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Shuaifeng Song (✉ ssf@mail.bnu.edu.cn)

State Key Laboratory of Earth Surface Processes and Resource Ecology

Xuezhen Zhang

Institute of Geographic Sciences and Natural Resources Research Chinese Academy of Sciences

Xiaodong Yan

State Key Laboratory of Earth Surface Processes and Resource Ecology <https://orcid.org/0000-0002-0774-9140>

Research Article

Keywords: CMIP6 models, Asia-Pacific, Climatology, Interannual variability

Posted Date: January 27th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1271963/v1>

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Evaluation of the Performance of CMIP6 Model Simulations for the Asian-Pacific Region: Perspectives from Multiple Dimensions

Shuaifeng Song¹ · Xuezhen Zhang^{2,3} · Xiaodong Yan¹

¹ State Key Laboratory of Earth Surface Processes and Resource Ecology, Faculty of Geographical Science, Beijing Normal University, Beijing 100875, People's Republic of China

² Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, People's Republic of China

³ University of Chinese Academy of Sciences, Beijing 100049, People's Republic of China

Corresponding author: Xiaodong Yan, yxd@bnu.edu.cn

Abstract

A comprehensive climate model assessment from multiple dimensions is critical for model selection to reduce uncertainties. Here, we evaluated the performance of seven models involved in the Coupled Model Intercomparison Project-6 (CMIP6) by comparing the simulated meteorological variables at the near-surface (sea ice cover and sea surface temperature) and pressure levels (air temperature, specific humidity, zonal wind, meridional wind, and geopotential height at 850 hPa, 500 hPa, and 200 hPa) to those using ERA5 reanalysis data for the 1995-2014 period from the perspectives of climatological and interannual variability. Then, a comprehensive rating index approach was applied to rank the models. The results show that the CMIP6 models could mostly reproduce the spatial variability of the climatology. However, there were also systematic biases. The sea ice cover and sea surface temperature exhibited noticeable biases of approximately -13.2% and 0.6 °C, respectively. Additionally, all models underestimated air temperature and geopotential height, while overestimating specific humidity in the middle troposphere and zonal and meridional wind speeds in the upper troposphere. Regarding interannual variability, the CMIP6 models performed well for the variables at a pressure level of 850 hPa and with sea ice cover. Taken together, all variables showed that NorESM2-MM exhibited good performance in terms of climatology, while MPI-ESM1-2-LR exhibited good interannual variability. Overall, in regard to the comprehensive rate index, MPI-ESM1-2-LR performed the best among the seven models. This study provides valuable scientific references for selecting the available CMIP6 models as lateral boundary conditions towards dynamical downscaling over Asian-Pacific area.

Keywords CMIP6 models; Asia-Pacific; Climatology; Interannual variability

1 Introduction

According to the sixth assessment report of the IPCC, the global surface temperature showed an upward linear trend, increasing by 0.99 °C since the 21st century compared to the preindustrial period (IPCC 2021). Global climate change exerts tremendous impacts on ecosystems and socioeconomics (Nolan et al. 2018; Neumann et al. 2020; Song et al. 2018). It is therefore immensely valuable to understand the causes of historical climate and to project future climate change to develop climate change strategies and measures. The Asian-Pacific region is one of the most populated regions of the world and has experienced great economic growth. Its natural environment, society, and economy are especially vulnerable and susceptible to climate change (Hu et al. 2003; Wang et al. 2017). In addition, due to the combined effects of multiple factors, such as the East Asian monsoon system, land-sea thermal contrast, and Tibetan Plateau topography, there are unique regional characteristics and complex climate variability (Sperber et al. 2013; Wang et al. 2021). In particular, frequent extreme weather and climate events such as floods (Yang et al. 2021b), droughts (Xu et al. 2021), cold surges (Abdillah et al. 2021), and heatwaves (Huang et al. 2021) have caused serious disasters (Chen et al. 2021; Ebi et al. 2021).

Previous studies have focused on the climate system change anomalies in East Asia based on observational data (Jiang et al. 2004; Ding et al. 2014; Li et al. 2021a). Under the context of global climate change, East Asian surface air temperature has exhibited a long-term increase over the past century and recent rapid warming (Zhai et al. 1999, Li et al. 2010, Li et al. 2021b). Relative humidity exhibited a declining trend in China (Mao et al. 2015). Precipitation increased, especially in the Asian monsoon region (Zhao et al. 2016; Li et al. 2019; Lu et al. 2007). In particular, the intensity, duration, and frequency of extreme temperature and precipitation events have increased noticeably over East Asia, which has caused economic losses and casualties, and even mortality (Easterling et al. 2000; Kotsuki et al. 2019; Ren et al. 2015; Lee et al. 2020; Zhang et al. 2020; Shi et al. 2018). Additionally, the surface annual mean and maximum wind speed showed a declining trend over Japan (Fujibe 2011) and China (Xu et al. 2006; Jiang et al. 2010; Wu et al. 2016). Waste heat release due to urbanization, large-scale atmospheric circulation anomalies, land use cover changes, and irrigated area expansion are the factors that are mainly responsible for the observed surface wind decline (Han et al. 2016; Song et al. 2018; Pryor and Ledolter 2010; Zha et al. 2017). Furthermore, from the dominant circulation mode over East Asia, the

intensity of the Aleutian low has strengthened and the Siberian high has weakened in the sea-level pressure field (Kim et al. 2005; Gan et al. 2017). Meanwhile, the East Asian trough (Song et al. 2019), Asian subtropical westerly jet stream (Kwon et al. 2007; Yu et al. 2021), and East Asian winter and summer monsoon (Wang and Chen 2014; Wang et al. 2008) are also weak and the East Asian Hadley cell is extending (Kang and Lu 2012). The variations in the above components are considered the main drivers that have led to the East Asian climate anomalies. Climate simulation in the Asian-Pacific region is of great importance for exploring the main climate features and improving forecasts to better reduce the risks of climate change (Akintomide et al. 2020).

With the development of climate models, global climate models (GCMs) are important tools for studying historical climate variations and future climate projections (Yang et al. 2018). The Coupled Model Intercomparison Project (CMIP) launched by the World Climate Research Program (WCRP) has entered the CMIP6 phase, which includes 112 GCMs from 33 research institutions and provides abundant scientific data for the sixth IPCC Assessment Reports. In comparison to CMIP5, CMIP6 models are significantly improved in their spatial resolution, physical parameterizations, carbon-nitrogen cycle parameterizations, representation of aerosols, and so on (Eyring et al. 2016; Wyser et al. 2019). The CMIP6 models can reproduce the spatial distribution of the mean climate and interannual variability well, but there are still some biases in the Asian-Pacific region (Wang et al. 2019; Xin et al. 2020; Seo et al. 2013). To reduce underlying errors and uncertainties, accurate assessments of CMIP6 models for multi-meteorological elements of the Asian-Pacific region are essential, which is conducive for understanding the potential shortcomings of models and enhances confidence in future climate change projections (Harrison et al. 2014, 2015; Notz 2015).

It has been reported that CMIP6 models can generally reproduce the spatial climatological distribution of the mean, maximum, and minimum temperatures reasonably well over the mid-high latitudes of Asia and China, but there are cold biases, especially on the Tibetan Plateau (Yang et al. 2021c; You et al. 2021). The simulated annual precipitation in CMIP6 also has significant improvements and good agreement with observations, which is attributed to the finer resolution and improved physical parameterizations (Eyring et al. 2016). Additionally, CMIP6 models underestimate the annual surface wind speed, and they have poor performance for reproducing the decreasing trend (Wu et al. 2020). However, from the simulation of sea surface temperature over the Indian Ocean, CMIP6 models

underestimate the warming trend and display little improvement compared to the CMIP5 models (Li and Su 2020a). Moreover, many scholars have evaluated the performance of the main atmospheric circulation factors over East Asia, such as the East Asian summer and winter monsoon (Xin et al. 2020; Yang et al. 2021a), Indian Ocean dipole (McKenna et al. 2020), and Hadley circulation (Grise and Davis 2020). In summary, existing studies have mostly evaluated a single climate variable, and few studies have been conducted with a comprehensive perspective considering multiple meteorological elements together over East Asia. Evaluation of the performance of CMIP6 models based on multiple criteria and multiple variables is therefore needed.

In this study, we attempted to examine the ability of seven CMIP6 models to reproduce climate over the Asian-Pacific region by considering several meteorological variables, as well as assessment metrics on climatological and interannual variability. The differences among CMIP6 models and the ranking of the models are highlighted based on a comprehensive rating index considering more than one meteorological factor. This was expected to provide valuable scientific references for selecting the available CMIP6 models as lateral boundary conditions for regional climate models (RCMs) to conduct dynamic downscaling for the Asian-Pacific area.

The structure of this paper is organized as follows. Section 2 introduces the CMIP6 models, observation data, and evaluation approach. Section 3 presents the evaluation results. A discussion and conclusion are presented in Section 4 and Section 5, respectively.

2 Data and methods

2.1 Data

The CMIP6 dataset is provided by the Earth System Grid Federation (ESGF, available at <https://esgf-node.llnl.gov/search/cmip6>). Since the selected CMIP6 projections were used as lateral boundary conditions of the RCMs, the selection of the CMIP6 models followed three criteria: (1) there were 6-hour intervals of air temperature, zonal wind, meridional wind, geopotential height, and specific humidity for pressure levels available, (2) there were monthly sea ice cover and sea surface temperature (SST), and (3) there were no missing data in the historical period, i.e., from 1995 to 2014, and future projections under the SSP2-4.5 senior (middle of the road). The historical period from 1995 to 2014 was considered the base term for bias correction and future climate change projection (Brunner et al. 2020). Following

these criteria, seven CMIP6 models were selected. The selected CMIP6 models had the finest horizontal resolution, 384 (latitude) $\times$ 192 (longitude), from MPI-ESM1-2-HR and the coarsest horizontal resolution, 144 (latitude) $\times$ 96 (longitude), from NorESM2-LM. More details are shown in Table 1.

This study also used ERA5 reanalysis data. This dataset is a new generation of reanalysis data developed by the European Centre for Medium-range Weather Forecast (ECMWF) (Hersbach et al. 2020). In comparison to the last generation of the ERA-Interim dataset, ERA5 has obvious improvements. ERA5 was derived from the 4DVAR assimilation system, integrating reprocessed observations into data assimilation, with a spatial resolution of 0.25° . ERA5 reanalysis data have good consistency with observations and are often used as observation data to assess global climate models (GCMs) and future scenario projections (Watters et al. 2021; Zhai et al. 2020). This study used surface meteorological variables, including SST and sea ice cover, zonal wind, meridional wind, temperature, geopotential, specific humidity, and pressure levels of 850 hPa, 500 hPa, and 200 hPa from 1995 to 2014. It is noted that the pressure levels of 850 hPa, 500 hPa, and 200 hPa represent the lower, middle, and upper levels of the troposphere, respectively.

Table 1 Information on the CMIP6 models used in this study.

No	Models	Institution and country	Grid numbers
1	IPSL-CM6A-LR	Institut Pierre-Simon Laplace (IPSL), France	144×143
2	MIROC6	National Institute for Environmental Studies, Japan	256×128
3	MRI-ESM2-0	Meteorological Research Institute (MRI), Japan	320×160
4	MPI-ESM1-2-LR	Max Planck Institute for Meteorology (MPI-M), Germany	192×96
5	MPI-ESM1-2-HR	Max Planck Institute for Meteorology (MPI-M), Germany	384×192
6	NorESM2-LM	Norwegian Climate Centre (NCC), Norway	144×96
7	NorESM2-MM	Norwegian Climate Centre (NCC), Norway	288×192

Fig. 1 Asian-Pacific domains over global land. Shaded colors indicate the elevation above sea level (units: m, from ETOPO2).

2.2 Metrics for the evaluation

Two indices were used to assess the performances of the CMIP6 simulations. They are the root mean square error (*RMSE*; Eq. 2) and bias (*BIAS*) (Eq. 1) and they measure the overall accuracy of the simulations. The closer the *RMSE* and bias are to 0, the better the performance of the model.

$$BIAS = \frac{1}{n} \sum_{i=1}^n (O_i - M_i) \quad (Eq. 1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - M_i)^2} \quad (Eq. 2)$$

Where O_i and M_i denote the observed and simulated values, respectively, and n denotes the number of samples.

Accurate simulation of interannual variability is important for research on climate change and its impacts. In this study, the interannual variability skill (*IVS*) score was used to quantify how well the CMIP6 models can reproduce the interannual variability (Zhu et al. 2020; Kim et al. 2020).

$$IVS = \left(\frac{STD_m}{STD_O} - \frac{STD_O}{STD_m} \right)^2 \quad (Eq. 3)$$

where STD_m and STD_O are the interannual standard deviations of the simulation and observation, respectively. Small *IVS* values indicate better performances of the CMIP6 simulation (Fan et al. 2020).

2.3 Comprehensive Rating Index

There are differences in the assessment of the same variable by different assessment metrics. To select the optimal models, the rank of each model can be obtained according to multiple evaluation indices. The comprehensive rating index (*CRI*) was introduced to quantify the comprehensive rank of each model (Jiang et al. 2015; Rivera and Arnould 2020).

$$CRI = 1 - \frac{1}{1 \times n \times m} \sum_{i=1}^n rank_i \quad (4)$$

where m is the number of models (here, it is 7); n is the number of indicators used for the evaluation; and $rank_i$ is the rank of the model according to its simulation ability based on evaluation index i . The closer $rank_i$ is to 1, the closer CRI is to 1, indicating a better performance of the model.

3 Results

3.1 Climatology

3.1.1 Sea surface temperature and sea ice cover

Figure 2 shows the spatial patterns of the annual mean SST climatology over the Asian-Pacific region from the ERA5 and CMIP6 simulations. ERA5 shows that the SST in the Asian-Pacific region is high in the south and low in the north. Such a spatial pattern of annual mean SST could be reproduced by the CMIP6 models, but there is still bias in comparison to ERA5. In detail, the IPSL, MIROC6, and MPI-ESM1-2-LR models exhibit noticeable cold biases of approximately 0.4 °C, especially in the low-latitude Pacific and Indian Ocean regions (McKenna et al. 2020). The other models overestimate the SST with BIAS values of 0.1°C (MRI-ESM2-0) to 2.5°C (NorESM2-LM) and RMSEs of 0.2°C (MRI-ESM2-0) to 2.5°C (NorESM2-LM). This overestimation is mainly for the mid-latitude Okhotsk Sea and Japan Sea regions. Taken together, the MRI-ESM2-0 model is the best for SST simulation in the Asian-Pacific region.

Figure 3 shows the spatial distribution of climatological sea ice cover fractions. We can find that most models can reproduce the characteristic that the sea ice cover is distributed in the high latitude region of the Northern Hemisphere (70°N-90°N). However, the models show a very clear bias. The seven CMIP6 models underestimate the sea ice cover, with BIAS values of -33.6% (MPI-ESM1-2-LR) to -2.6% (NorESM2-MM) and RMSEs of 3.4%

(NorESM2-MM) to 33.7% (MPI-ESM1-2-LR). Existing studies, such as Davy et al. (2020), also reported that negative biases of sea ice cover abroad exist in both CMIP5 and CMIP6 models. Specifically, this negative bias mainly exists in the Canadian Arctic Archipelago and is a persistent challenge for the simulation of thermodynamic and dynamic processes due to the complex terrain and diverse land cover (Kwok et al. 2015). Moreover, we also found a positive bias exceeding 20% around the Barents Sea and the Kara Sea. Taken together, the performance of the NorESM2-MM model is better than the others.

Table 2 BIAS and RMSE of sea surface temperature and sea-ice cover simulations in Asia-Pacific from the 7 CMIP6 models

		IPSL	MIROC6	MPI-ESM1-2-LR	MPI-ESM1-2-HR	NorESM2-LM	NorESM2-MM	MRI-ESM2-0
BIAS	Sea-ice cover (%)	-13.6	-7.4	-33.6	-15.6	-7.7	-2.6	-12.2
	SST (°C)	-0.3	-0.4	-0.4	0.7	2.5	2.2	0.1
RMSE	Sea-ice cover (%)	13.8	7.8	33.7	15.7	8.0	3.4	12.5
	SST (°C)	0.3	0.5	0.4	0.7	2.5	2.2	0.2

Fig. 2 Climatology mean (through 1995–2014) of surface sea temperature from ERA5 and CMIP6 models.

Fig. 3 Same as Fig. 2 but for sea-ice cover.

3.1.2 Meteorological variables for pressure levels

3.1.2.1 Air temperature

Figure 4 shows the BIAS and RMSE of CMIP6 modeling for multiple meteorological variables at different pressure levels. We find that the performances of CMIP6 models vary with pressure levels. Regarding the air temperature, the model underestimates all layers of temperature except MPI-ESM1-2-HR, and the underestimations on the Tibetan Plateau are more prominent than those in other areas (Fig. 5). Actually, it has been extensively reported that the cold bias of temperature was a common phenomenon in the CMIP models (Chen et al. 2015; Yang et al. 2021c). The cold bias may be caused by the sparse stations in complex topography, which influences the quality of data assimilation (You et al. 2020), by the poor performance of snow-albedo feedbacks leading to the weakness of warming (Ji and Kang 2013), and by a failure to reproduce black carbon aerosol pollution (Kang et al. 2019). Thus, it is vital to improving the physical parameterizations to reduce the temperature bias.

At a pressure level of 850 hPa, a negative bias exists in the ocean region, with a maximum bias of -1.9 °C from the IPSL and a minimum bias of -0.3 °C from the MPI-

ESM1-2-HR. In particular, this negative bias in the equatorial Pacific region reaches up to -3
-1 °C, which is larger than that in other areas. At pressure levels of 500 hPa and 200 hPa,
most models underestimate temperature in the mid-high latitudes and overestimate it in the
equatorial Pacific. For example, at a pressure level of 500 hPa, the centre of negative bias is
located over the Tibetan Plateau region in the MIROC6 model and over the Japan Sea region
in the IPSL model. At a pressure level of 200 hPa, the centre of positive bias is located over
the low-latitude regions in both the MPI-ESM1-2-HR model and NorESM2-LM. Taken
together, the MPI-ESM1-2-HR model achieves the best performance for the temperature at a
pressure level of 850 hPa, whereas it is the NorESM2-MM for the temperature at pressure
levels of 500 hPa and 200 hPa.

Fig. 4 BIAS and RMSE between simulated values of meteorological variables and ERA5
for 7 CMIP6 models at different geopotential height (The dotted line is BIAS=0)

Fig. 5 BIAS and RMSE between simulated values of meteorological variables and ERA5 for 7 CMIP6 models at different geopotential height (The dotted line is BIAS=0)

3.1.2.2 Specific humidity

ERA5 shows that the specific humidity is higher in the south-central and Indian Peninsulas as well as nearby seas, while it is lower in the inland areas. CMIP6 models capture these spatial patterns of specific humidity but with bias. As shown in Fig. 6, the CMIP6 models mostly overestimate the specific humidity in the middle level of the troposphere. At a pressure level of 500 hPa, the BIAS is in a range of 0.2×10^{-4} kg/kg (MRI-ESM2-0) to 2.2×10^{-4} kg/kg (NorESM2-LM), and the RMSE is in a range of 0.4×10^{-4} kg/kg (MPI-ESM1-2-LR) to 2.3×10^{-4} kg/kg (NorESM2-LM). Overestimations mostly exist in the North Pacific region.

At the lower and higher levels of the troposphere, there are both overestimations and underestimations. At a pressure level of 850 hPa, the MPI-ESM1-2-LR, NorESM2-MM, and NorESM2-LM models underestimate the specific humidity with low centres on the Indian Peninsula and Iranian Plateau. The other models overestimate the specific humidity, especially the MIROC6 model, with BIAS and RMSE values of 3.6×10^{-4} kg/kg and 3.8×10^{-4} kg/kg, respectively. At pressure levels of 200 hPa, IPSL, MIROC6, and MPI-ESM1-2-LR have a negative bias, with a mean bias of -3.0×10^{-6} kg/kg, while the models from MPI-M and NCC institutions have a positive bias, with a mean bias of 2.1×10^{-6} kg/kg. Taken together, MPI-ESM1-2-LR performs better than the other models in the troposphere specific humidity simulations.

Fig. 6 Same as Fig. 5 but for Specific humidity.

3.1.2.3 Geopotential height

In regard to geopotential height, the CMIP6 models underestimate the geopotential height at pressure levels of 850 hPa and 200 hPa, especially at high latitudes (Fig. 7). The BIAS is -1.0 gpm (MPI-ESM1-2-HR) to -21.3 gpm (MIROC6) at a pressure level of 850 hPa and -1.1 gpm (NorESM2-MM) to -111.2 gpm (IPSL) at a pressure level of 200 hPa. Ao et al. (2015) reported that CMIP5 models, such as IPSL, MPI, MRI, and NCC, mostly underestimated the geopotential height at a pressure level of 200 hPa in the high latitudes of the Northern Hemisphere (50°N -90°N) during 2002-2008; in particular, the IPSL displayed a worse performance with a bias of -51 gpm. The systematically negative bias in the latest generation of CMIP6 models may thus be inherited from the last generation of CMIP5 models. It may still be a great task to improve the performance of geopotential height simulations for the CMIP6 models.

At a pressure level of 500 hPa, there are both positive and negative biases. Positive bias exists in MPI-ESM1-2-HR, NorESM2-LM, and NorESM2-MM, with a mean bias of 8.6 gpm. Negative bias exists in IPSL, MIROC6, MPI-ESM1-2-LR, and MRI-ESM2-0, with a mean bias of -26.5 gpm. Among them, the largest bias exists in the IPSL model. Taken together, MPI-ESM1-2-HR is the best at pressure levels of 850 hPa and 500 hPa, and NorESM2-MM is the best at a pressure level of 200 hPa.

Fig. 7 Same as Fig. 6 but for geopotential height.

3.1.2.4 Zonal wind

Figure 8 shows the spatial pattern of zonal wind from ERA5 and CMIP6 simulations. At pressure levels of 850 hPa and 500 hPa, the IPSL and MIROC6 models underestimate the zonal wind, while the others overestimate it. Largest biases of 0.4 m/s (850 hPa) and 1.4 m/s (500 hPa) are from the NorESM2-LM model. At a pressure level of 200 hPa, all seven CMIP6 models overestimate the zonal wind, with a BIAS of 0.4 m/s (NorESM2-MM)-2.4 m/s (MRI-ESM2-0) and RMSE of 1.0 m/s (IPSL)-2.6 m/s (MRI-ESM2-0). Overestimations mainly occur in the mid-low latitudes of the Asian-Pacific region. It is notable that most CMIP6 models present a negative bias along with approximately 40°N at a pressure level of 200 hPa. Such negative bias remains consistent with the underestimations of East Asian westerlies, which was reported by Fu et al. (2020). Moreover, it was reported that such

underestimation exists in both CMIP5 and CMIP6 models (Fu et al. 2020). These results suggest that the performances of CMIP6 models for zonal wind vary with pressure level. The performances of MPI-ESM1-2-LR, MIROC6, and NorESM2-MM for zonal wind at pressure levels of 850 hPa, 500 hPa, and 200 hPa, respectively, are better than those of the other models. Taken together, the MPI-ESM1-2-LR model may have the best performance for the whole troposphere.

Fig. 8 Same as Fig. 7 but for Zonal wind.

3.1.2.5 Meridional wind

The spatial distribution of meridional wind is mainly characterized by north wind at high latitudes and south wind at low latitudes in the Asian-Pacific region (Fig. 9). CMIP6 models reproduce these characteristics well but with bias. More than 70% of the CMIP6 models have

a negative bias at pressure levels of 850 hPa and 500 hPa, with BIAS values of -0.01 m/s (MPI-ESM1-2-LR) to -0.25 m/s (MRI-ESM2-0) and -0.04 m/s (IPSL) to -0.20 m/s (MRI-ESM2-0), respectively. All CMIP6 models overestimate the meridional wind at a pressure level of 200 hPa. Among them, the NorESM2-MM model has the smallest BIAS, 0.06 m/s, and RMSE, 0.26 m/s. Taken together, NorESM2-LM and NorESM2-MM may have the best performance for meridional wind.

Fig. 9 Same as Fig. 8 but for Zonal wind.

3.2 Interannual variability

3.2.1 Sea surface temperature and sea ice cover

In addition to climatology, interannual variability can reflect the temporal variation in the climate system and is an important metric for examining model performance (Tang et al. 2021). In this section, we calculate the standard deviation of the observations and simulations and use the IVS index to measure model performance (*Eq. 3*). A smaller IVS value suggests a better performance. For sea ice cover, the IVS values are below 1.0 except for NorESM2-MM (Table 3). This finding suggests that the interannual variability in sea ice cover could be reproduced well by most CMIP6 models. Among them, the lowest IVS value, zero, is from MIROC6.

For SST, the MRI and MPI families reproduce SST variations better with an IVS value less than 1.0. Among them, the lowest IVS value, 0.027, is from MPI-ESM1-2-HR. However, MIROC6 has higher IVS values, which is contrary to its lowest values for sea ice. This finding suggests the complexity of ocean modeling. Among the eight CMIP6 models, MIROC6 has the best performance for sea ice over the simulations and the worst performance for SST simulations. Halder et al. (2021) reported that the best performance for interannual variability of tropical Indian Ocean SST was from the KACE-1-0-G model. These results suggest that the performance of SST simulations varies with the spatial domain. Hence, this finding confirms the complexity of ocean modeling.

Table 3 IVS values for SST and sea-ice cover simulations from seven CMIP6 models

	IPSL	MIROC6	MPI-ESM1-2-LR	MPI-ESM1-2-HR	NorESM2-LM	NorESM2-MM	MRI-ESM2-0
Sea-ice cover	0.232	0.000	0.587	0.593	0.279	4.095	0.839
SST	1.040	1.862	0.148	0.027	0.793	1.269	0.078

3.2.2 Meteorological variables for pressure levels

Figure 10 shows the performance of CMIP6 on the interannual variability of multiple meteorological variables at different pressure levels. In the columns, the IVS values of MPI-ESM1-2-LR, MPI-ESM1-2-HR, and MRI-ESM2-0 are below 1.3 for all meteorological variables. This suggests that these models can reproduce interannual variability well. The dark color indicates higher IVS values, and hence worse performance mostly occurs with MIROC6, NorESM2-LM, and NorESM2-MM. This suggests that they cannot reproduce interannual variability.

In the rows, dark colours mostly occur at specific humidity and geopotential height, while less dark colours occur at temperature and wind. In addition, except for specific humidity, dark colours mostly occur at 200 hPa and 500 hPa, while fewer occur at 850 hPa. All these findings suggest that the CMIP6 models present better performance for temperature and wind at a pressure level of 850 hPa and worse performance for geopotential height at pressure levels of 200 hPa and 500 hPa. This is consistent with the findings of annual near-surface temperature in China by Yang et al. (2021c). In summary, the best performance for interannual variability of zonal wind and geopotential height is from MPI-ESM1-2-LR, and the best performance for interannual variability of temperature, meridional wind, and specific humidity are from MRI-ESM2-0.

Fig. 10 Heatmap for model performance evaluated using IVS at different geopotential height

3.2.3 Overall model ranking

The above findings show that the model performances vary greatly with meteorological variables and evaluation metrics. To assess the comprehensive performance of CMIP6 models, the comprehensive rating index (CRI) is used. Figure 11 shows the ranking of the CRI for meteorological variables at different pressure levels and models taking together three metrics: BIAS, RMSE, and IVS. A smaller ranking indicates better performance. We find that the MPI models exhibit better overall performance for most variables compared to the

other models, while IPSL and MIROC6 exhibit poor performance. Table 3 further depicts the ranking of three indices, i.e., RMSE, BIAS, and IVS, as well as the CRI over the Asian-Pacific region for all variables. This shows that NorESM2-MM and MPI-ESM1-2-LR exhibit the best simulation performance for climatological and interannual variability, respectively. Overall, MPI-ESM1-2-LR and MPI-ESM1-2-MR from the MPI have better comprehensive performances with lower ranks.

Fig. 11 CMIP6 model performance summary (Numbers indicate ranks, and the smaller number, the better performance)

Table 4 Ranks of the three index and CRI values for CMIP6 models

	IPSL-CM6A-LR	MIROC6	MPI-ESM1-2-LR	MPI-ESM1-2-HR	NorESM2-LM	NorESM2-MM	MRI-ESM2-0
BIAS	7	6	2	3	4	1	5
RMSE	7	6	3	2	4	1	5
IVS	4	6	1	3	5	7	2
CRI	6	7	1	2	5	3	4

4 Discussion

This study evaluated the performance of seven CMIP6 models in regard to Asian-Pacific climate modelling. It is noted that only seven models were considered rather than more models in CMIP6. The main reason for this was that there were only seven models whose 6-

hour interval data of CMIP6 outputs under the historical period and SSP2-4.5 senior were available. This study sets a target to select the better performance modelling, which could be used as the lateral boundary for dynamic downscaling. Therefore, a 6-hour interval of modelling output is necessary. Most existing studies set the target to evaluate the model performance to improve the model (Luo et al. 2020; Guo, et al. 2021). Hence, the daily and monthly intervals of data are sufficient. Therefore, dozens of CMIP6 models were usually involved in these studies.

In regard to the evaluation metrics, this study is prominently different from existing studies. First, this study considered multiple metrics, from surface to pressure level and from ocean to land. There have been more comprehensive and full-scale studies than the existing studies. Second, in this study, the evaluation was carried out from two perspectives: climatological means and interannual variability. The existing study evaluated model performance by using metrics such as spatial variation (Jiang et al. 2015), long-term trend (Fan et al. 2020), standard deviation (Roach et al. 2020), annual cycle (Jiang et al. 2020), decadal variation (Yu et al. 2020), probability density distribution (Guo et al. 2021), and empirical orthogonal function (EOF) mode (Halder et al. 2021). Third, this study applied the CRI to rank the overall performance, which displayed the comprehensive ability of the individual CMIP6 models.

The quality of the observation data is a critical factor influencing our understanding of the performance of models. Satellite, reanalysis, and meteorological station data are broadly used in climate model evaluations (Vignesh et al. 2020; Krishnan and Bhaskaran 2020; Li et al. 2020b). In this study, the ERA5 reanalysis data were used as a reference. ERA5 data have also been used by existing climate model evaluation studies, such as Roussel et al. (2020) and Watters et al. (2021). It is noted that the ERA5 reanalysis data are not “real” observations, and it is difficult to completely reproduce the true atmospheric state, dynamics, and variability (Bosilovich et al. 2013; Bengtsson et al. 2004). The uncertainties of ERA5 reanalysis data mainly arise from data assimilation, forecast errors, numerical simulations, and errors in observation systems (Nie et al. 2015; Dee et al. 2014; Parker 2016). There are deficiencies and poor performance in high elevation and complex terrain areas (Jiang et al. 2021). Thus, multisource observation data could be increasingly acceptable to describe model performance and to enhance the accuracy and credibility (Kim et al. 2020; Fan et al. 2020; Hu et al. 2021) of predictions on near-surface (sea ice cover and sea surface temperature) and

pressure levels (air temperature, specific humidity, zonal wind, meridional wind, and geopotential height at 850 hPa, 500 hPa, and 200 hPa).

5 Conclusion

This study examined the performance of 7 GCMs from CMIP6 in the Asian-Pacific region. The near-surface (sea ice cover and SST) and pressure level (air temperature, specific humidity, zonal wind, meridional wind, and geopotential height at 850 hPa, 500 hPa, and 200 hPa) meteorological variables were evaluated considering three metrics: climatology, interannual variability, and the comprehensive rating index. This paper aimed to explore the performance and difference over the Asian-Pacific region and to select the best model based on CMIP6 models. The following main conclusions are as follows:

(1) According to the climatological results from different climate variables, the models show negative bias for sea ice cover and positive bias for sea surface temperature. For the pressure levels, air temperature and geopotential height are underestimated in the whole troposphere, especially in the Tibetan Plateau region. Conversely, the CMIP6 models overestimate the specific humidity in the middle troposphere and zonal and meridional wind speeds in the upper troposphere. For the interannual variability simulation, CMIP6 models have better performance for sea ice cover. The models from MRI and MPI capture the SST simulation better with an IVS value of less than 1.0. Remarkably, the CMIP6 models are better for 850 hPa meteorological element simulations.

(2) In this study, we evaluate CMIP6 models for multi-meteorological elements in the Asian-Pacific region by using three indices. In addition, the optimal model is selected by the CRI. The best models for climatological and interannual variability are NorESM2-MM and MPI-ESM1-2-LR, respectively. Overall, MPI-ESM1-2-LR has the best performance for the Asian-Pacific region, which could be considered as the future projection and lateral boundary conditions for dynamic downscaling. It is of great importance to help us to make full use of the advantages of the individual model in the Asian-Pacific region. These results provide end-users or policymakers with a better understanding of climate characteristics and mechanisms in the Asian-Pacific region.

(3) In future studies, we will use more released CMIP6 models and other metrics to evaluate their comprehensive performance in the Asian-Pacific region from different perspectives. In

addition, we will correct the CMIP6 models using different observation datasets that will enable us to improve their ability for future climate projection and dynamic downscaling based on refined assessment. Furthermore, it is essential to find the sources of uncertainties and to reduce systematic biases in future work.

Acknowledgements

We thank the World Climate Research Programme (WCRP) Working Group on Coupled Modelling and the European Centre for Medium-Range Weather Forecasts (ECMWF), which is responsible for CMIP6 and ERA5, respectively. This work was jointly supported by the National Key Research and Development Program of China (2019YFA0606600 and 2019YFA0606904).

Author contributions

Conceptualization: Xiaodong Yan; Software, Shuaifeng Song; Resources, Xuezhen Zhang; Material preparation and analysis: Xuezhen Zhang; Writing-original draft preparation: Shuaifeng Song and Xuezhen Zhang; writing-review and editing, Xiaodong Yan; Visualization, Shuaifeng Song; All authors read and approved the final manuscript.

Funding This study has been supported by the National Key Research and Development Program of China (2019YFA0606600 and 2019YFA0606904).

Data Availability The CMIP6 data were provided by the WCRP group at <https://esgf-node.llnl.gov/projects/cmip6/>. The ERA5 datasets can be accessed from ECMWF (<https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5>).

Competing interests The authors have no conflicts of interest to declare that are relevant to the content of this article.

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