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Validating the dynamic downscaling ability of WRF for East Asian summer climate

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Abstract To better understand the regional climate model (RCM) performance for East Asian summer climate and the influencing factors, this study evaluated the dynamic downscaling ability of the Weather Research Forecast (WRF) RCM. According to the comprehensive comparison studies on different physical processes and experimental settings, the optimal combination of WRF model setups can be obtained for East Asian precipitation and temperature simulations. Furthermore, based on the optimal combination, when compared with climate observations, WRF shows high ability to downscale NCEP DOE Reanalysis-2, which provided initial and lateral boundary conditions for the WRF, especially for the precipitation simulation due to the better simulated low-level water vapor flux. However, the strengthened Western North Pacific Subtropical High (WPSH) from WRF simulation results in the positive anomaly for summer rainfall.

1 Introduction

Regional or meso-scale models embedded within general circulation models (GCMs) may be able to obtain the spatially

explicit information on regional climate. In this kind of dynamic downscaling method (DDM), regional climate models (RCMs) are forced by surface boundary conditions from a coupled ocean and/or land surface model, together with lateral boundary conditions (LBCs) from GCMs or reanalyses, which are also applied as initial conditions of RCMs. The RCMs have been widely used for both past climate simulations (Chou et al. 2002; Iizuka 2010; De Sales and Xue 2013) and future climate projection (Liang et al. 2008; Chen et al. 2010; Boberg and Christensen, 2012; Mearns et al. 2012; Yu and Wang 2013). However, many issues related to the downscaling capability of this method usually cause skepticism for the application of RCMs (Laprise et al. 2000; Castro et al. 2005; Rockel et al. 2008; Xue et al. 2014), mainly because it is unclear that whether the DDM is really capable of adding more climate information at different scales compared with the GCM results or reanalysis, especially for long-term run, and if so under what conditions?

Several factors, including RCM experiment settings (e.g., domain position, grid size) as well as physical processes (especially convective and radiative schemes), have consistently demonstrated strong impact on dynamic downscaling ability in seasonal climate simulation (Xue et al. 2007; Ikeda et al. 2010; Gao et al. 2011; Diaconescu and Laprise 2013). However, most dynamic downscaling assessment was conducted as single-factor experiment, lacking the comprehensive investigation on the dynamic downscaling capacity to ensure the reasonable spatial patterns of climate simulations. For example, studies on the impact of soil moisture on regional climate (Kim and Hong 2007; Sato and Xue 2013; Liu et al. 2014) hardly consider the different model performance between physical schemes combinations. Although the new general meso-scale forecast models (such as Weather Research and Forecasting (WRF) model) were developed to consist of broad selections of physical parameterizations, sensitivity

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studies were mainly conducted for different model settings and physical processes, respectively (Flaounas et al. 2011; Waliser et al. 2011; Yang et al. 2012; Ratna et al. 2014).

Former studies suggested that only under certain conditions, including proper convective schemes and radiative schemes, land surface parameterizations and initializations, adequate LBCs, as well as sufficiently large domains, RCMs can at least reproduce the large-scale characteristics of the GCM results or reanalyses and add more spatio-temporal information. Due to the interactions of these physical processes, any significant weaknesses in one of these aspects could impede the RCMs from adding information in their dynamic downscaling (Mariotti et al. 2011; Solman and Pessacq 2012). This is why RCMs with different convective and radiation schemes and land surface parameterizations produce significant different output when compared with those using different parameterizations but only one single model (De Elia et al. 2008; Pielke 2013). Thus, it is essential to conduct systematic comparison to define the optimal combination of different parameters for certain regional climate studies (Gao et al. 2013; Xue et al. 2014). Furthermore, the RCMs' simulations with optimal combination and the data used for specifying LBCs should be compared with the reference datasets to adequately show whether the RCMs really provide new information (Shukla and Lettenmaier 2013).

Therefore, in this paper, the Weather Research and Forecasting (WRF) model was applied for dynamic downscaling assessment of summer precipitation and temperature in East Asia. A number of tests were conducted to investigate the sensitivity of WRF outputs to different combinations of model settings and physical processes, including horizontal resolution, and convective, radiative, and microphysics schemes, and the improvement of WRF simulations with the optimal combination over reanalysis data. The specific purposes are as follows: (1) to systematically assess the WRF models' sensitivity and (2) to evaluate the state-of-the-art RCM's ability to produce spatially detailed climate features for East Asia.

2 Experimental design and statistical verification

2.1 WRF model and setups

The regional meteorological model used in this study is the Weather Research and Forecasting (WRF) Model with Advanced Research WRF (ARW) dynamic core version 3.3 (Skamarock et al. 2008), which is developed by the National Center for Atmospheric Research (NCAR), National Centers for Environmental Prediction (NCEP), and other governmental agencies as well as several universities. The WRF is a Euler non-hydrostatic with run-time, fully compressible meso-scale model with terrain following eta-coordinate, designed as the

next numerical weather prediction and atmospheric simulation system. The horizontal grid of WRF is the Arakawa C-grid (Arakawa and Lamb 1977), in which u and y grid points are each offset from mass points to improve the numerical accuracy. In time integration, a second- or third-order Runge-Kutta scheme was used for treating acoustic and gravity wave modes. More details about WRF can be found in the report of Skamarock et al. (2008), available in the WRF web site (<http://www.mmm.ucar.edu/wrf/users/>).

WRF contains multiple physics options, including atmospheric radiation, cloud microphysics, cumulus parameterization, land surface physics, and planetary boundary layer (PBL) physics. Each of these physics parameterizations work together in order to represent important atmospheric processes. Therefore, within the WRF framework, it is possible to mix the dynamical core with differing physics packages to optimize performance since each physics option has strengths and weaknesses in different areas. This feature is particularly advantageous for inter-model comparisons and sensitivity studies. WRF has been used for climate and meteorology simulation in East Asia (Yu et al. 2010; Zeng et al. 2012) and was proven to be of great value in modeling regional climatic characteristics when compared with observations.

The initial conditions (for atmosphere, soil moisture, and soil temperature); lateral boundary conditions; ocean surface boundary conditions (sea surface temperature (SST) and sea ice); and initial snow depth for the WRF runs in this study are given by the NCEP DOE Reanalysis-2 (Kanamitsu et al. 2002), hereafter NCEP R-2, at 6-h intervals. SST and sea ice are reinitialized from NCEP R-2 at the beginning of each successive 6-h simulation. The model domain is centered at 35° N and 110° E with dimensions of 196 × 154 horizontal grid points with spacing of 30 km (Fig. 1) according to the study of Gao et al. (2011). This domain covers the areas of the upper-level westerly jet (ULJ) and low-level jet (LLJ), the Tibetan Plateau (TP), the moisture sources from the South China Sea and the Bay of Bengal, and the southeast trade wind, all of which are important for the East Asia summer monsoon. The Lambert conformal conic projection is used as the model horizontal coordinates.

2.2 Experimental design

There are four groups of sensitivity experiments for DDM of the WRF model, listed in Tables 1 and 2. In this paper, the impact of different microphysics, cumulus and radiation schemes, and grid sizes on simulated precipitation is addressed. The model was integrated from 0000 UTC 25 May 2000 to 0000 UTC 1 July 2000. The first 7 days (25 May to 31 May) are considered as a spin-up period and the outputs during this period are excluded from the analysis. Case 1 serves as the control experiment. Cases 1–5 apply different microphysics parameterizations and are used to assess the effects of

Fig. 1 Experimental domain (*shaded*) and topography (units: m). This domain covers the areas that are important for the East Asia summer monsoon. The altitudinal gradient can be identified clearly

microphysics schemes on precipitation simulation. The comparison between cases 1 and 6–8 shows the influences of cumulus convection parameterizations on downscaling ability. Cases 9 and 10, along with case 1, are designed to explore the downscaling capacity to longwave and shortwave radiation schemes. Cases 11–13 are set to illustrate the impact of both

horizontal resolutions and radiation schemes on the DDM performance. The model outputs at every 6-h are used for model evaluation. The Asian Precipitation-Highly Resolved Observational Data Integration towards Evaluation of the Water Resource (Yatagai et al. 2012) called APHRO, and Global Telecommunication System (GTS), released by World

Table 1 Experiments for the sensitivity of WRF dynamic downscaling to physical schemes and horizontal resolutions

Experiments	Cases	Microphysics schemes	Cumulus schemes	Longwave radiation schemes	Shortwave radiation schemes	Grid sizes (km)
Microphysics sensitivity	1	WSM 3	Kain-Frirsch	RRTM	MM5 (Dudhia)	60
	2	Kessler	Kain-Frirsch	RRTM	MM5 (Dudhia)	60
	3	Purdue Lin	Kain-Frirsch	RRTM	MM5 (Dudhia)	60
	4	WSM5	Kain-Frirsch	RRTM	MM5 (Dudhia)	60
	5	Ferrier	Kain-Frirsch	RRTM	MM5 (Dudhia)	60
Cumulus sensitivity	6	WSM 3	Betts-Miller-Janjic	RRTM	MM5 (Dudhia)	60
	7	WSM 3	Grell	RRTM	MM5 (Dudhia)	60
	8	WSM 3	New Grell	RRTM	MM5 (Dudhia)	60
Radiative sensitivity	9	WSM 3	Kain-Frirsch	CAM	CAM	60
	10	WSM 3	Kain-Frirsch	RRTMG	RRTMG	60
Grid sizes sensitivity	11	WSM 3	Kain-Frirsch	RRTM	MM5 (Dudhia)	30
	12	WSM 3	Kain-Frirsch	CAM	CAM	30
	13	WSM 3	Kain-Frirsch	RRTMG	RRTMG	30

Table 2 Descriptive statistics of WRF simulated precipitation from different cases

Cases	Bias	R	BS	TS
1	1.68	0.70	1.25	0.57
2	-1.02	0.37	0.72	0.39
3	2.64	0.65	1.41	0.49
4	2.84	0.67	1.44	0.43
5	2.81	0.66	1.42	0.45
6	0.81	0.51	1.16	0.46
7	0.37	0.53	1.08	0.48
8	0.75	0.57	1.12	0.50
9	1.91	0.65	1.33	0.53
10	3.04	0.67	1.51	0.41
11	1.95	0.74	1.27	0.59
12	2.23	0.71	1.38	0.55
13	3.20	0.75	1.52	0.43

Meteorological Organization (WMO), were developed to be the state-of-the-art daily precipitation and temperature datasets, respectively, with high-resolution (0.25 and 0.5 °) for Asia, and thus are employed to assess the models' sensitivity to setups.

In addition, in order to reveal the improvement of WRF simulations over the NCEP R-2, another experiment was carried out to detect the discrepancies and consistency between WRF simulations, NCEP R-2, and verification datasets. This experiment was integrated from 0000 UTC 1 March to 0000 UTC 1 September for the years of 1998, 2000, and 2004 with the months from March to May as a spin-up period; thus, the ensemble summer climate (June, July, and August (JJA)) was applied to evaluate the superiority of simulated precipitation, surface temperature, and circulation from the WRF model over NCEP R-2 at seasonal scales.

It should be pointed out that because there are a limited number of observations for the atmospheric variables, several studies applied reanalysis data to validate the atmospheric

circulation simulations (Leung et al. 2003; Seth et al. 2007; Brands et al. 2012; Sato and Xue, 2013). In this study, the Japanese 25-year Reanalysis (JRA-25) (Onogi et al. 2007), which was designed as the high-quality reanalysis dataset with relatively high spatial resolution (around 120 km) based on the state-of-the-art numerical assimilation system and collected observational data, was applied to assess the model results of circulation and other atmospheric variables. One important reason for the application is that the JRA-25 precipitation influenced by multiple physical processes, together with atmospheric circulation, were better simulated when compared with some other reanalysis datasets, including the NCEP R-2 applied as the LBC in this study. Moreover, since its model characteristics are the same as the seasonal forecast model, the JRA-25 is an appropriate reference to validate the seasonal climate simulations (Tosiyuki 2008; Marquesa et al. 2010; Yokoi 2015).

2.3 Statistical verification techniques

The correlation coefficient (R), bias, and root mean square error (RMSE) were adopted as the statistical parameters to verify the simulated precipitation, temperature, and other atmospheric variables. Their calculation equations can be found in many published materials, such as Lo et al. (2008) and Xu et al. (2009). Actually, these three parameters can be used to assess the model performance from different aspects. Bias and RMSE can represent systematic error and overall accuracy of the model simulations, respectively, while R is a measurement of spatial patterns. The model with the lower bias and RMSE values and the higher R value means a better fit to the observed data and better model performance.

Additionally, since the precipitation is a model diagnostic field that is more difficult to simulate, the other two statistical variables, i.e., the bias score (BS) and the threat score (TS),

Fig. 2 APHRO daily precipitation (mm/day) (a) and GTS daily temperature (°C) (b) for June 2000

were applied to measure the accuracy of the simulated precipitation. BS is used to detect whether the model over-estimate or under-estimate the fractional areal coverage of precipitation for a certain threshold, while TS measures the skill of predicting the area of precipitation for a certain threshold. The BS and TS for precipitation simulations are defined as:

$$BS = \frac{PPT_P}{PPT_O} \quad (1)$$

$$TS = \frac{PPT_H}{PPT_P + PPT_O - PPT_H} \quad (2)$$

where PPT_P is the number of grid points that the precipitation threshold amount was simulated, PPT_O is the number of grid points in which the threshold amount was observed, and PPT_H is the number of grid points that threshold precipitation was both simulated and observed.

Fig. 3 Simulated daily precipitation (mm/day). **a** Case 1. **b** Case 9. **c** Case 10. **d** Case 11. **e** Case 12. **f** Case 13

Table 3 Descriptive statistics of temperature from WRF models with different radiation schemes and grid sizes

Cases	Variables	Bias	RMSE	<i>R</i>
1	Temperature	-3.48	4.65	0.89
9	Temperature	-2.97	4.08	0.88
10	Temperature	-2.24	3.65	0.89
11	Temperature	-3.60	4.88	0.88
12	Temperature	-2.96	4.20	0.87
13	Temperature	-2.31	3.87	0.87

The threshold amount is set as 6 mm, around the mean value of precipitation.

Comparisons between statistical values and spatial patterns for precipitation and temperature are limited in the area of 18–52° N, 86–136° E. The effective simulated values are mainly located in this domain, where East Asian summer monsoon formation (e.g., subtropical high, airflow from the Bay of the Bengal and westerly jet) plays important roles in the regional climate change.

Fig. 4 Simulated daily temperature (°C). **a** Case 1. **b** Case 9. **c** Case 10. **d** Case 11. **e** Case 12. **f** Case 13

3 Results and analyses

3.1 Sensitivity of WRF simulations to model setups

According to the above-mentioned experimental design, the comprehensive impacts of different microphysical processes, convective processes, radiative processes, and horizontal resolutions on precipitation simulations were mainly addresses in this study. Table 2 shows that microphysics schemes generate different precipitation simulations based on the comparative results of statistical indicators. The R for case 1 (0.70), set as the control experiment, is significantly larger than case 2 (0.37) with the smallest TS value, which indicates that the spatial pattern of precipitation from case 1 is more reasonable (Figs. 2a, 3a). Case 1, with the positive bias and the BS value larger than 1 (Table 2), overestimates daily precipitation when compared with APHRO observation, while case 2 is the only one to under-predict precipitation. Despite cases 3–5 having similar R (0.65, 0.67, 0.66, respectively) to case 1, case 1 creates spatial distribution for precipitation superior to the other three cases (not shown), together with smaller bias and BS values and larger TS value (Table 2). Thus, when comparing statistical values and spatial patterns of precipitation simulations from the first five cases, it is clear that WSM3 microphysics scheme, used in case 1, produces the highest downscaling skill than the other four schemes.

Precipitation simulations from different cumulus schemes in the WRF (i.e., cases 1 and 6–8) are also compared in the same way. As shown in Table 2, despite of the closer values from cases 6–8 to APHRO precipitation interpolation, as well as less over-prediction when compared with case 1, their R values are obviously smaller than case 1. On the other hand, among these four cases, only case 1 (Fig. 3a) can simulate two rainfall bands in 24–36° N, 100–120° E, as shown in APHRO (Fig. 2a). Consequently, the TS value of case 1 is relatively bigger than cases 6–8. By the validation for these two factors, microphysics and cumulus schemes used in case 1 are more suitable to simulating precipitation in East Asia.

Different from the impact of microphysics and cumulus parameterizations, longwave and shortwave radiation schemes could profoundly influence both precipitation and temperature simulations. The comparisons between different radiation schemes for precipitation and temperature can be found in Tables 2 and 3. All these three cases (cases 1, 9, and 10) simulate the above-mentioned two rainfall bands (Figs. 2a, 3a–c). Although the rainfall bands are identified more clearly from case 9 than case 1 and case 10, the smaller BS value and the larger TS and R values can be obtained for case 1. Comparatively, the Rapid Radiative Transfer Model (RRTM) longwave and MM5 (Dudhia) shortwave radiation

schemes applied in case 1 are more appropriate to model precipitation.

Surface temperature in East Asia can be reasonably simulated by cases 1, 9, and 10 with the R of 0.88 at least (Table 3, Fig. 4a–c), when compared with GTS temperature interpolation (Fig. 2b). The temperature trend of decreasing from southeast to northwest of China can be identified clearly from both the simulations and the observation. Case 10 has the best model performance for temperature, followed by case 9, and the downscaling skill of temperature for case 1 is comparatively lowest. In addition, it should be noticed that all these three cases produce positive systematic errors to some extent.

Corresponding to the above radiative sensitivity studies with horizontal resolution of 60 km, comparisons between different radiative schemes for 30-km simulations produce the same conclusion. The downscaling simulation of precipitation using the RRTM longwave and MM5 (Dudhia) shortwave radiation schemes (i.e., case 11) shows the highest skill with the largest TS and the smallest bias and BS (Table 2), and for temperature simulations, the order is reversed (Table 3, Figs. 2b and 4). Although the precipitation simulations with spatial resolution of 60 km produce smaller bias and BS values (Table 2), the correlations between simulations and observation, meaning the spatial patterns, are significantly improved by the corresponding WRF models with 30-km grid size (Table 2, Figs. 2a and 3). Comprehensively, the CAM longwave and shortwave radiation schemes applied in cases 9 and

Table 4 Descriptive statistics of daily precipitation (mm/day), temperature (°C), and other atmospheric variables for WRF and NCEP R-2

Variables	Models	Bias	RMSE	R
Precipitation	WRF	1.57	3.16	0.78
	NCEP R-2	1.95	4.22	0.60
Temperature	WRF	−2.29	4.21	0.85
	NCEP R-2	−1.93	3.62	0.86
U200	WRF	−0.01	0.97	0.92
	NCEP R-2	0.04	0.31	0.99
H500	WRF	0.76	5.81	0.86
	NCEP R-2	0.48	2.69	0.97
RV500	WRF	−0.01	0.57	0.67
	NCEP R-2	−0.01	0.36	0.77
VQ700	WRF	−1.37	7.49	0.70
	NCEP R-2	2.89	11.38	0.65
SH700	WRF	0.02	0.55	0.97
	NCEP R-2	0.44	1.56	0.82

U200: Zonal wind with zonal mean removed at 200 hpa (m/s); H500: Geopotential height with zonal mean removed at 500 hpa (gpm); RV500: relative vorticity at 500 hpa (10^{-5} s^{-1}); VQ700: Water vapor flux at 700 hpa ($\text{g kg}^{-1} \text{ m s}^{-1}$); SH700: Specific humidity at 700 hpa (g kg^{-1})

12 can simulate reasonable precipitation and temperature, and thus are selected as the physics options in the following simulations. Furthermore, we can determine the better grid size of 30 km based on the comparison between the simulations with different horizontal resolutions.

Therefore, based on the comparisons of summer precipitation and temperature simulations with different physics schemes and grid sizes in East Asia, the optimal combination of model setups can be obtained (i.e., case 12): WSM 3 microphysics scheme, Kain-Fritsch cumulus scheme, CAM longwave and shortwave radiation scheme, and 30-km grid size. This combination produces the highest downscaling ability and can provide basis for the following study on the comparison between WRF simulations and NCEP R-2.

3.2 Evaluation of WRF dynamic downscaling simulations

Once the influence of model setups combinations on simulations is quantified, subsequent study will examine whether the WRF produces reasonable climate simulations for East Asia in more detail. Generally, it is recognized that the final quality of the results from the RCMs depends in part on the reality of the large-scale forcing provided by GCMs' results or reanalyses, because the RCM needs to impose the lateral boundary condition from GCMs or reanalyses. Thus, it is important to assess RCM's ability and weakness in simulating the climatic features at regional scales by comparing with GCMs or reanalyses. In this part, we compare the climate features from WRF and NCEP R-2 with the aforementioned

Fig. 5 Ensemble JJA mean daily precipitation (mm/day) **a** APHRO, **b** NCEP R-2, **c** WRF, and surface temperature (°C) **d** GTS, **e** NCEP R-2, and **f** WRF

validation data (i.e., APHRO precipitation dataset, GTS daily temperature dataset, JRA-25) to evaluate the ensemble simulations of WRF. The physics schemes and grid size used in case 12 in the part of Section 3.1 were applied. Not only precipitation and temperature but also circulation and other atmospheric variables are addressed.

Table 4 lists the model output statistics for precipitation, temperature, and other atmospheric variables from WRF and NCEP R-2. It is shown that WRF outperforms NCEP R-2 in simulating precipitation, because WRF produces more significant correlation with observed precipitation than NCEP R-2, together with lower BS (1.35 for WRF, 1.68 for NCEP R-2) and bias and higher TS (0.66 for WRF, 0.45 for NCEP R-2).

Fig. 5a–c show the ensemble JJA mean rainfall for 1998, 2000, and 2004 from APHRO, NCEP R-2 and WRF, respectively. Both WRF and NCEP R-2 simulates the macro-spatial pattern of precipitation and the most rainfall occurring in the south of China, especially in the south of Yangtze River. The rainfall belt and the center of maximum rainfall shown in observation are clearer in WRF; however, WRF still produces more rainfall than observed.

WRF and NCEP R-2 shows similar spatial patterns (Fig. 5e, f) and statistics (Table 4) for surface temperature in East Asia. In the south of about 38°N , the temperature mainly increases from northwest to southeast with the minimum temperature in Qinghai-Tibetan Plateau (Fig. 5). The higher and

Fig. 6 Ensemble JJA mean zonal wind at 200 hpa (m/s): **a** JRA-25, **d** WRF, geopotential height at 500 hpa (gpm): **b** JRA-25, **e** WRF, and relative vorticity at 500 hpa (10^{-5} s^{-1}): **c** JRA-25, **f** WRF

the lower temperature also exist in the northwest and northeast of China, respectively. The simulated 24 °C isotherm coincides with the transition zone. The WRF simulated high temperature located around 37° N, 116° E does not exist in the observation. Although negative systematic error of about 2 °C exists in both WRF and NCEP R-2 temperature simulations when compared with GTS (Fig. 5d), which may be caused by either the unreasonable calculation in physical parameterizations or the lack of consideration about land surface biochemical processes and greenhouse gasses, WRF presents spatial information for temperature in more spatial details, especially

in the southwest and the northeast of China, and in Mongolia, which proves it is an effective tool to downscaling temperature.

Because of the importance of Western North Pacific Subtropical High (WPSH), airflow from the Bay of Bengal and westerly jet to East Asian summer monsoonal rainfall, several atmospheric variables, such as zonal wind at 200 hpa, geopotential height at 500 hpa and water vapor flux at 700 hpa, were applied to explain the improved precipitation simulations from the WRF and the simulated positive bias of summer precipitation (Figs. 6 and 7, Table 4).

Fig. 7 Ensemble JJA mean wind vector at 700 hpa (m/s): **a** JRA-25, **d** WRF, specific humidity at 700 hpa (g kg^{-1}): **b** JRA-25, **e** WRF, and water vapor flux at 700 hpa ($\text{g kg}^{-1} \text{m s}^{-1}$): **c** JRA-25, **f** WRF

The basic spatial features of atmospheric variables are consistent between WRF simulation and JRA-25. If the westerly jet is defined as the zonal wind with speed larger than 25 m/s, then both WRF and JRA-25 show its center located around 42° N (Fig. 6a, d). However, it is shown that WRF simulated westerly jet is weaker than that from JRA-25 and NCEP R-2 (Table 4), also with smaller influencing areas (Fig. 6). As for the geopotential height at 500 hpa, which represents the location of WPSH, the spatial distribution is similar for WRF, JRA-25 and NCEP R-2 (Fig. 6b, e). The WRF model produces significantly higher geopotential height at 500 hpa (Table 4), and correspondingly, the stronger monsoon than JRA-25. The differences in relative vorticity at 500 hpa can also reflect the stronger subtropical high from WRF (Fig. 6c, f, Table 4). The ensemble JJA mean wind vector at 700 hpa is well simulated, and the large-scale and low-layer moisture source of the Bay of Bengal and the South China Sea is displayed clearly (Fig. 7a, d). Both specific humidity and water vapor flux are better simulated by the WRF (Table 4); however, when compared with JRA-25 and NCEP R-2, the lower values in WRF simulations can be found for the east of China (Fig. 7b, c, e, f), due to the weaker wind flow from the Bay of Bengal (Fig. 7d).

Overall, the simulations of high-level variables from WRF are not improved, while the low-level specific humidity and water vapor flux, which are important for the formation of East Asian summer rainfall, are better simulated. Thus, the main reason for the better rainfall simulation from the WRF (Table 4, Fig. 5) is the improved simulation of the low-level water vapor flux, which is a crucial factor affecting convective activity in East Asian summer monsoon. On the other hand, the impact of weaker westerly jet and weaker wind flow from the Bay of Bengal on summer rainfall by decreasing moisture vapor is offset by the stronger subtropical high, which means that the positive rainfall anomaly in Fig. 5c is mainly caused by the strengthened WPSH. These findings are the same as other studies of dynamic downscaling assessment, where the GAME reanalysis data, generally believed as the most reliable for the East Asian region, was applied as the reference.

4 Conclusions and discussion

Considering the resolution limitation of GCM models for the regional climate simulations, the WRF model, which can present cloud-radiation interactions, realistic hydrodynamic moist processes, and comprehensive land surface processes with relatively high horizontal and vertical spatial resolution, was applied to dynamically downscale East Asian summer monsoonal climate. A number of former studies have shown that the results from the DDM were sensitive to different parameters, especially for convective scheme, domain size, and location (Jones et al. 1995; Seth and Giorgi 1998; Hong and Pan 2000). The different model setups were very sensitive to a

certain climate condition; however, the comprehensive comparisons studies for several factors were relatively weak (Xue et al. 2014). In this study, the sensitive experiments indicated that the combinations of model physics schemes and grid sizes were crucial for the model's dynamic downscaling ability.

Furthermore, based on the optimal combination of WRF setups, this paper proved the high ability of the WRF to downscale NCEP R-2, which provided initial and lateral boundary conditions, for East Asian summer climate, especially for the precipitation simulation due to the better simulated low-level water vapor flux. Compared with NCEP R-2, the macro-scaled spatial pattern of precipitation, the rainfall belt, and the center of maximum rainfall were well simulated by the WRF. Although the scale mismatch between validation datasets and WRF simulations lowered the WRF downscaling ability, the characteristics of atmospheric circulation and surface temperature were still clearly simulated. It produced spatial information for temperature in more details, especially in the southwest and the northeast of China, and in Mongolia. Additionally, the weaker westerly jet and the wind flow from the Bay of Bengal resulted in less specific humidity and water vapor flux in WRF simulation. However, the higher WPSH from WRF offset their influences to enhance summer rainfall, when compared with JRA-25.

Several studies indicated that the reinitialization may be beneficial to RCM simulations by solving the problem of increasing systematic error in long integrations. However, there are some factors limiting the application of this downscaling method; for example, the long spin-up time of RCMs constrains the reinitialization frequency, especially for reaching dynamical equilibrium of soil components (Chen et al. 1997). In contrast, the long-term continuous simulation with one single initialization of large-scale fields and frequent updates of LBCs, is currently the most common approach in regional climate simulation (Leung et al. 2003).

The scale mismatch, which means the absence of fine scale features in JRA-25 reanalysis, may affect the comparison between WRF simulations and reanalyses to some extent in this study. The lack of validation data for small-scale circulation features made it difficult to decide whether the RCM simulations were superior over low-resolution reanalyses or not. The “Big Brother” approach, adopted by Denis et al. (2002), provides an option; however, the nested domain just well down-scales the features in the driving model, which may not represent the real conditions.

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Compliance with ethical standards

Conflicts of interest The authors declare that they have no competing interests.

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