, the ensembles for temperature and Qvapor~~
354 ~~(Figs. 6c and d) are underdispersive compared to their RMSEs.~~

355 ~~Regarding reanalysis RMSE, overall ERA5 RMSE is smaller than AdvHG RMSE for all~~
356 ~~variables (Fig. 5). The vertically averaged RMSEs of ERA5 are smaller by 0.15 m s⁻¹ for wind,~~
357 ~~0.08 K for temperature, and 0.01 g kg⁻¹ for Qvapor than those of AdvHG. Regarding reanalysis~~
358 ~~RMSE, overall AdvHG RMSE is greater than ERA5 RMSE for all variables (Fig. 6). The~~
359 ~~vertically averaged RMSEs of AdvHG are greater by 0.16 m s⁻¹ for wind, 0.09 K for~~

360 temperature, and 0.01 g kg⁻¹ for Qvapor than those of ERA5. Nonetheless, the wind RMSEs of
361 AdvHG are similar to those of ERA5 for the middle of troposphere (400–850 hPa), and the
362 Qvapor RMSEs of AdvHG are similar to those of ERA5 except for 1000 hPa.

363 In addition, regarding 24 h forecast RMSE, ~~ERA5 shows smaller RMSE than AdvHG for~~
364 ~~all variables (Fig. 6).~~—AdvHG shows larger RMSE than ERA5 for all variables (Fig. 7).
365 The vertically-averaged RMSE differences of wind, temperature, and Qvapor variables
366 between AdvHG and ERA5 are approximately 0.2 m s⁻¹, 0.07 K, and 0.03 g kg⁻¹, respectively.
367 These differences are smaller, compared to the 24 h forecast RMSE difference between ERA-
368 I and ERA5 shown in Fig. 34 (i.e., wind, temperatureTemp, and Qvapor RMSE difference: 0.4
369 m s⁻¹, 0.11 K, and 0.06 g kg⁻¹ for January 2017, 0.25 m s⁻¹, 0.05 K, and 0.04 g kg⁻¹ for July
370 2017).

371 4.2 Evaluation of precipitation for January and July in 2017.

372 4.2.1 Evaluation metrics

373 4.2.1.1 Equitable threat score and Frequency bias index

374 In this section, for the point-based Equitable threat score (ETS) and Frequency bias index
375 (FBI) based on Table 24, the 6 h accumulated precipitation fields based on the 6 h forecast of
376 E3DVAR, AdvHG, WRF-based ERA-I, WRF-based ERA5, ERA-I_fromECMWF, and
377 ERA5_fromECMWF are evaluated every 6 h (00, 06, 12, and 18 UTC) for January and July in
378 2017 (Fig. 78). Here, all the WRF-based precipitation fields are based on 12-km horizontal
379 resolution, and ERA-I_fromECMWF and ERA5_fromECMWF have 79- and 31-km horizontal
380 resolutions, respectively. Generally, ETS decreases as a threshold increases for both two
381 months (Figs. 78a and c). For January in 2017 (Fig. 78a), AdvHG ETS is the greatest among
382 others. Compared to precipitation reforecasts from ECMWF (i.e., ERA-I_fromECMWF,
383 ERA5_fromECMWF), AdvHG shows the higher ETS, indicating that AdvHG is able to
384 simulate more accurate precipitation fields than ERA-I and ERA5 from ECMWF in January

385 2017. Surprisingly, ETS of ERA5_fromECMWF for January in 2017 is the lowest among all
386 the results compared and is even lower than that of ERA-I_fromECMWF.

387 Since the precipitation reforecasts from ECMWF have not only coarser resolutions but
388 also different forecast model (i.e., the forecasting system of ECMWF), the precipitation
389 forecasts of ERA5 and ERA-I are additionally produced by using the same forecast model with
390 the same resolution as AdvHG and E3DVAR in this study, as explained in section 2.4. For
391 January 2017 (Fig. 78a), ETS of ERA5 (i.e., WRF-based ERA5) is higher than that of
392 ERA5_fromECMWF for all thresholds, whereas ETS of ERA-I (i.e., WRF-based ERA-I) is
393 lower than that of ERA-I_fromECMWF except for ~~strong-high~~ thresholds (8 and 16 mm (6 h)⁻¹).
394 The ERA5 ETS is greater than the ERA-I ETS, but is smaller than the AdvHG ETS. The
395 AdvHG shows the greatest ETS among others with the same resolution and forecast model,
396 and E3DVAR, ERA5, and ERA-I follow.

397 Regarding FBI in winter (Fig. 78b), ~~for strong thresholds for 4, 8, and 16 mm (6 h)⁻¹~~
398 thresholds, all the results show the FBI smaller than 1, implying the underestimation of
399 frequency of precipitation ~~for strong thresholds for high-threshold events. While FBIs of~~
400 ~~ERA5_fromECMWF and ERA-I_fromECMWF are greater than 1 for weak thresholds, those~~
401 ~~WRF-based results are similar to 1 or smaller than 1.~~ In general, AdvHG shows the FBI closest
402 to 1 among all the results, which is consistent with the greatest ETS of AdvHG. The E3DVAR
403 FBI is similar to the AdvHG FBI, and ERA5 and ERA-I FBIs are similar to each other. ~~FBIs~~
404 ~~of ERA5 and ERA-I are smaller than those of AdvHG and E3DVAR.~~

405 Meanwhile, overall, the ETS values for January whose maximum is around 0.4 (Fig. 78a)
406 are much greater than those for July in 2017 whose maximum is around 0.2 (Fig. 78c), implying
407 that the precipitation forecast in summer is more difficult than that in winter. The ETS
408 difference between the results in July is smaller than those in January. Particularly, for the
409 thresholds 4 and 8 mm (6 h)⁻¹, ETSs in July are similar to each other (Fig. 78c). Except for

410 those two thresholds, the ETS of ERA-I_fromECMWF is the smallest. At the threshold 16 mm
411 (6 h)⁻¹, ERA5 ETS is the highest, followed by AdvHG, E3DVAR, ERA-I, ERA5_fromECMWF,
412 and ERA-I_fromECMWF. At the threshold 0.5 and 1 mm (6 h)⁻¹, the E3DVAR ETS is the
413 greatest, followed by ERA5, AdvHG, ERA5_fromECMWF, ERA-I, and ERA-I_fromECMWF.

414 With respect to FBI in July 2017, the WRF-based results show the FBIs greater than 1,
415 whereas reforecast from ECMWF show the FBIs greater than 1 for ~~weak-0.5, 1, and 4 mm (6~~
416 ~~h)⁻¹ thresholds and smaller than 1 for higher thresholds (8 and 16 mm (6 h)⁻¹) strong thresholds~~
417 (Fig. 78d). For July in 2017, in general, ERA5_fromECMWF FBI is the closest to 1, followed
418 by E3DVAR, AdvHG, ERA5, ERA-I, and ERA-I_fromECMWF FBI.

419 4.2.1.2 Probability of detection and False alarm ratio

420 The Probability of Detection (POD or Hit Rate) and False Alarm Ratio (FAR) are
421 calculated for precipitation simulated from E3DVAR, AdvHG, WRF-based ERA-I, WRF-
422 based ERA5, ERA-I_fromECMWF, and ERA5_fromECMWF for January and July in 2017
423 (Fig. 89). For January in 2017, AdvHG POD is the greatest among the WRF-based results,
424 followed by E3DVAR, ERA5, and ERA-I (Figs. 89a). ~~Overall, the results of reforecast from~~
425 ~~ECMWF (i.e., ERA-I_fromECMWF and ERA5_fromECMWF) have greater POD than the~~
426 ~~WRF-based POD for weak thresholds, whereas those have smaller POD than the WRF-based~~
427 ~~POD for strong thresholds. Regarding FAR, notably, ERA5_fromECMWF shows extremely~~
428 ~~great FAR and ERA5 shows the smallest FAR among all the results, which is a consistent result~~
429 ~~with the smallest ETS of ERA5_fromECMWF.~~ In addition to the lowest ETS of
430 ERA5_fromECMWF for January in 2017 as discussed in the section 4.2.1.1, FAR of
431 ERA5_fromECMWF is extremely high with low POD in winter. ~~Therefore, especially for~~
432 ~~January in 2017, the precipitation fields simulated from ERA5_fromECMWF over East Asia~~
433 ~~are much less accurate than any other results from this study. Therefore, especially for January~~
434 ~~in 2017, the precipitation fields simulated from EARR (AdvHG) over East Asia are a lot more~~

435 accurate than those from ERA5_fromECMWF.

436 ~~For July in 2017, generally, ERA5 shows the largest POD, followed by AdvHG, ERA-I,~~
437 ~~E3DVAR, ERA5_fromECMWF (Figs. 8e and d). For July in 2017, generally, AdvHG shows~~
438 ~~the largest POD, except for ERA5 (Fig. 9c). The ERA-I POD shows the largest POD for weak~~
439 ~~thresholds and the smallest POD for strong thresholds, compared to other results.~~ With respect
440 to FAR, FAR values in July ~~is~~ are much greater than those in January, which is consistent with
441 the ETS difference between these two seasons. ~~Overall, for strong thresholds, ERA-I shows~~
442 ~~the highest FAR and ERA-I_fromECMWF shows the smallest FAR. For weak thresholds, the~~
443 ~~ERA-I_fromECMWF shows the highest FAR and E3DVAR shows the smallest FAR among~~
444 ~~all the results.~~

446 4.2.1.3 Brier skill score

447 The neighborhood sizes are chosen to be $3\Delta x$, $5\Delta x$, $9\Delta x$, and $11\Delta x$, which are 36, 60,
448 108, and 132 km, respectively, and the thresholds 0.5, 1, 4, 8, and 16 mm (6 h)⁻¹ are considered.
449 The probabilistic precipitation forecasts are calculated at every model grid point depending on
450 neighborhood sizes and thresholds. Regarding each observation, the nearest model grid point
451 to observations is considered as the center of neighborhood. For verification, 6 h accumulated
452 precipitation fields are extracted from the first 0–6 h forecast fields of WRF-based ERA-I,
453 WRF-based ERA5, E3DVAR, and AdvHG every 6 h (00, 06, 12, and 18 UTC). BSSs of
454 ERA5_fromECMWF and ERA-I_fromECMWF are not calculated, because they have different
455 resolution from WRF-based results.

456 Based on the neighborhood approach, Brier skill score (BSS) is calculated depending on
457 different neighborhood sizes for January and July in 2017, respectively (Fig. 910). Because the
458 reference of Brier score is chosen as the ERA-I, the positive BSS implies better accuracy than
459 ERA-I. In general, for both two months, AdvHG BSS is greater than ERA5 BSS. Although the

460 E3DVAR BSS is the greatest in July 2017, the AdvHG BSS is the greatest in January 2017.

461 For January in 2017, as a neighborhood size increases, AdvHG and E3DVAR BSSs tend
462 to increase except for ERA5. Overall, AdvHG BSS is the greatest among other BSSs for all
463 thresholds for all neighborhood sizes. The ERA5 BSS is greater than E3DVAR BSS except for
464 16 mm (6 h)⁻¹. The highest BSS of AdvHG and the lowest BSS of ERA-I are consistent with
465 ETS result. Unlike greater E3DVAR ETS than ERA5 ETS, ERA5 BSS is greater than E3DVAR
466 BSS in January 2017.

467 For July 2017, while the ETS difference between the WRF-based results is not distinct
468 (Fig. 78c), the BSS difference is rather noticeable. Generally, E3DVAR BSS is the greatest
469 among other BSSs for all thresholds except for 16 mm (6 h)⁻¹ for neighborhood sizes 9 and 11.
470 Although E3DVAR BSS is the largest, AdvHG outperforms ERA5 and ERA-I. The worst
471 performance of ERA-I precipitation is consistent with ETS result. At ~~weak-0.5, 1, and 4 mm (6~~
472 ~~h)⁻¹ thresholds, E3DVAR BSS is the greatest, which is similar to ETS. For strong-At 8 and 16~~
473 ~~mm (6 h)⁻¹ thresholds, ERA5 ETS is the highest, followed by AdvHG and E3DVAR, whereas~~
474 overall E3DVAR BSS is the highest, followed by AdvHG and ERA5.

475 4.2.2 Spatial distribution

476 4.2.2.1 6 h accumulated precipitation with the pattern correlation coefficient

477 In this section, the spatial distributions of 6 h accumulated precipitation from the WRF-
478 based forecast and reforecast from ECMWF are compared. In addition, pattern correlation
479 coefficients (PCC) are calculated and shown at the bottom right of Figs. ~~10 and 11~~ and 12.

480 The PCC is computed according to the usual Pearson correlation operating on the N
481 observed point pairs of 6 h accumulated precipitation fields simulated from (re)forecast and
482 observations at the specific time. For the calculation of PCC, 6 h accumulated precipitation
483 fields from (re)forecast fields are interpolated bilinearly to the N observed points.

484 ~~Firstly, on 29th and 30th of January in 2017 (Fig. 10), it is noticeable that the precipitation~~

485 ~~of ERA5_fromECMWF does not match observations well over East Asia compared to other~~
486 ~~simulated precipitation fields. As shown in Fig. 10g, ERA5_fromECMWF incorrectly~~
487 ~~simulates precipitation over South East China, whereas other results do not forecast~~
488 ~~precipitation over this area. In addition, ERA5_fromECMWF overestimates precipitation over~~
489 ~~inland area of China (Fig. 10zz), whereas other results simulate precipitation similar to~~
490 ~~observations regarding its position and intensity. ERA5_fromECMWF also shows noticeably~~
491 ~~smaller PCC (Figs. 10g, n, and zz). Although PCC does not represent the exact accuracy or~~
492 ~~predictability of precipitation, the overall feature of PCC is consistent with the results found so~~
493 ~~far. In particular, PCCs of ERA5_fromECMWF are much smaller than those of other~~
494 ~~precipitation fields. For January in 2017, the averaged PCC of AdvHG is the greatest (i.e., 0.61)~~
495 ~~and that of ERA5_fromECMWF is the smallest (i.e., 0.46) (not shown). Firstly, on 29th and~~
496 ~~30th of January in 2017 (Fig. 11), it is noticeable that the precipitation fields of AdvHG match~~
497 ~~observations well over East Asia, whereas, in particular, those of ERA5_fromECMWF do not.~~
498 For example, ERA5_fromECMWF overestimates precipitation over inland area of China (Fig.
499 11zz), while AdvHG simulates precipitation similar to observations regarding its position and
500 intensity (Fig. 11x). ERA5_fromECMWF also shows noticeably smaller PCC (Figs. 11g, n,
501 and zz). Although PCC does not represent the exact accuracy or predictability of precipitation,
502 the overall feature of PCC is consistent with the results found so far. For January in 2017, the
503 averaged PCC of AdvHG is the greatest (i.e., 0.61) and that of ERA5_fromECMWF is the
504 smallest (i.e., 0.46) (not shown).

505 Secondly, for 1st and 2nd of July in 2017 (Fig. 11), overall, the precipitation simulated from
506 ERA5_fromECMWF is well represented, compared to January in 2017 shown in Fig. 10. The
507 ERA-I_fromECMWF fails to simulate heavy rain for summer season due to its coarse
508 resolution. Furthermore, during July in 2017, ERA5 and ERA-I simulate heavier precipitation
509 than AdvHG (not shown), which is consistent with larger FBI of ERA5 and ERA-I at strong

510 ~~thresholds.~~ For 1st and 2nd of July in 2017 (Fig. 12), in general, AdvHG, E3DVAR, and ERA5
511 well simulate not only overall features of precipitation fields but also their intensity. During
512 July in 2017, ERA5 and ERA-I simulate heavier precipitation than AdvHG (not shown), which
513 is consistent with larger FBI of ERA5 and ERA-I at higher thresholds. For one-month period
514 of July in 2017, the averaged PCC of ERA5 is the greatest (i.e., 0.37) and that of AdvHG is
515 0.34, but the PCC difference between ERA5 and AdvHG is not distinctive. Moreover, the
516 overall range of averaged PCC of different datasets in summer (i.e., 0.29-0.35) is smaller than
517 that in winter (i.e., 0.46-0.61), which is consistent with the seasonal difference of ETS in this
518 study.

519 4.2.2.2 Monthly accumulated precipitation

520 In this section, the monthly accumulated precipitation fields of rain gauge based
521 observations, E3DVAR, AdvHG, ERA-I, ERA5, ERA-I_fromECMWF, and
522 ERA5_fromECMWF are compared to each other for two one-month periods in January and
523 July in 2017, respectively.

524 ~~Although all the results similarly represent overall features of precipitation in January (Fig.~~
525 ~~12), ERA5_fromECMWF (Fig. 12g) simulates the overestimated precipitation over South~~
526 ~~China, compared to other results and observations, which is consistent with the results in the~~
527 ~~previous section as well as its larger FBI at weak thresholds shown in Fig. 7b. It is noticeable~~
528 ~~that all results fail to represent the observed precipitation area over Tibetan Plateau (25°–40°N,~~
529 ~~95–105°E). The monthly accumulated precipitation fields simulated by E3DVAR and AdvHG~~
530 ~~(Figs. 12b and c) are similar to each other, and E3DVAR and AdvHG produce the best fit to~~
531 ~~observed fields. Especially, for the north-western part of Japan (e.g., Chugoku and Kinki),~~
532 ~~E3DVAR and AdvHG are able to represent precipitation correctly, whereas ERA-~~
533 ~~I_fromECMWF and ERA5_fromECMWF fail to do so (Fig. 12).~~ The monthly accumulated
534 precipitation fields simulated by E3DVAR and AdvHG (Figs. 13b and c) are similar to each

535 other, and E3DVAR and AdvHG produce the best fit to observed fields. Especially, for the
536 north-western part of Japan (e.g., Chugoku and Kinki), E3DVAR and AdvHG are able to
537 represent precipitation correctly, whereas ERA-I_fromECMWF and ERA5_fromECMWF fail
538 to do so (Fig. 13). Moreover, although all the results similarly represent overall features of
539 precipitation in January (Fig. 13), ERA5_fromECMWF (Fig. 13g) simulates the overestimated
540 precipitation over South China, which is consistent with the results in the previous section as
541 well as its larger FBI at lower thresholds (0.5 and 1 mm (6 h)⁻¹) shown in Fig. 8b. It is noticeable
542 that all results fail to represent the observed precipitation area over Tibetan Plateau (25°–40°N,
543 95°–105°E).

544 For the monthly accumulated precipitation in July 2017, overall, the ERA5_fromECMWF
545 (Fig. 143g) and the WRF-based results (Fig. 143b, c, and e) except for ERA-I (Fig. 134d) well
546 simulate precipitation similar to observations. ~~ERA-I_fromECMWF is not able to simulate~~
547 ~~heavy precipitation over Korea. For western and southern part of Japan, while ERA-~~
548 ~~I_fromECMWF and ERA5_fromECMWF simulate similar precipitation fields to observed~~
549 ~~fields, WRF-based results overestimate precipitation over these regions. Compared to ERA-~~
550 ~~I_fromECMWF and ERA5_fromECMWF, the WRF-based results tend to overestimate~~
551 ~~precipitation in South China, Korea, and Japan. This is consistent with the result in Fig. 7d, in~~
552 ~~which FBIs from WRF-based results are generally greater than 1 for strong thresholds, whereas~~
553 ~~those from ECMWF are smaller than 1. The WRF-based results including AdvHG overestimate~~
554 ~~precipitation over western and southern part of Japan, while ERA-I_fromECMWF and~~
555 ~~ERA5_fromECMWF simulate similar precipitation fields to observed fields. The WRF-based~~
556 ~~results tend to overestimate precipitation in South China, Korea, and Japan, compared to ERA-~~
557 ~~I_fromECMWF and ERA5_fromECMWF. This is consistent with the result in Fig. 8d, in which~~
558 ~~FBIs from WRF-based results are generally greater than for higher thresholds (8 and 16 mm (6~~
559 ~~h)⁻¹), whereas those from ECMWF are smaller than 1.~~

560 Even though detailed precipitation features of WRF-based results are different, overall
561 features of precipitation from WRF-based results are similar to each other, which implies that
562 predictability of precipitation strongly depends on the physics schemes as well as NWP model,
563 especially for summer season. According to Que et al. (2016), depending on the combinations
564 of physics options in WRF model, the spatial distribution of precipitation can be significantly
565 different over Asian summer monsoon area and YSU PBL scheme which is used in this study
566 tends to overestimate precipitation over the same area. Thus, different physics options could
567 simulate the different spatial distribution of precipitation.

568 In addition, compared to ERA5 based on WRF model (Fig. 134e), ECMWF model for
569 ERA5_fromECMWF (Fig. 134g) seems to suppress precipitation. Thus, WRF model with the
570 physics schemes used in this study might simulate more precipitation than ECMWF model,
571 although the initial condition is the same. Therefore, it is important to consider the consistency
572 of the systems for data assimilation and forecast model for a good performance of ~~precipitation.~~
573 forecast weather variables like precipitation.

574 **5. Data Availability**

575 The EARR data presented in this study are available every 6 h (i.e., 00, 06, 12, and 18
576 UTC) for the period of 2010-2019 from Harvard Dataverse Repository
577 (<https://dataverse.harvard.edu/dataverse/EARR>). The EARR 6 hourly data on pressure levels
578 (<https://doi.org/10.7910/DVN/7P8MZT>, Yang and Kim 2021b) and 6 hourly precipitation data
579 (<https://doi.org/10.7910/DVN/Q07VRC>, Yang and Kim 2021c) are provided in NetCDF file
580 format.

581 The EARR 6 hourly data on pressure levels (Yang and Kim 2021b) include u-component
582 of wind, v-component of wind, temperature, geopotential height, and specific humidity
583 variables of reanalysis on pressure levels (i.e., 925, 850, 700, 500, 300, 200, 100, and 50 hPa).

584 The EARR 6 hourly precipitation data (Yang and Kim 2021c) contain 6 h accumulated total
585 precipitation variable of 6 h reforecast on single level. The 6 h accumulated total precipitation
586 is obtained from 6 h reforecast field which is integrated for 6 h from reanalysis field every 6 h
587 (i.e., 00, 06, 12 and 18 UTC).

588 **6. Summary and conclusions**

589 In this study, to develop the regional reanalysis system over East Asia, the advanced
590 hybrid gain algorithm (AdvHG) is newly proposed and evaluated with traditional hybrid DA
591 method (E3DVAR) as well as existing reanalyses from ECMWF (ERA5 and ERA-I) for
592 January and July in 2017. ~~The East Asia Regional Reanalysis (EARR) system is developed
593 based on the AdvHG as the data assimilation method using WRF model and conventional
594 observations, and the high-resolution regional reanalysis and reforecast fields with 12 km
595 horizontal resolution are produced over East Asia for the ten-year period of 2010–2019. The
596 East Asia Regional Reanalysis (EARR) system is developed based on the AdvHG as the data
597 assimilation method using WRF model and conventional observations. The high-resolution
598 regional reanalysis and reforecast fields over East Asia with 12 km horizontal resolution are
599 produced and evaluated against observations with ERA5 for the ten-year period of 2010–2019.~~

600 The AdvHG newly proposed in this study is based on the hybrid gain approach, weighting
601 analyses from variational-based and ensemble-based DA algorithms to generate optimal
602 hybrid analysis, which can play an important role as a simple and practical method in the
603 foreseeable future to take advantage of each strength of two different DA methods. The
604 advanced hybrid gain method is different from the hybrid gain approach in that 1) E3DVAR is
605 used instead of EnKF, 2) 6 h forecast of ERA5 is used instead of deterministic analysis for a
606 more balanced and consistent analysis with WRF model, and 3) the pre-existing and state-of-
607 the-art reanalysis data (i.e. ERA5) is simply used instead of producing our own analysis fields

608 from a variational DA method. Thus, it can be regarded as an efficient approach to generate
609 regional reanalysis dataset because of cost savings as well as the use of the state-of-the-art
610 reanalysis from ECMWF that assimilates all available observations.

611 For a verification, the latest ECMWF reanalysis and reforecast datasets (i.e., ERA5 and
612 ERA-I) are used. With respect to forecast variables, two different forecast fields of ECWMF
613 are used: 1) reforecast fields from ECMWF (i.e., ERA5_fromECMWF and ERA-
614 I_fromECMWF) and 2) forecast fields (i.e., WRF-based ERA5 and WRF-based ERA-I)
615 integrated in WRF model with 12 km resolution using ERA5 and ERA-I as initial conditions.

616 ~~To evaluate this newly proposed algorithm, analysis and forecast wind, temperature, and~~
617 ~~humidity variables are evaluated with respect to RMSE and spread for January and July in 2017.~~
618 Analysis and forecast wind, temperature, and humidity variables of AdvHG are evaluated with
619 ERA5 for the ten-year period and evaluated with five different experiments (i.e., E3DVAR,
620 ERA5, ERA-I, ERA5_fromECMWF, ERA-I_fromECMWF) for January and July in 2017.

621 Overall, the analysis RMSE of E3DVAR is the smallest among others but comparable to that
622 of ERA5, especially for January in 2017. Regarding forecast variables, AdvHG outperforms
623 E3DVAR ~~and ERA5 outperforms ERA-I~~ for January and July in 2017. Although ERA5
624 outperforms AdvHG for upper air variables for two seasons in 2017, AdvHG outperforms
625 ERA-I in January and shows comparable performance to ERA-I in July. Additionally the
626 verification results of AdvHG and ERA5 for the period of 2010-20197-18 are consistent with
627 those for two one-month period in 2017.

628 The precipitation forecast variables are also verified regarding a neighborhood-based
629 verification score (i.e., Brier skill score) as well as the point-based verification scores (i.e., ETS,
630 FBI, POD, and FAR). According to the point-based verification scores, the precipitation
631 forecast of AdvHG in January is the most accurate, followed by E3DVAR, ERA5, ERA-I. ~~The~~
632 ~~precipitation reforecast of ERA5_fromECMWF shows the worst performance with the lowest~~

633 ~~ETS and the highest FAR among other results in January.~~ For July, overall ETS values of all
634 results are relatively lower compared to those in January, implying the lower predictability in
635 summer season. ~~For July, ERA5 shows the greatest ETS for strong thresholds followed by~~
636 ~~AdvHG and E3DVAR, and E3DVAR ETS is the greatest followed by ERA5 and AdvHG for~~
637 ~~weak thresholds. However, the ETS differences between the results are not distinctive.~~ In
638 addition, the ETS differences between the results are not distinctive in July. For higher
639 thresholds (8 and 16 mm (6 h)⁻¹) in July, AdvHG ETS is greater than E3DVAR ETS and smaller
640 than ERA5 ETS, whereas E3DVAR ETS is the greatest followed by ERA5 and AdvHG for
641 lower thresholds (0.5 and 1 mm (6 h)⁻¹).

642 To prevent from double penalty when verifying a highly variable data with high resolution
643 (e.g., precipitation), Brier skill score (BSS) based on neighborhood approach is calculated for
644 6 h accumulated precipitation forecasts depending on different neighborhood sizes for January
645 and July in 2017. In general, BSS of AdvHG is greater than that of ERA5 and ERA-I for both
646 two months. Although the E3DVAR BSS is the greatest in July 2017, the AdvHG BSS is the
647 greatest in January 2017.

648 Lastly, the spatial distributions of 6 h and monthly accumulated precipitation forecast for
649 AdvHG, E3DVAR, ERA-I, ERA5, ERA-I_fromECMWF, and ERA5_fromECMWF are
650 compared with rain-gauge based observations. For January 2017, it is noticeable that AdvHG
651 precipitation is the closest to observations with highest PCC (i.e., 0.61) and
652 ERA5_fromECMWF overestimates precipitation over South China with the lowest PCC (i.e.,
653 0.46). ~~For July in 2017, due to a coarse resolution of ERA-I_fromECMWF, it fails to represent~~
654 ~~heavy rain over East Asia. Meanwhile, the WRF-based results tend to overestimate~~
655 ~~precipitation compared to ERA-I_fromECMWF and ERA5_fromECMWF.~~ For July in 2017,
656 the WRF-based results tend to overestimate precipitation compared to ERA-I_fromECMWF
657 and ERA5_fromECMWF. In addition, even though the averaged PCC of ERA5 (i.e., 0.37) is

658 slightly greater than that of AdvHG (i.e., 0.34), the PCC difference between ERA5 and AdvHG
659 is not distinctive and overall range of averaged PCC of all datasets in summer (i.e., 0.29-0.357)
660 is smaller than that in winter (i.e., 0.46-0.6).

661 In conclusion, for upper air variables, overall, ERA5 outperforms EARR based on AdvHG,
662 but the RMSE difference between ERA5 and EARR (AdvHG) is smaller than that between
663 ERA5 and ERA-I. In addition, EARR outperforms ERA-I for January 2017 and shows
664 comparable performance to ERA-I for July 2017. On the contrary, according to the evaluation
665 results of precipitation, in general, EARR better represents precipitation than ERA5 as well as
666 ERA5_fromECMWF for January and July in 2017. Even if E3DVAR precipitation is better
667 represented than EARR precipitation for July, the difference is not considerable for July and
668 EARR better simulates precipitation for January than E3DVAR. Therefore, although the
669 uncertainties of upper air variables of EARR should be considered when analyzing them, the
670 precipitation reforecast of EARR is more accurate than that of ERA5 for both two seasons.

671

672 **Author contribution**

673 Hyun Mee Kim proposed the main scientific ideas and Eun-Gyeong Yang contributed the
674 supplementary ideas during the process. Eun-Gyeong Yang developed the reanalysis system
675 and produced the 10-year regional reanalysis data. Eun-Gyeong Yang and Hyun Mee Kim
676 analyzed the simulation results and completed the manuscript. Dae-Hui Kim contributed to
677 analyzing the reanalysis data and to the preparation of software and computing resources for
678 the reanalysis system.

679

680 **Competing interests**

681 The authors declare that they have no competing interests.

682

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899

900 **Table caption**

901 Table 1. Model configuration.

902 Table 2. Summary of observations used in this study. The default observation error statistics
903 provided in WRFDA system are used for assimilation in this study. The variables u, v, T, RH,
904 Ps, and TPW denote zonal wind, meridional wind, temperature, relative humidity, surface
905 pressure, and total precipitable water, respectively.

906 Table 3. (Re)analyses and (re)forecasts and corresponding experiments used in this study.

907 Table 24. The 2×2 contingency table for dichotomous (yes-no) events.

908

909 **Figure caption**

910 ~~Figure 1. The model domain over East Asia with verification area (black dashed box).~~

911 Figure 1. The East Asia Regional Reanalysis domain with different types of NCEP PrepBUFR
912 observations available for assimilation at 00 UTC on 1st of January in 2017. The black dashed
913 box denotes a verification area.

914 Figure 2. The schematic diagram of the advanced hybrid gain data assimilation method in the
915 East Asia regional reanalysis system.

916 Figure 23. RMSEs of analysis of (a,b) zonal wind, (c,d) meridional wind, (e,f) temperature,
917 and (g,h) Qvapor (water vapor mixing ratio) from ERA-I (black dashed), ERA5 (black solid),
918 E3DVAR (blue dashed), AdvHG (blue solid) depending on pressure levels for (left) January
919 and (right) July in 2017.

920 Figure 34. Same as Fig. 23 except for 24 h forecast.

921 Figure 45. Same as Fig. 23 except for 36 h forecast.

922 Figure 56. RMSEs of analysis of (a) zonal wind, (b) meridional wind, (c) temperature, and (d)
923 Qvapor (water vapor mixing ratio) from ERA5 (black solid) and AdvHG (blue solid) and
924 spreads of analysis (black dashed) and 6 h forecast (gray dashed) of AdvHG depending on
925 pressure levels averaged over the two-year period of 2017–2018.

926 Figure 67. Same as Fig. 56 except for RMSE of 24 h forecast.

927 Figure 78. (a,c) ETS and (b,d) FBI for (a,b) January and (c,d) July in 2017 depending on
928 thresholds 0.5, 1, 4, 8, and 16 mm (6 h)⁻¹.

929 Figure 89. (a,c) POD and (b,d) FAR for (a,b) January and (c,d) July in 2017 depending on
930 thresholds 0.5, 1, 4, 8, and 16 mm (6 h)⁻¹.

931 Figure [910](#). Brier skill score of the probabilistic postprocessed forecast with reference to the
932 WRF-based ERA-I for (a-d) January and (e-h) July in 2017 (Blue solid: AdvHG, blue dashed:
933 E3DVAR, red solid: WRF-based ERA5).

934 Figure [1011](#). The spatial distribution of 6 h accumulated precipitation of (1st column)
935 observation, (2nd column) E3DVAR, (3rd column) AdvHG, (4th column) ERA-I, (5th column)
936 ERA5, (6th column) ERA-I_fromECMWF, and (7th column) ERA5_fromECMWF and the
937 pattern correlation coefficient (PCC) shown at the bottom right of each figure at valid time (1st
938 low, 3rd low) 06 UTC and (2nd low, 4th low) 18 UTC on 29th and 30th of January in 2017.

939 Figure [1112](#). As in Fig. [1011](#), but for 1st and 2nd of July in 2017.

940 Figure [1213](#). The spatial distribution of the monthly accumulated precipitation of (a)
941 observations, (b) E3DVAR, (c) AdvHG, (d) ERA-I, (e) ERA5, (f) ERA-I from ECMWF, and
942 (g) ERA5 from ECMWF for January 2017.

943 Figure [1314](#). As in Fig. [1213](#), but for July 2017.

944

945 Table 1. Model configuration

	Description
Hori. Resol.	12 km (540×432 grid points)
Vert. Lev.	50 vertical levels (up to 5 hPa)
Model	WRF Model (v3.7.1, Skamarock et al. 2008)
LBC	ERA5 (Hersbach et al. 2020)
Data assimilation	E3DVAR (Zhang et al. 2013), Advanced hybrid gain method
Microphysics	Thompson scheme (Thompson et al. 2008)
Cumulus convection	Grell–Freitas ensemble scheme (Grell and Freitas 2014)
PBL	Yonsei University scheme (Hong et al. 2006)
Radiation	Rapid Radiative Transfer Model (RRTMG) scheme (Iacono et al. 2008)
Surface layer	Revised MM5 Monin-Obukhov scheme (Jiménez et al. 2012)
Surface model	Unified Noah Land Surface Model (Tewari et al. 2004)

946

947

948 Table 2. Summary of observations used in this study. The default observation error statistics
 949 provided in WRFDA system are used for assimilation in this study. The variables u, v, T, RH,
 950 Ps, and TPW denote zonal wind, meridional wind, temperature, relative humidity, surface
 951 pressure, and total precipitable water, respectively.

<u>Observations</u>	<u>Descriptions</u>	<u>Variables</u>	<u>Observation errors</u> <u>(depending on vertical</u> <u>levels)</u>
<u>SOUND</u>	<u>Upper-air observation from radiosonde</u>	<u>u, v</u>	<u>1.1-3.3 m/s</u>
		<u>T</u>	<u>1 K</u>
		<u>RH</u>	<u>10-15%</u>
<u>PROFILER</u>	<u>Upper-air wind profile from wind profiler</u>	<u>u, v</u>	<u>2.2-3.2 m/s</u>
<u>PILOT</u>	<u>Upper-air wind profile from pilot balloon or</u> <u>radiosonde</u>	<u>u, v</u>	<u>2.2-3.2 m/s</u>
<u>AIREP</u>	<u>Upper-air wind and temperature from aircraft</u>	<u>u, v</u>	<u>3.6 m/s</u>
		<u>T</u>	<u>1 K</u>
<u>Scatwind</u>	<u>Scatterometer oceanic surface winds</u>	<u>u, v</u>	<u>2.5-3.8 m/s</u>
<u>SHIPS</u>	<u>Surface synoptic observation from ship</u>	<u>u, v</u>	<u>1.1 m/s</u>
		<u>T</u>	<u>2 K</u>
		<u>Ps</u>	<u>1.6 hPa</u>
		<u>RH</u>	<u>10%</u>
<u>SYNOP</u>	<u>Surface synoptic observation from land station</u>	<u>u, v</u>	<u>1.1 m/s</u>
		<u>T</u>	<u>2 K</u>
		<u>Ps</u>	<u>1 hPa</u>
		<u>RH</u>	<u>10%</u>
<u>BUOY</u>	<u>Surface synoptic observation from buoy</u>	<u>u, v</u>	<u>1.4-1.6 m/s</u>
		<u>T</u>	<u>2 K</u>
		<u>Ps</u>	<u>0.9-1 hPa</u>
		<u>RH</u>	<u>10%</u>
<u>GPSPW</u>	<u>Precipitable water vapor from global positioning</u> <u>system (GPS)</u>	<u>TPW</u>	<u>0.2 mm</u>
<u>METAR</u>	<u>Aviation routine weather report from automatic</u> <u>weather station (AWS)</u>	<u>u, v</u>	<u>1.1 m/s</u>
		<u>T</u>	<u>2 K</u>
		<u>Ps</u>	<u>1 hPa</u>
		<u>RH</u>	<u>10%</u>
<u>AMV</u>	<u>Conventional atmospheric motion vector data</u> <u>from geostationary satellite</u>	<u>u, v</u>	<u>2.5-4.5 m/s</u>

952

953

954

955 Table 3. (Re)analyses and (re)forecasts and corresponding experiments used in this study.

<u>Experiment</u>	<u>(Re)analysis</u>	<u>(Re)forecast</u>
<u>AdvHG (EARR)</u>	<u>Reanalysis from AdvHG</u>	<u>Generated using WRF</u>
<u>E3DVAR</u>	<u>Analysis from E3DVAR</u>	<u>Generated using WRF</u>
<u>WRF-based ERA5</u>	<u>Reanalysis from ERA5</u>	<u>Generated using WRF</u>
<u>WRF-based ERA-I</u>	<u>Reanalysis from ERA-I</u>	<u>Generated using WRF</u>
<u>ERA5_fromECMWF</u>	<u>Reanalysis from ERA5</u>	<u>Downloaded from ECMWF</u>
<u>ERA-I_fromECMWF</u>	<u>Reanalysis from ERA-I</u>	<u>Downloaded from ECMWF</u>

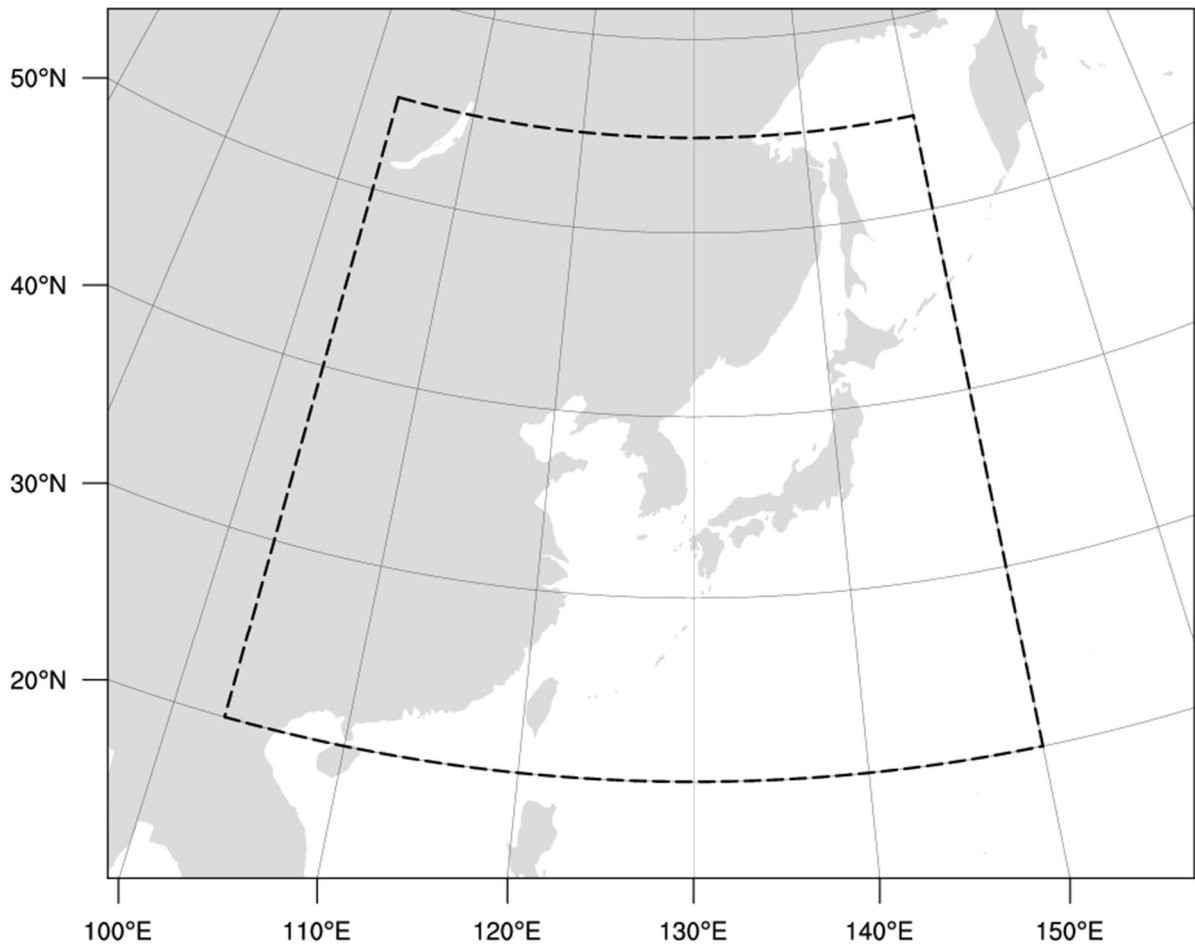
956 _____

957 Table 24. The 2×2 contingency table for dichotomous (yes-no) events.

Forecast	Observed		
	Yes	No	
Yes	Hits (A)	False alarms (B)	A + B
No	Misses (C)	Correct rejections (D)	C + D
	A + C	B + D	Total = A + B + C + D

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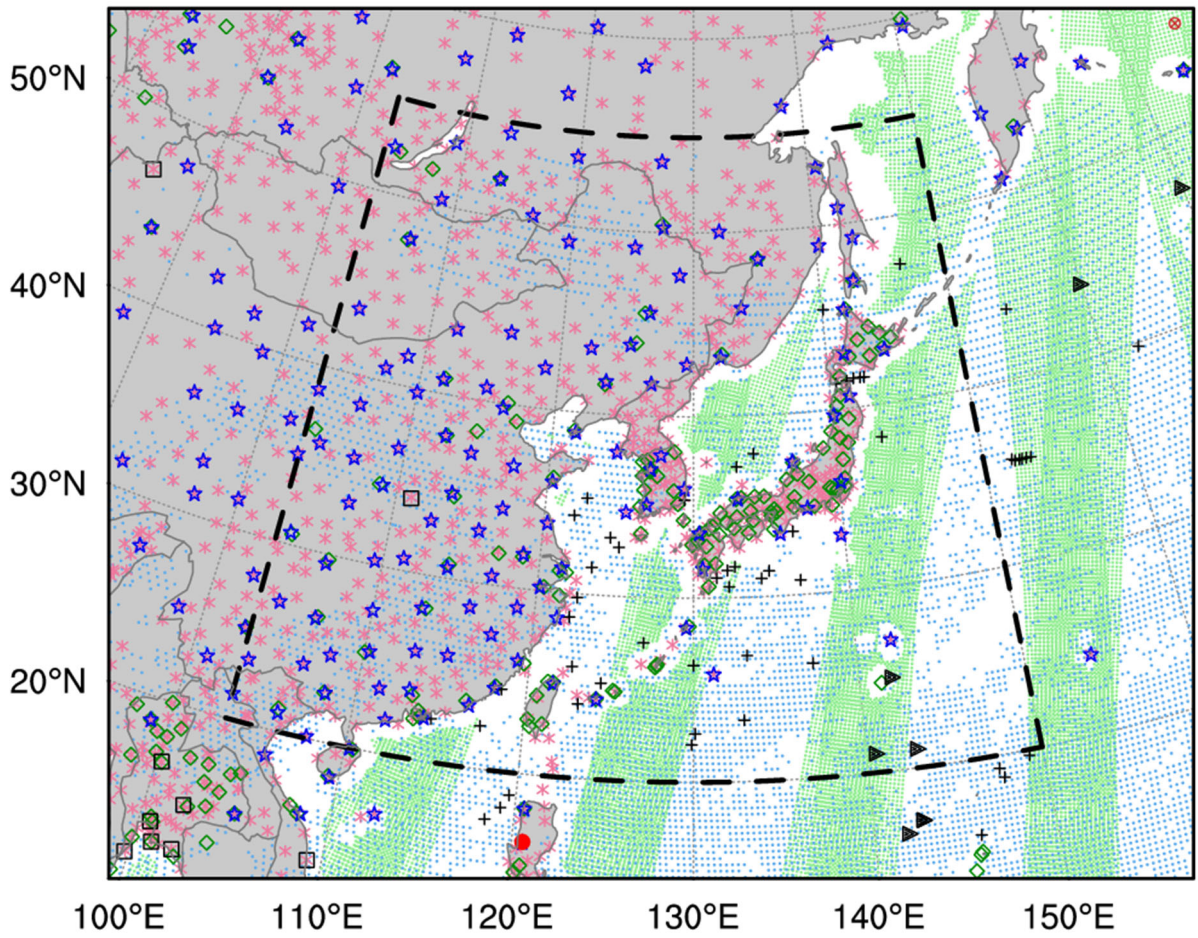


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Figure 1. The model domain over East Asia with verification area (black dashed box).

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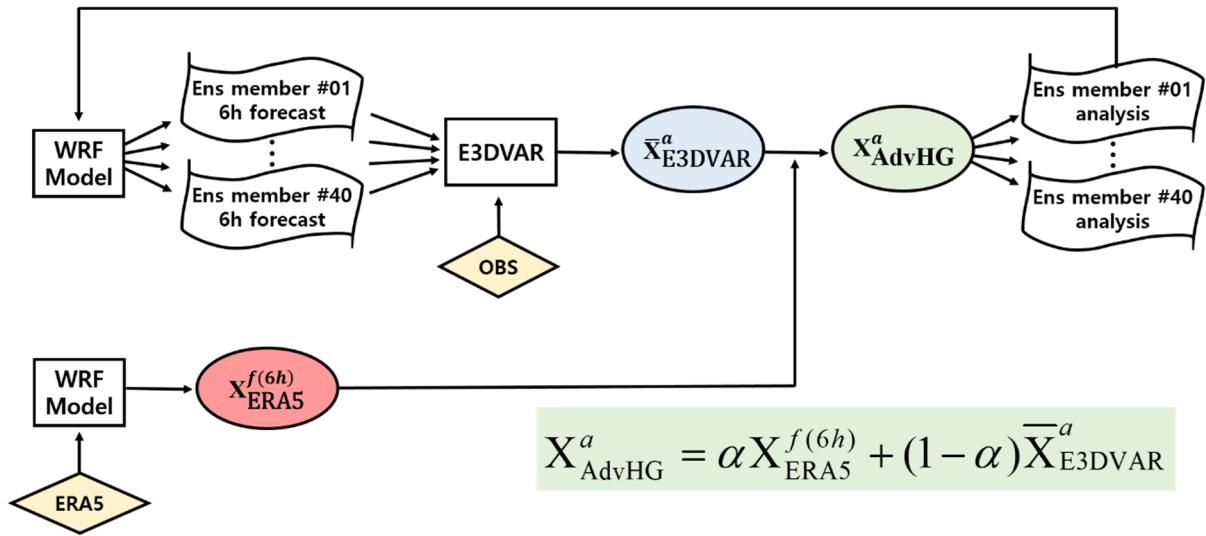


- Scatwind * SYNOP + SHIP ▴ AIREP ⊗ BUOY
- AMV ◊ METAR ☆ SOUND □ PILOT ● PROFL

962

963 Figure 1. The East Asia Regional Reanalysis domain with different types of NCEP PrepBUFR
964 observations available for assimilation at 00 UTC on 1st of January in 2017. The black dashed
965 box denotes a verification area.

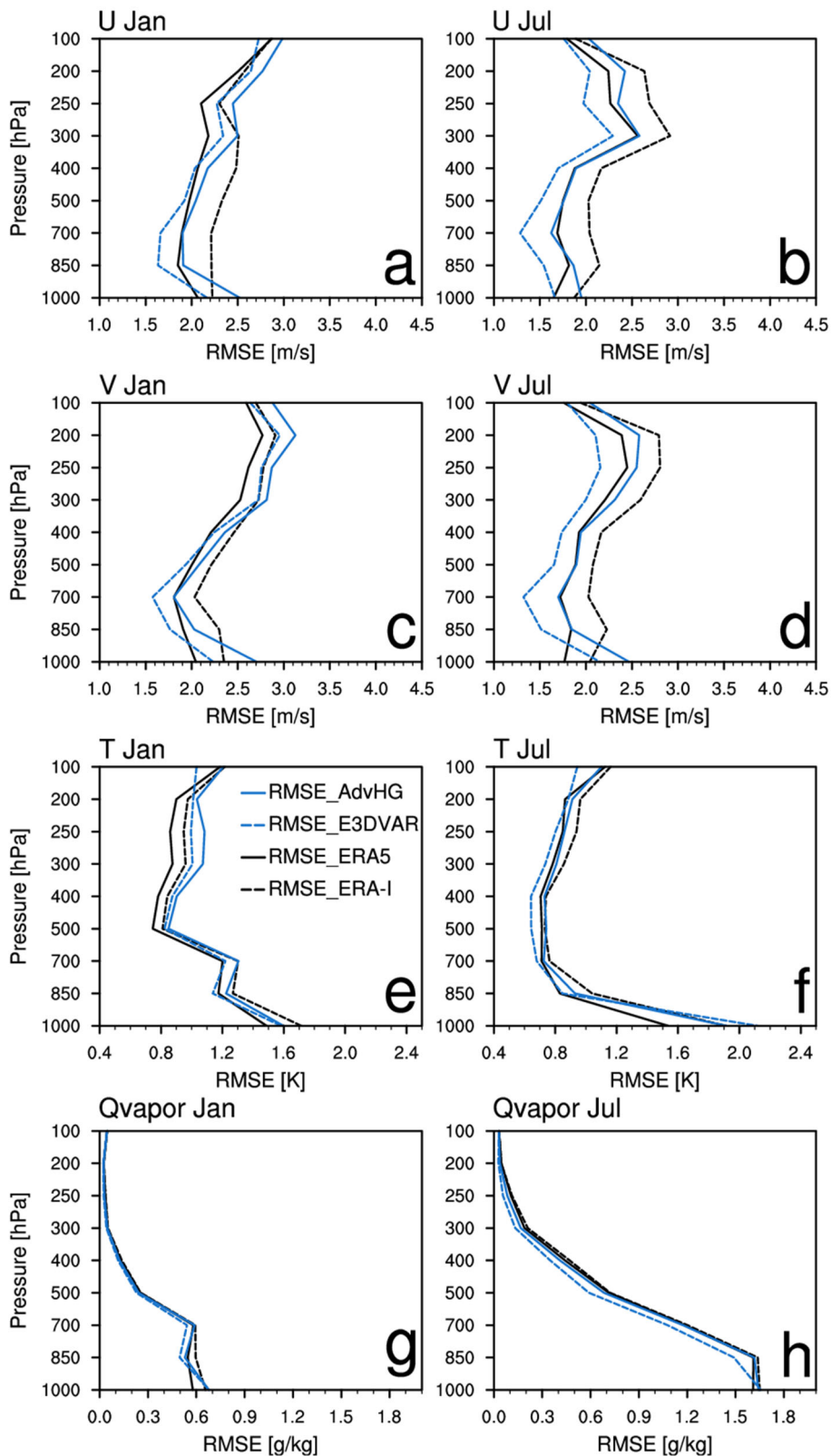
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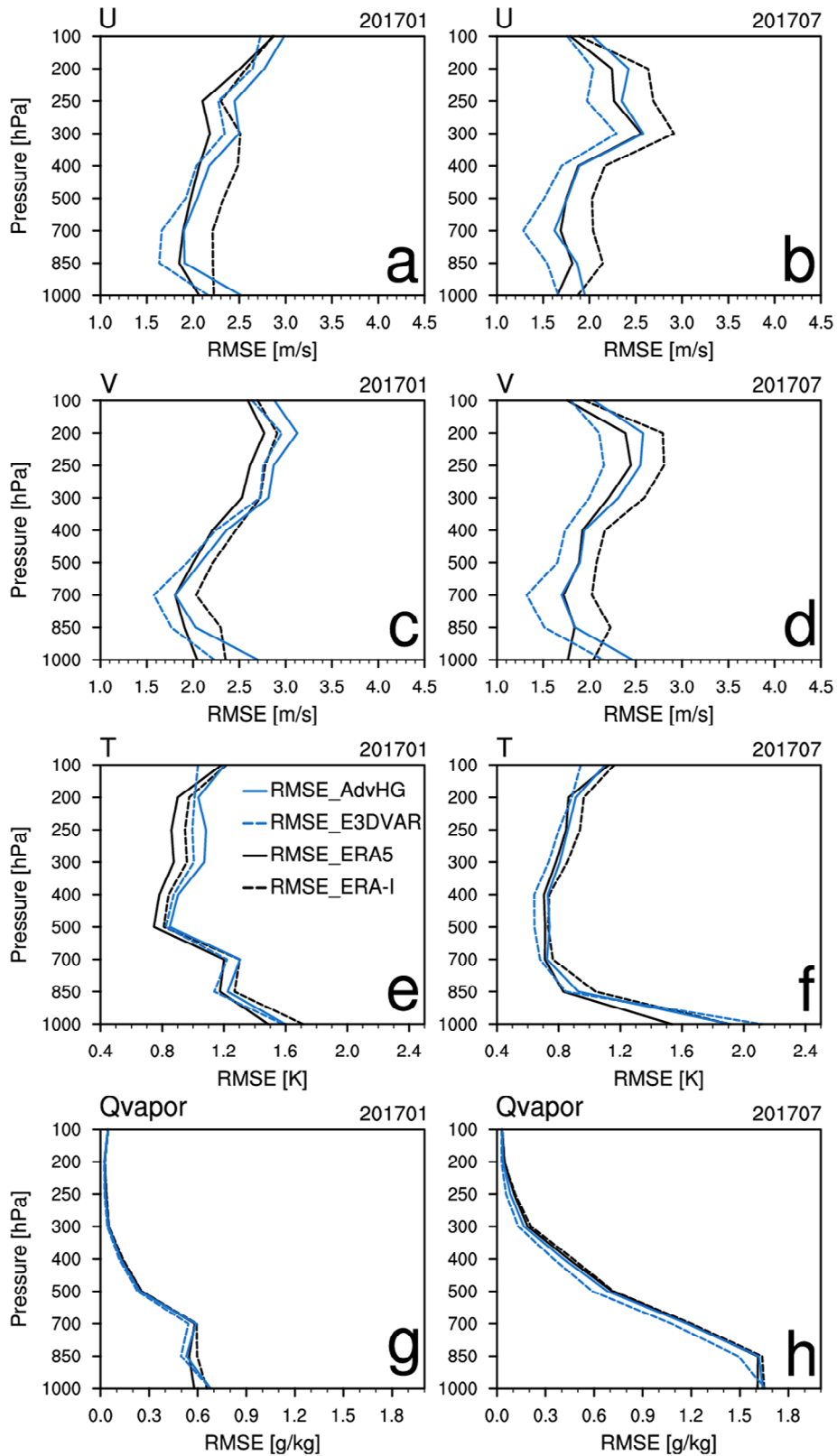
968 Figure 2. The schematic diagram of the advanced hybrid gain data assimilation method in the
 969 East Asia regional reanalysis system.

970



971

972 **Figure 2. RMSEs of analysis of (a,b) zonal wind, (c,d) meridional wind, (e,f) temperature, and**
 973 **(g,h) Qvapor (water vapor mixing ratio) from ERA-I (black dashed), ERA5 (black solid),**
 974 **E3DVAR (blue dashed), AdvHG (blue solid) depending on pressure levels for (left) January**
 975 **and (right) July in 2017.**



976

977 Figure 3. RMSEs of analysis of (a,b) zonal wind, (c,d) meridional wind, (e,f) temperature, and
 978 (g,h) Qvapor (water vapor mixing ratio) from ERA-I (black dashed), ERA5 (black solid),
 979 E3DVAR (blue dashed), AdvHG (blue solid) depending on pressure levels for (left) January
 980 and (right) July in 2017.

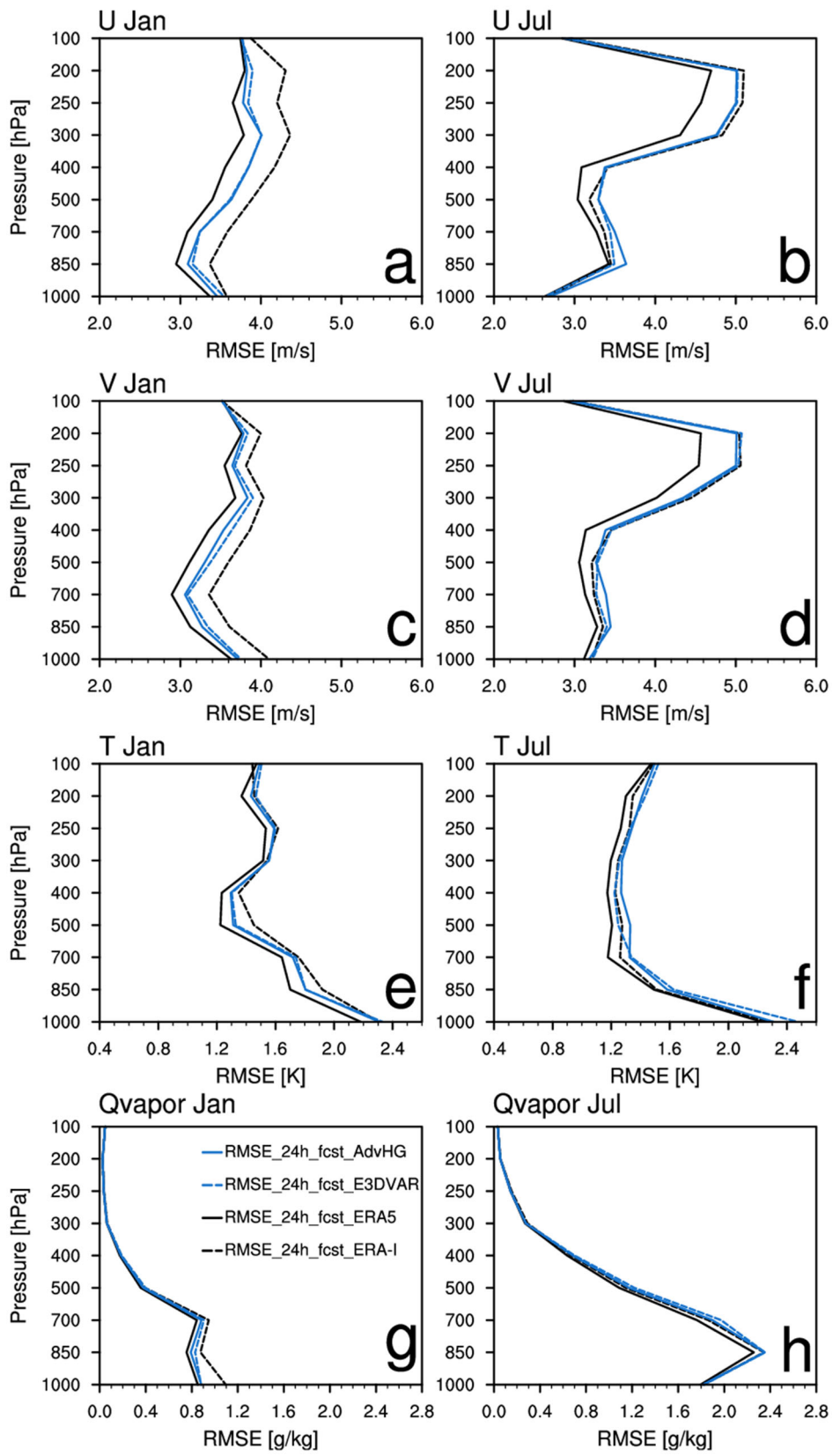
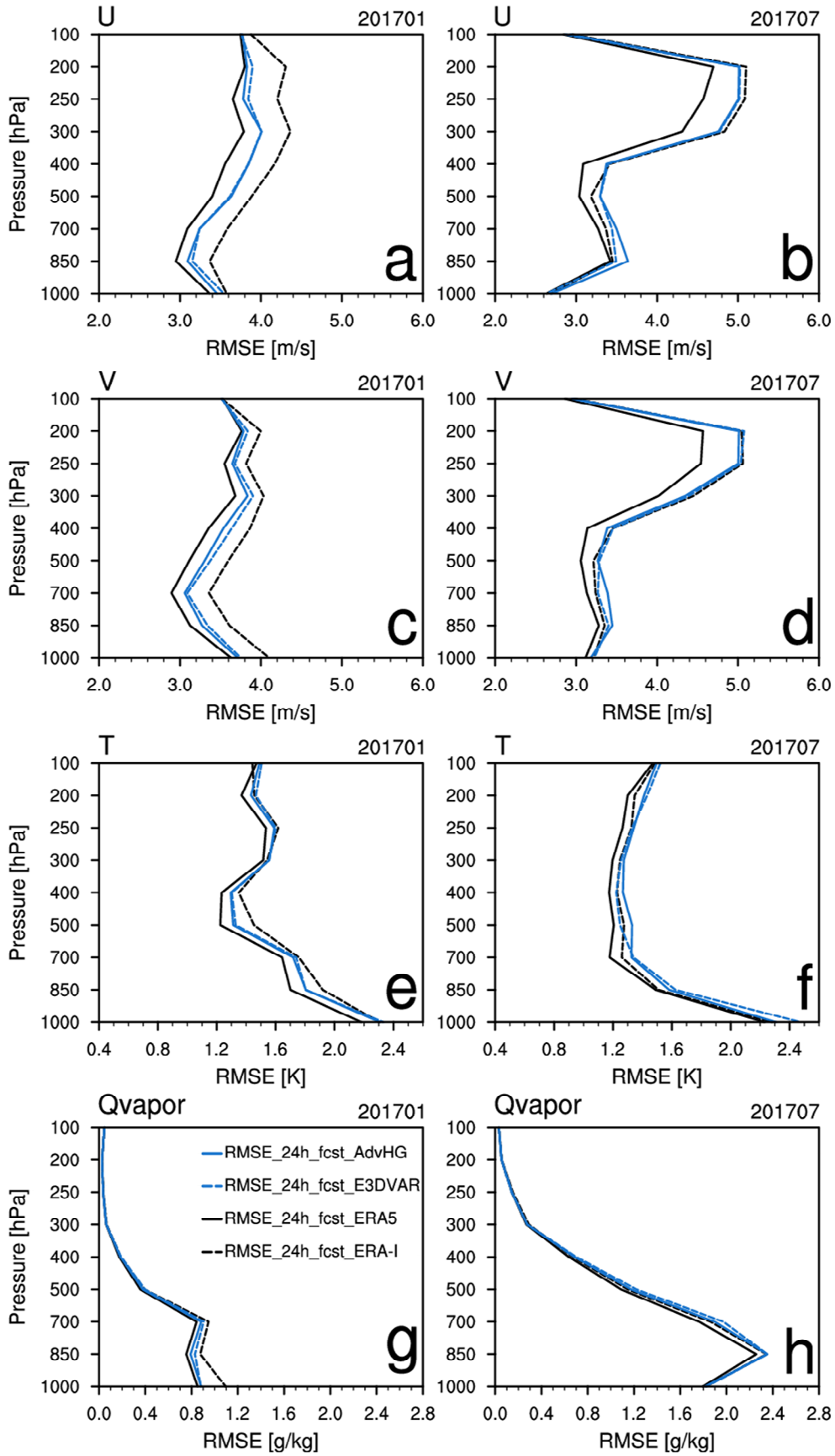


Figure 3. Same as Fig. 2 except for 24 h forecast.

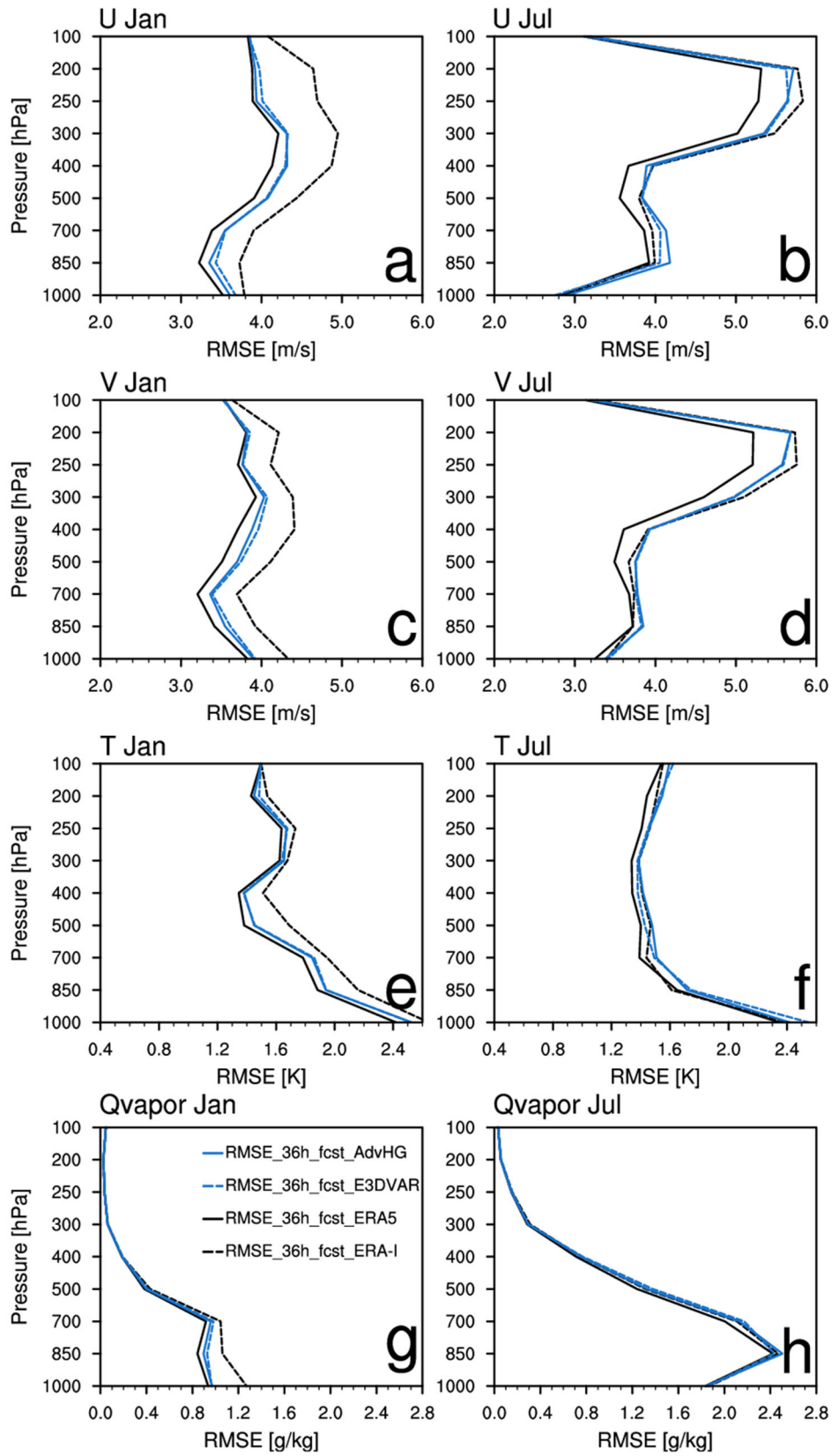
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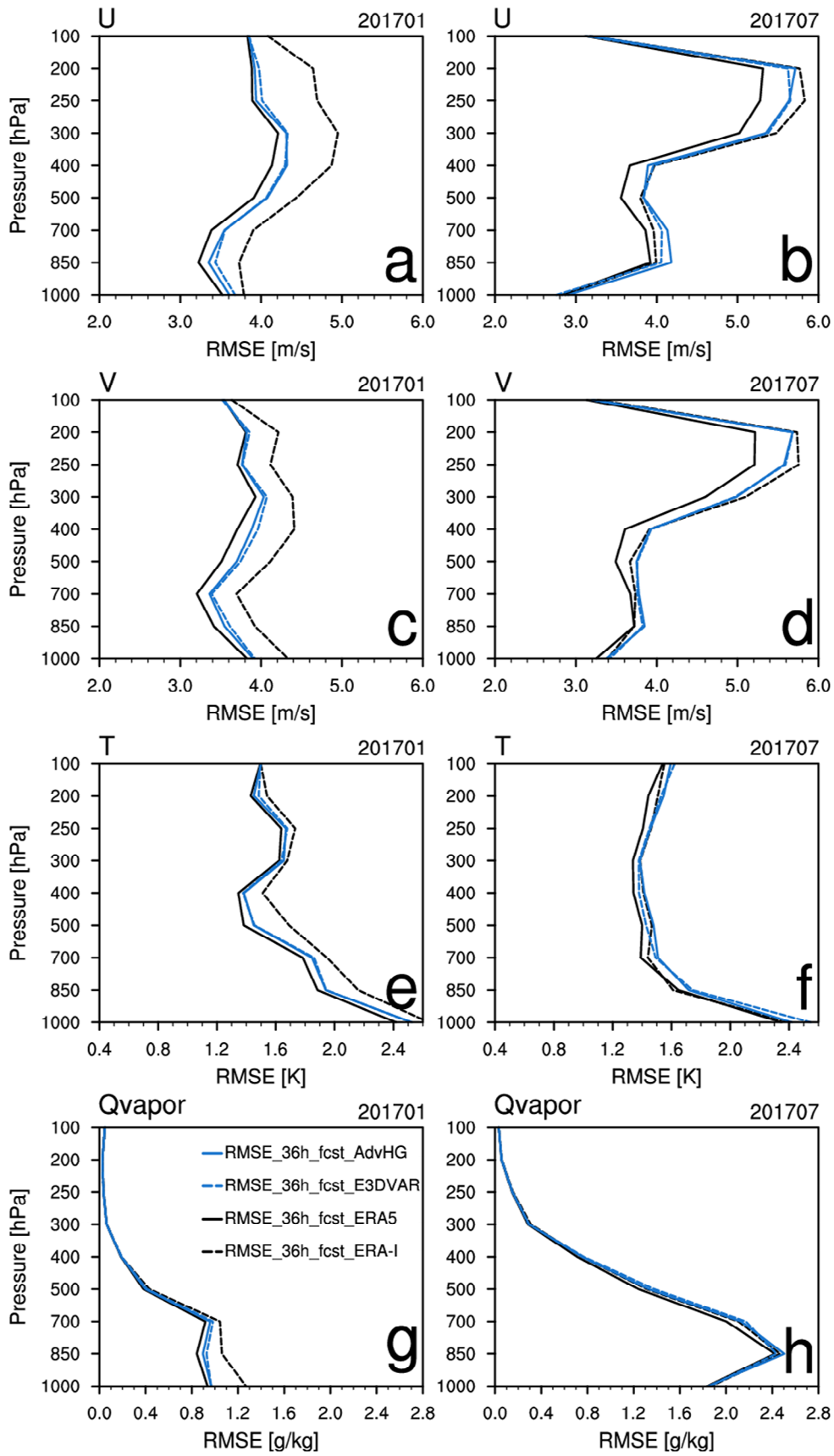
984 Figure 4. Same as Fig. 3 except for 24 h forecast.



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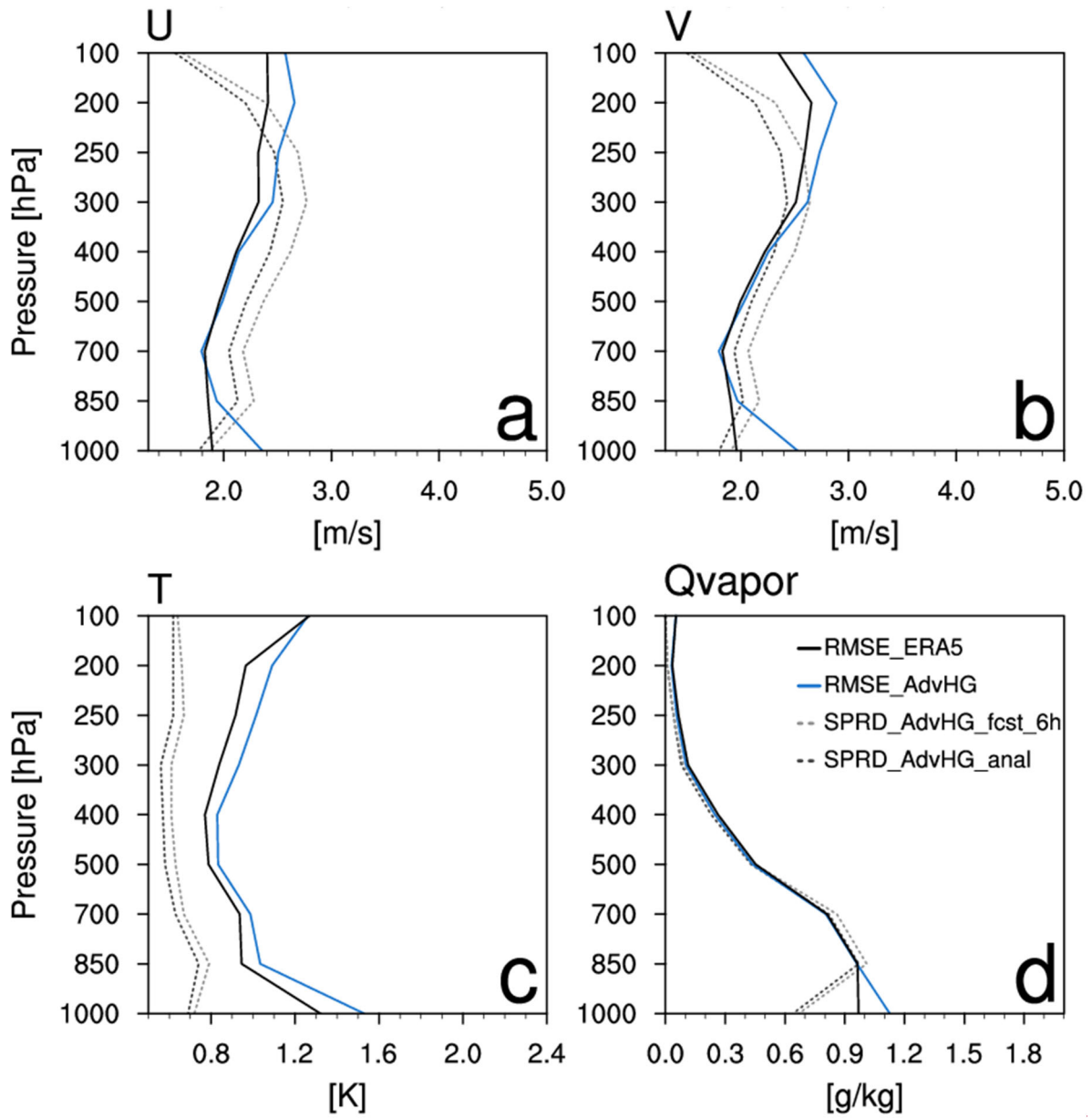
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Figure 4. Same as Fig. 2 except for 36 h forecast.



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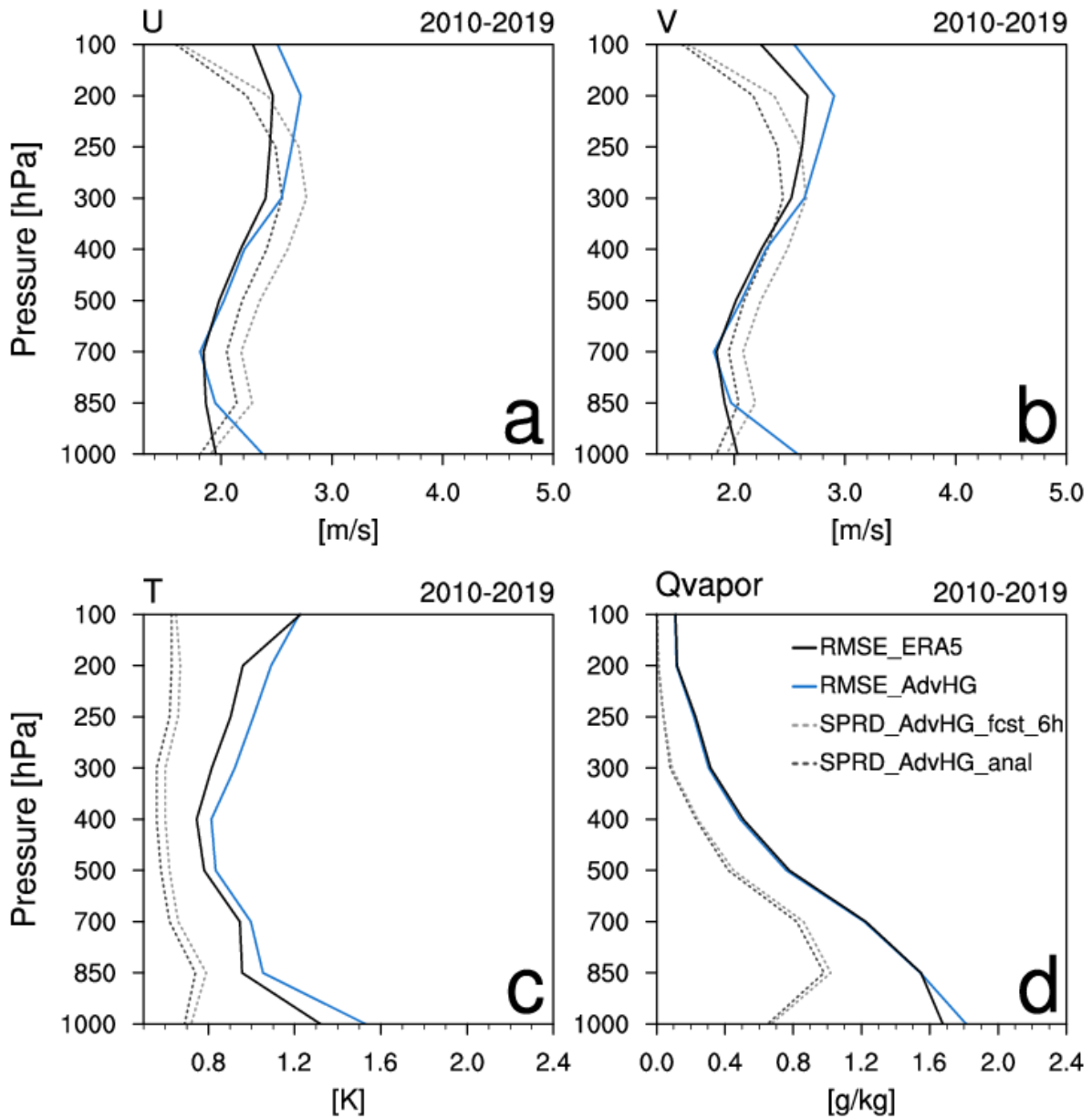
988 Figure 5. Same as Fig. 3 except for 36 h forecast.



989

990 **Figure 5. RMSEs of analysis of (a) zonal wind, (b) meridional wind, (c) temperature, and (d)**
 991 **Qvapor (water vapor mixing ratio) from ERA5 (black solid) and AdvHG (blue solid) and**
 992 **spreads of analysis (black dashed) and 6 h forecast (gray dashed) of AdvHG depending on**
 993 **pressure levels averaged over the two-year period of 2017–2018.**

994



995

996 Figure 6. RMSEs of analysis of (a) zonal wind, (b) meridional wind, (c) temperature, and (d)
 997 Qvapor (water vapor mixing ratio) from ERA5 (black solid) and AdvHG (blue solid) and
 998 spreads of analysis (black dashed) and 6 h forecast (gray dashed) of AdvHG depending on
 999 pressure levels averaged over the ten-year period of 2010–2019.

1000

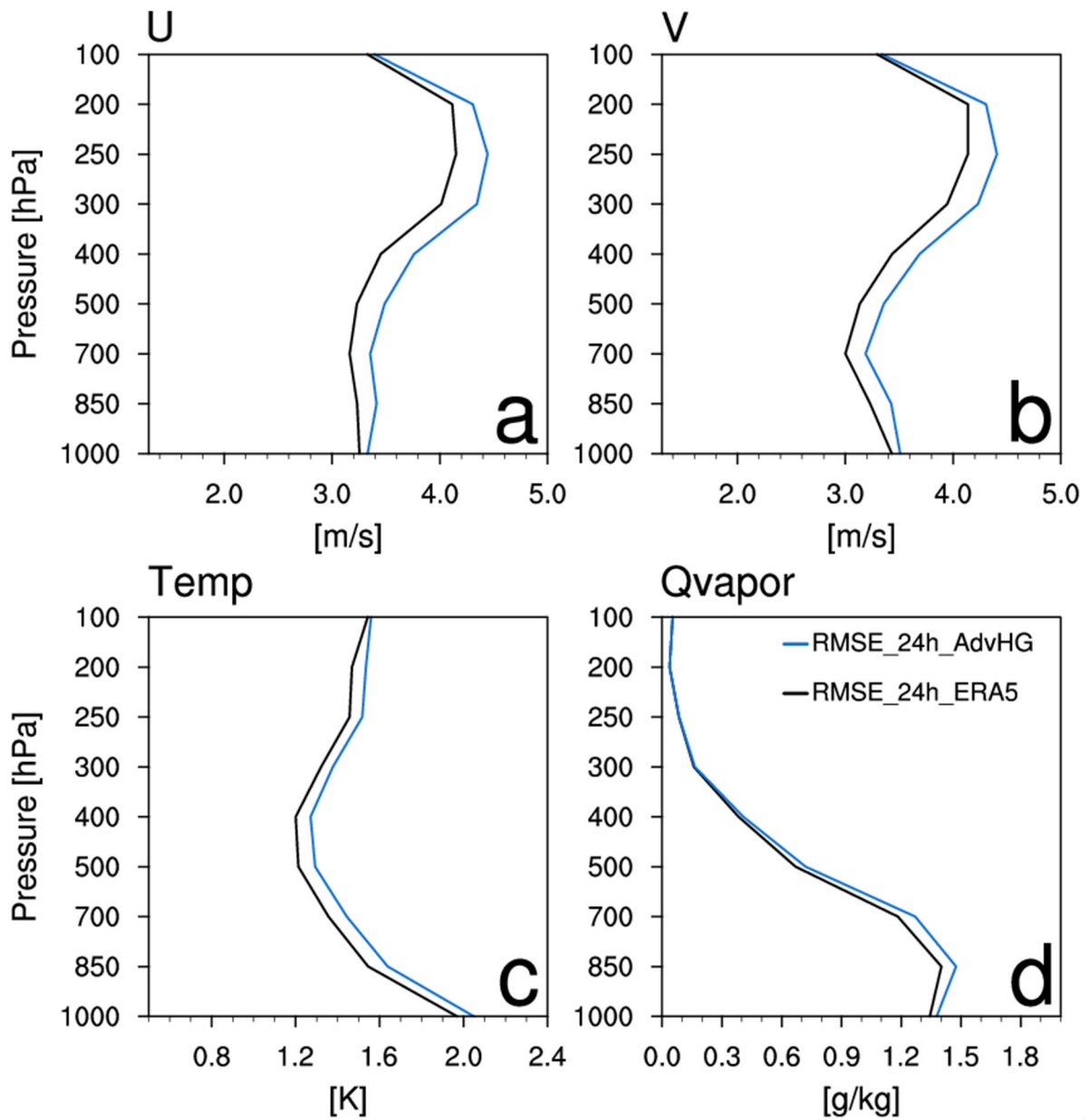


Figure 6. Same as Fig. 5 except for RMSE of 24 h forecast.

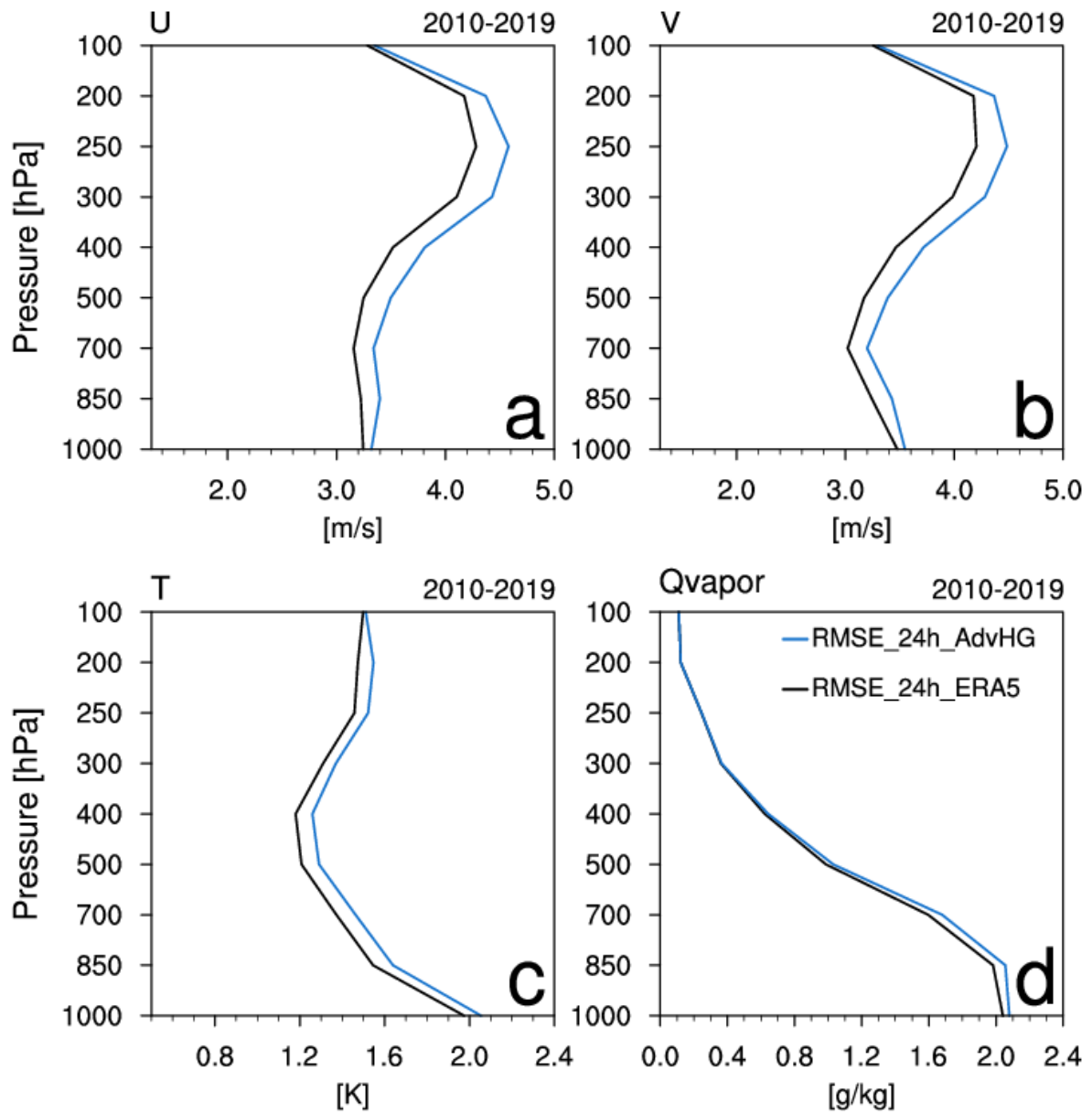
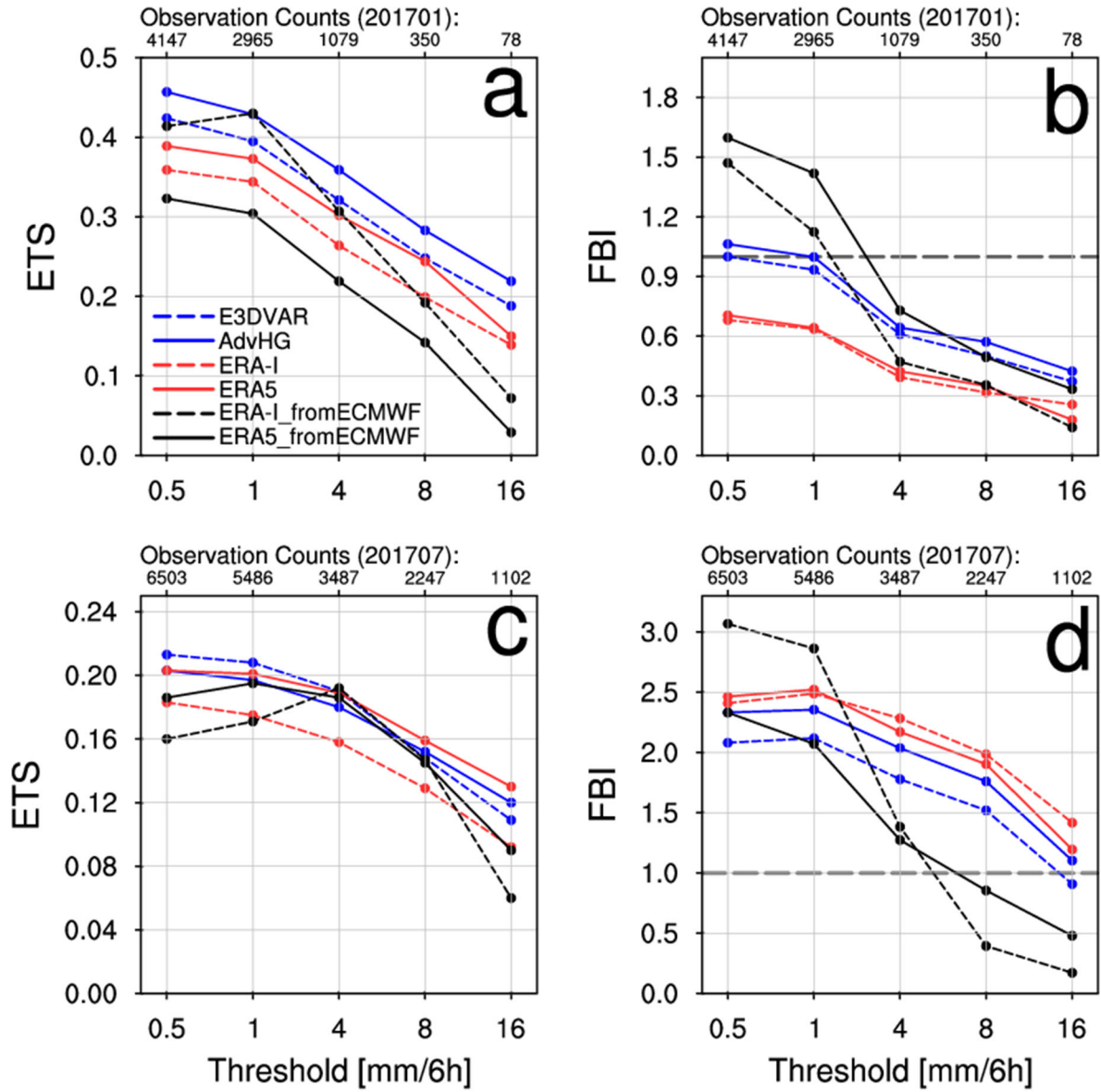


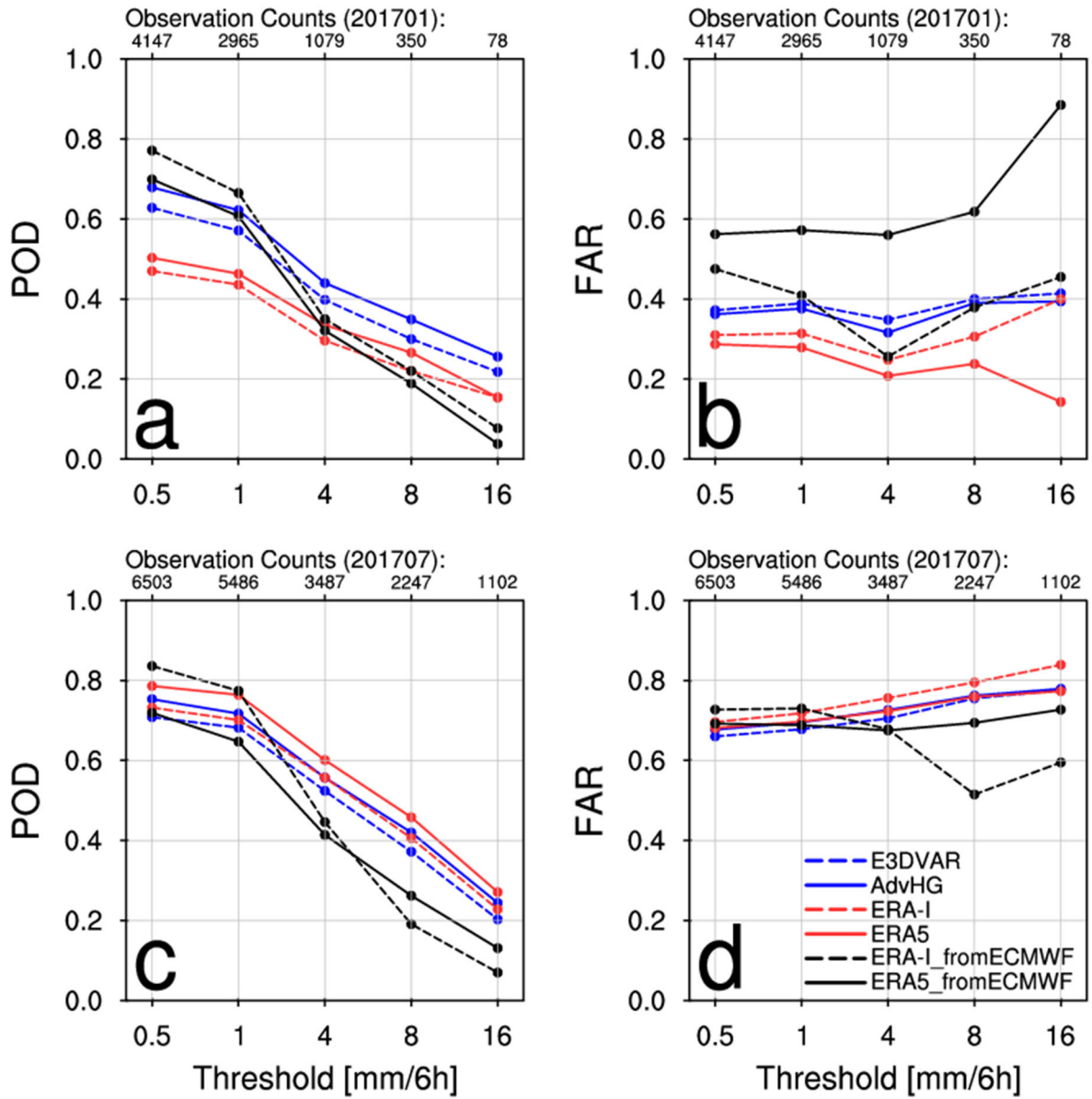
Figure 7. Same as Fig. 6 except for RMSE of 24 h forecast.



1007

1008 Figure 78. (a,c) ETS and (b,d) FBI for (a,b) January and (c,d) July in 2017 depending on
 1009 thresholds 0.5, 1, 4, 8, and 16 mm (6 h)⁻¹.

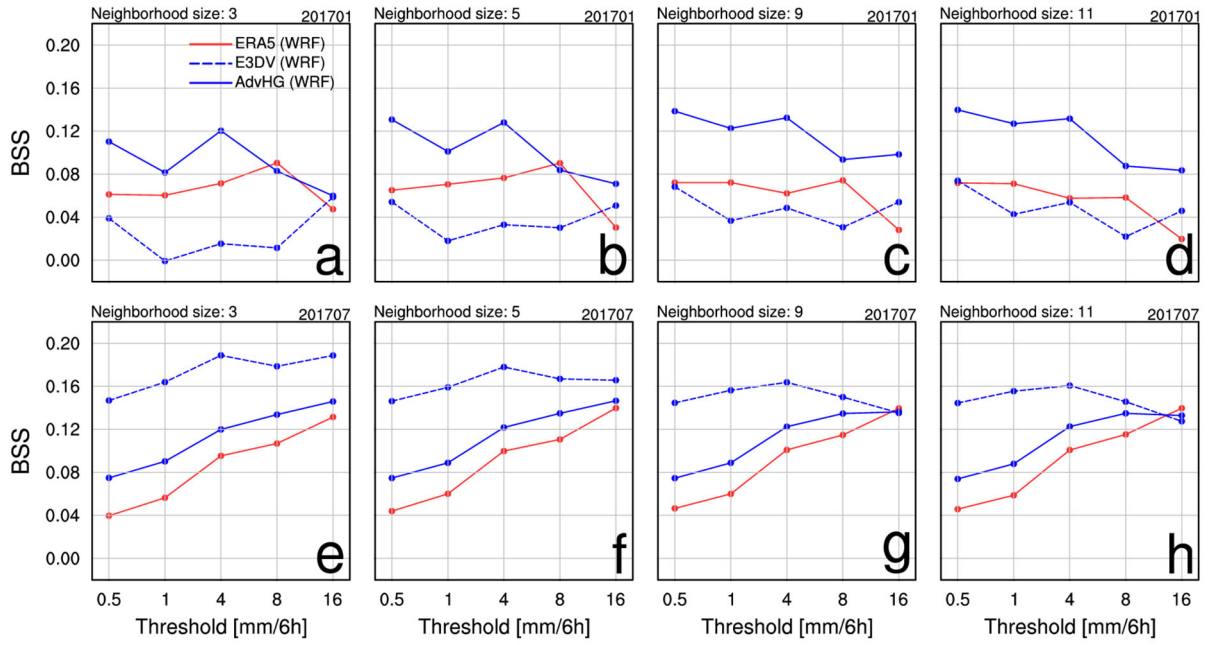
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1011

1012 Figure 89. (a,c) POD and (b,d) FAR for (a,b) January and (c,d) July in 2017 depending on
 1013 thresholds 0.5, 1, 4, 8, and 16 mm (6 h)⁻¹.

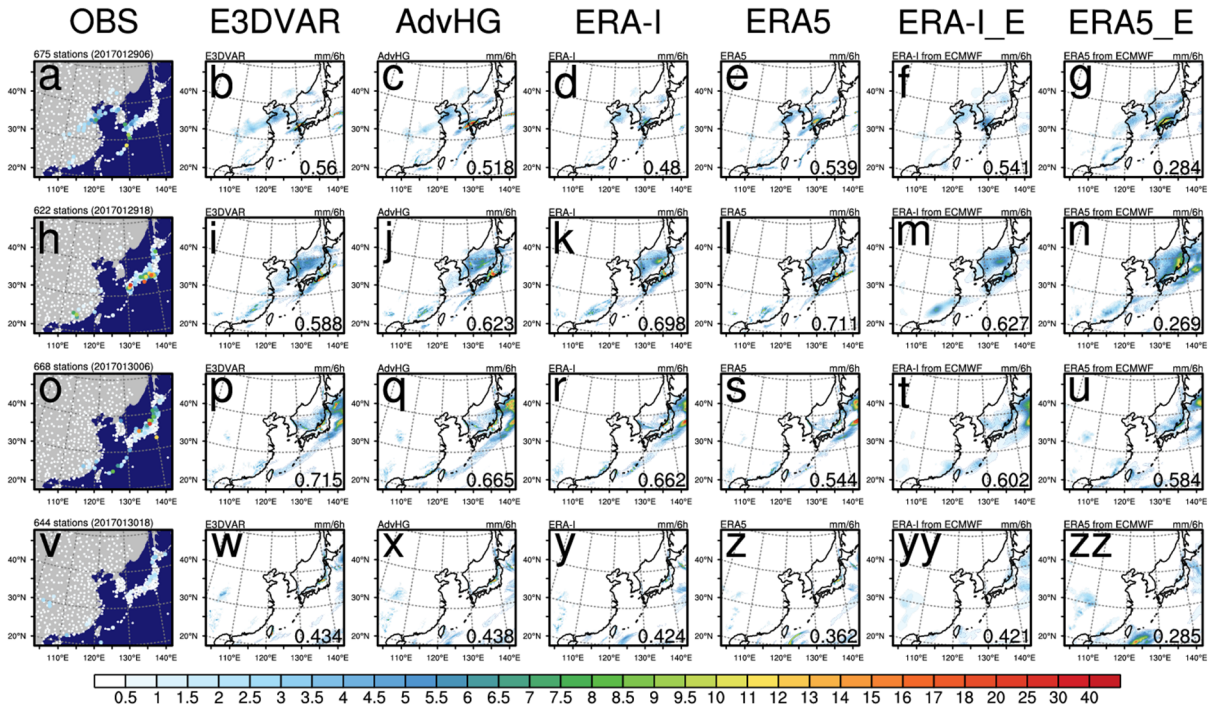
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1015

1016 Figure 910. Brier skill score of the probabilistic postprocessed forecast with reference to the
 1017 WRF-based ERA-I for (a-d) January and (e-h) July in 2017 (Blue solid: AdvHG, blue dashed:
 1018 E3DVAR, red solid: WRF-based ERA5).

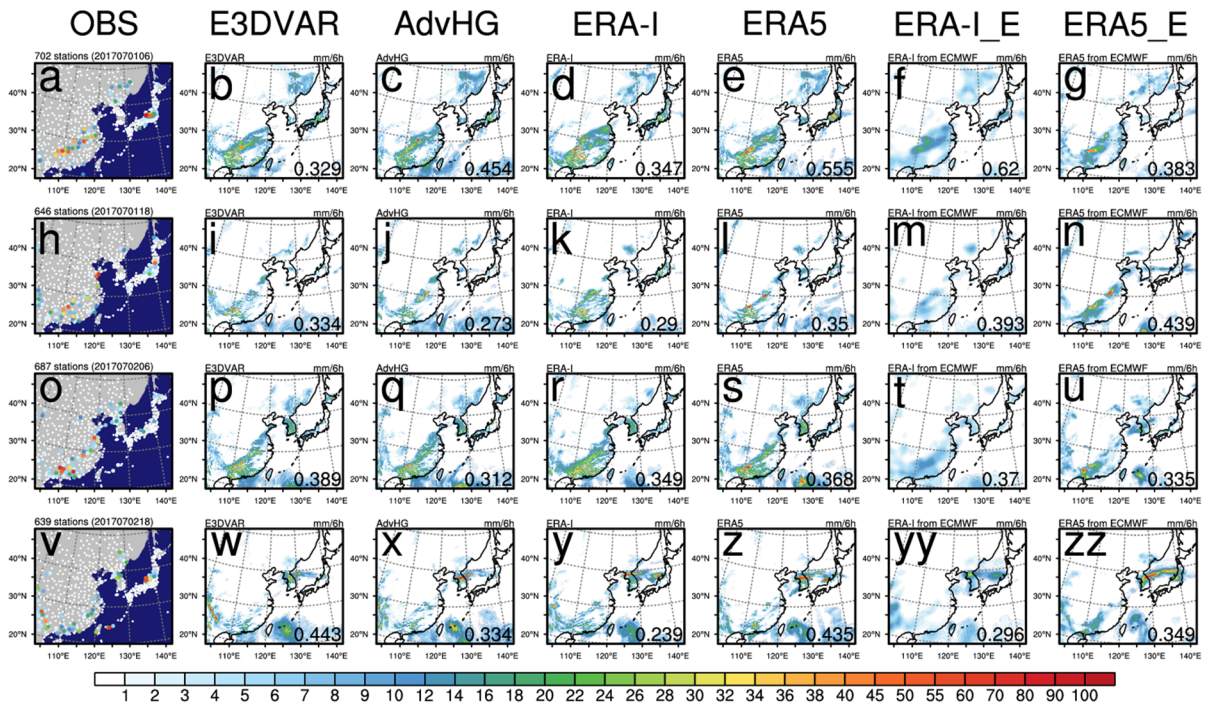
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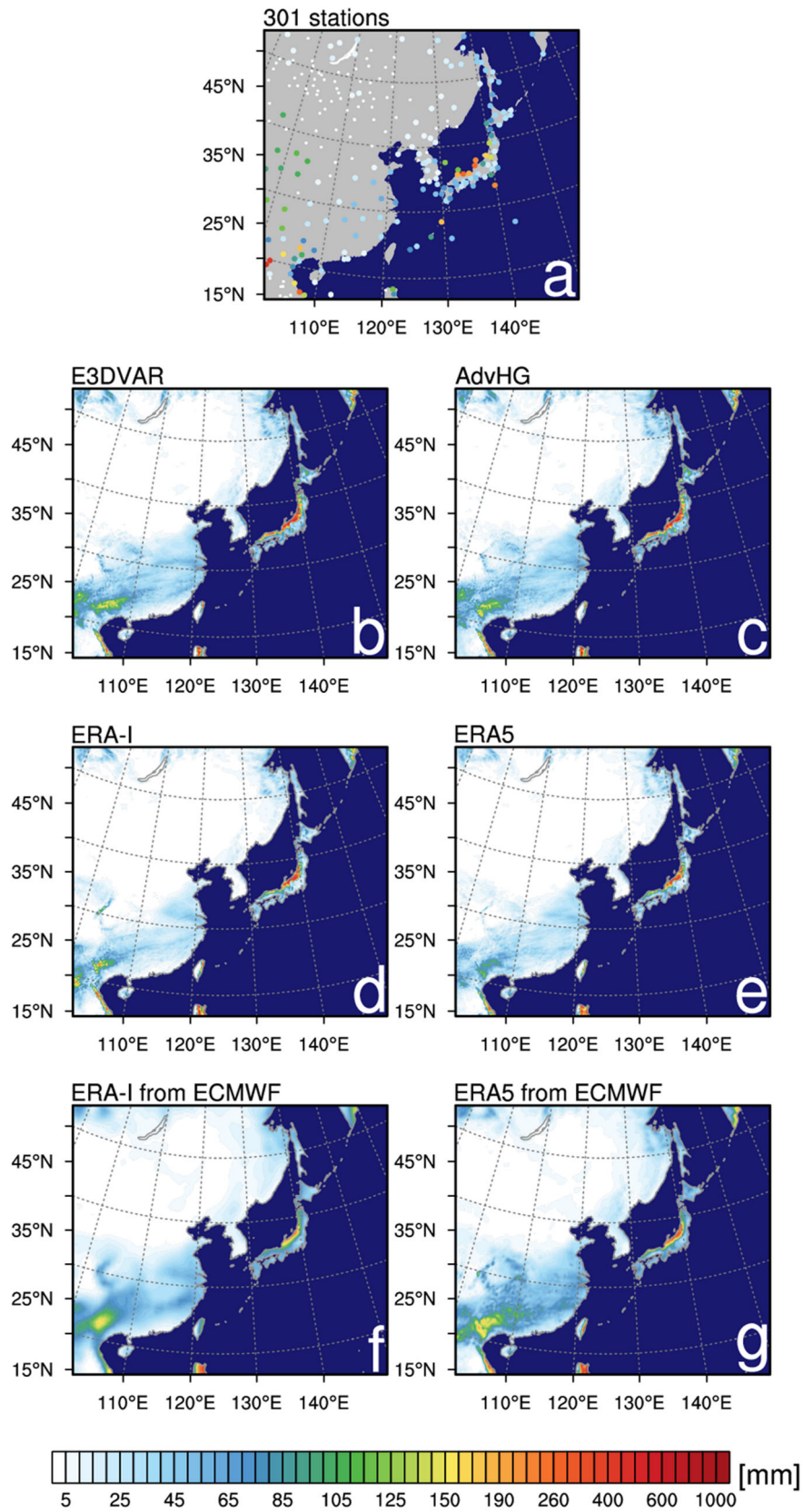
1021 Figure 1011. The spatial distribution of 6 h accumulated precipitation of (1st column)
 1022 observation, (2nd column) E3DVAR, (3rd column) AdvHG, (4th column) ERA-I, (5th column)
 1023 ERA5, (6th column) ERA-I_fromECMWF, and (7th column) ERA5_fromECMWF and the
 1024 pattern correlation coefficient (PCC) shown at the bottom right of each figure at valid time (1st
 1025 low, 3rd low) 06 UTC and (2nd low, 4th low) 18 UTC on 29th and 30th of January in 2017.

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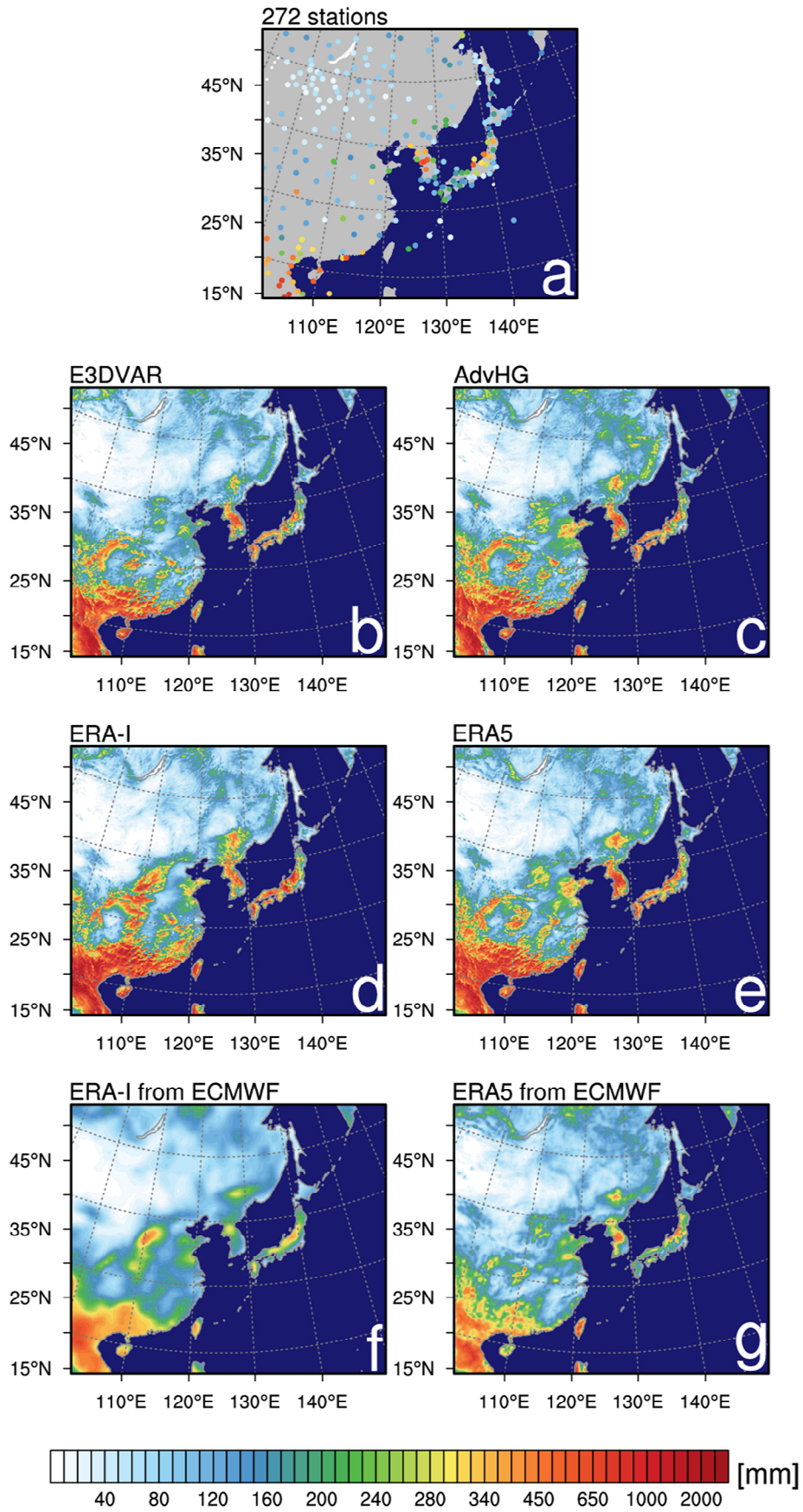
1027

1028 Figure 11. As in Fig. 10, but for 1st and 2nd of July in 2017.



1029

1030 Figure 1213. The spatial distribution of the monthly accumulated precipitation of (a)
 1031 observations, (b) E3DVAR, (c) AdvHG, (d) ERA-I, (e) ERA5, (f) ERA-I from ECMWF, and
 1032 (g) ERA5 from ECMWF for January 2017.



1033

1034 Figure 1314. As in Fig. 1213, but for July 2017.