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Global surface air temperatures in CMIP6: historical performance and future changes

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Abstract

Surface air temperature outputs from 16 global climate models participating in the sixth phase of the coupled model intercomparison project (CMIP6) were used to evaluate agreement with observations over the global land surface for the period 1901–2014. Projections of multi-model mean under four different shared socioeconomic pathways were also examined. The results reveal that the majority of models reasonably capture the dominant features of the spatial variations in observed temperature with a pattern correlation typically greater than 0.98, but with large variability across models and regions. In addition, the CMIP6 mean can capture the trends of global surface temperatures shown by the observational data during 1901–1940 (warming), 1941–1970 (cooling) and 1971–2014 (rapid warming). By the end of the 21st century, the global temperature under different scenarios is projected to increase by 1.18 °C/100 yr (SSP1-2.6), 3.22 °C/100 yr (SSP2-4.5), 5.50 °C/100 yr (SSP3-7.0) and 7.20 °C/100 yr (SSP5-8.5), with greater warming projected over the high latitudes of the northern hemisphere and weaker warming over the tropics and the southern hemisphere. Results of probability density distributions further indicate that large increases in the frequency and magnitude of warm extremes over the global land may occur in the future.

1. Introduction

Warming of the climate system is unequivocal, and according to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the global surface temperature warmed by 0.85 °C over the period 1880–2012 (IPCC 2013). The rising global temperatures have prompted great concern regarding the relationship between nature and society. Previous studies have suggested that the widespread temperature increases have substantial impacts on the global hydrologic cycle (Alfieri et al 2017, Sun and Miao 2018, Zheng et al 2019, Gou et al 2020), food production (Asseng et al 2015), energy allocation (Mcglade and Ekins 2015), disease spread (Levy et al 2016, Colón-González et al 2018), natural disasters (Miao et al 2010, 2011, Diffenbaugh et al 2017, Sun et al 2020) and socioeconomic development (Burke et al 2015). In addition, warming of 2 °C is projected to

lead to an average global ocean rise of 20 cm (Jevrejeva *et al* 2016), and warming of 1.5 °C is projected to lead to glaciers melting in the high mountains of Asia, such that only $64\% \pm 7\%$ of their present-day ice mass will remain by the end of the century (Yao *et al* 2012, Kraaijenbrink *et al* 2017). Hence, it is imperative to study the patterns and trends in global temperature change and their implications for sustainable development and future adaptation measurements that may be needed.

Global climate models (GCMs) are regarded as the primary tools for climate change studies, being widely used to simulate and project climate change at global and regional scales. The outputs of GCMs offer opportunities to analyze the projections for 21stcentury climate change and the potential effects of those changes at global and regional scales (Su *et al* 2013, Bannister *et al* 2017). In response to the challenges of comprehensive modeling in climate science,

a more federated structure for the sixth phase of the coupled model intercomparison project (CMIP6) has been adopted, with a substantial increase in the number and scope of experiments that have been performed. In comparison with the previous model generation (CMIP5), the CMIP6 GCMs have shown significant improvements in spatial resolution, physical parameterizations (in the representation of clouds, for example) and inclusion of additional Earth system processes (such as nutrient limitations on the terrestrial carbon cycle) and components (such as ice sheets) (Eyring et al 2016, 2019). A new conceptual framework (Moss et al 2010) has been developed using a diverse range of socioeconomic and technological development scenarios, named the shared socioeconomic pathways (SSPs), which are distinguished on the basis of anticipated challenges to adaptation and mitigation, rather than on emissions pathways as was done for the IPCC Special Report on Emissions Scenarios (Ebi et al 2013, O'Neill et al 2016). Two main axes of the scenario matrix architecture are (1) the future climate radiative forcing level, characterized by the representative concentration pathways (RCPs) and (2) a set of alternative plausible trajectories of future global development (the SSPs) (O'Neill et al 2013, van Vuuren et al 2013, Kriegler et al 2014). The SSPs are based on five narratives describing alternative pathways for socioeconomic development, including sustainable development (SSP1) (van Vuuren et al 2017), middle-of-the-road development (SSP2) (Fricko et al 2017), regional rivalry (SSP3) (Fujimori et al 2017), inequality (SSP4) (Calvin et al 2017) and fossil-fueled development (SSP5) (Kriegler et al 2017). This new generation of scenarios will facilitate society's understanding of plausible climate and socioeconomic futures.

Recently, some experimental results from the new generation of GCMs have become available. How well the new generation of CMIP6 GCMs simulate climate at global and regional scales and how the global temperature will change under the new emissions scenarios in the future is of great interest to both researchers and decision makers. In this study, as a basis for comparison with observational data sets, we evaluate the historical variability of the global surface air temperature simulated by 16 GCMs participating in CMIP6 and then investigated how the global temperature will change in the 21st century.

2. Models, data and methods

2.1. Modeled and observational data sets

2.1.1. Modeled data.

We obtained monthly surface air temperature output from 16 GCMs in the CMIP6 archive, the relevant details are presented in table S1 (available online at stacks.iop.org/ERL/15/104056/mmedia). Five sets of experiments were used focusing on the global land area and the continental scale: one historical simulations for the period 1901–2014 were processed for the performance analysis; Four scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5) were used for future projections from 2015 to 2099, which provide a full range of forcing targets similar in both magnitude and distribution to the RCPs as used in CMIP5 (Gidden *et al* 2019). All the models were bilinearly interpolated onto a common grid of $1^{\circ} \times 1^{\circ}$ for comparison between simulations and observations.

2.1.2. Observational data.

To ensure that our assessment of model performance is not biased by our choice of observations, two different observed data sets of monthly surface air temperature were used to evaluate the GCMs' performance. The first is the University of East Anglia Climatic Research Unit (CRU) Time-Series (TS) data version 4.03 (Harris et al 2020), gridded to $0.5^{\circ} \times 0.5^{\circ}$ resolution and based on analysis of over 4000 individual weather station records, with data extending from 1901 to 2014. The second is the University of Delaware Air Temperature (UDEL) v5.01 data set (Willmott and Robeson 1995), based on land stations from GHCNv2 (Global Historical Climatology Network—Version 2) and a few other sources; it has the same spatial resolution as CRU, and its time period also extends from 1901 to 2014. For consistency with the model resolution, we regridded the two observational data sets to a $1^{\circ} \times 1^{\circ}$ grid.

2.2. Historical climate simulation performance metrics

To facilitate validation of the GCMs against the observational data, we simply averaged the temperature values to define the globally averaged monthly and annual time series and spatial patterns of GCM simulations and observations. The annual mean temperature anomalies were calculated as the deviations from the climatology during the period 1970-1999. Considering the warming temperature trends observed during 1901-1940 and 1971-2014 in contrast to a cooling temperature trend during 1941-1970 (figure S1), we split the interannual variations of temperature into three time periods, 1901-1940 (period 1), 1941–1970 (period 2) and 1971–2014 (period 3). Then we calculated the climatological temperature patterns and linear trends for three time blocks and compared the consistency between the model and the observations. To quantify the agreement between observations and model simulations, we constructed Taylor diagrams (Taylor 2001), for which we calculated the Pearson correlation coefficients, standard deviations of the error and root-mean-square errors between the CMIP6 models' data sets and the observational data sets. We calculated the trends using linear least-squares fitting. T-test was employed to calculate the statistical significance of the temperature trends.



Figure 1. Spatial distribution of annual mean temperature biases (models minus CRU) of the 16 GCMs and observations over the global land surface during 1901–2014.

3. Evaluation of model performance

3.1. Spatial climatological means and trends

We start by comparing the spatial patterns of the bias between the observed and simulated climatological annual mean temperature during 1901– 2014 (figures 1 and S2). In general, most CMIP6 models can capture the climatological temperature patterns over the global land surface. Almost all models commonly show demonstrable underestimation in the Tibetan Plateau by more than 5 °C. CESM2-WACCM, CESM2, MIROC-ES2L, MIROC6 and MRI-ESM2-0 show warm biases in most global land regions but slightly underestimate temperatures in tropical regions. The warm biases are most pronounced in the simulations by MIROC-ES2L and MIROC6, especially in western Asia and east of 130°E in Asia. However, other models tend to underestimate annual temperature in most global land regions, and their underestimations in Greenland and the Tibetan Plateau are considerable. Furthermore, FGOALS-g3 exhibits noticeable cold biases in high northern latitude regions of Eurasia by 5 °C-7.5 °C. The multimodel ensemble average show better agreement than many single models in simulating the spatial patterns of the annual mean temperature, with most biases within 2.5 °C. But the common cold biases seen in the Greenland and the Tibetan Plateau and the warm biases in east of 130°E in Asia are also evident in the CMIP6 ensemble mean. These cold biases of the models in the Greenland and the Tibetan Plateau is likely linked to the uneven spatial distribution of





meteorological station, which may introduce some uncertainties in the interpolated observations in these regions (Reeves Eyre and Zeng 2017). The spatial patterns of the annual mean temperature during the three historical periods (figures S3–S8) suggest there are similar biases of the models relative to the entire historical period.

The agreement between model-simulated and observed temperature was further evaluated through the Taylor diagrams. Figures 2, S9–S11 show the results for the climatology of the entire historical period and three subperiods for individual CMIP6 models. In general, the performance of the models over the entire historical period has no obvious difference from that of the three subperiods. Based on the Taylor diagrams, there is good agreement between UDEL observations and CRU observations. This provides positive evidence that verification against CRU data is reasonable and appropriate. As with the spatial pattern of global annual mean temperature, all the models show good performance, with a correlation coefficient typically >0.98 and a close match to CRU observations. BCC-CMS2-MR, EC-Earth3, EC-Earth3-Veg, CESM2-WACCM and CESM2 perform somewhat better over the global land surface. Based on a comparison of the Taylor diagrams for each continent, the CMIP6 models are generally more skillful in Asia and North America but perform relatively poorly in Africa. There is a more dispersed distribution of the results of the 16 models in Africa than for other continents, indicating that the models differ widely in their simulation ability to reproduce the spatial variations of temperature climatology. Furthermore, the correlation coefficients of six models are below 0.90 for Africa, while the majority of models show higher correlation coefficients (generally between 0.95 and 0.99). However, the lower correlation coefficients might be



attributable to the poorer availability of CRU observational data over Africa (Collins 2011, Harris et al 2014). EC-Earth3 and EC-Earth3-Veg exhibit better skill in Asia, Europe and North America than in Africa, South America and Australia. MIROC-ES2L, MIROC6 and CanESM5 present relatively poor performance compared to other models over global land and for each continent (except for the performance of CanESM5 in Australia and Europe and the performance of MIROC6 in North America). As shown in figure 1, the poor skill of MIROC-ES2L and MIROC6 is related to the noticeable overestimation in most regions of the global land, and CanESM5 largely underestimates temperature in Greenland, Tibetan Plateau, Andes and Sahara. Other notable discrepancies include FGOALS-g3 results for Europe, which differ substantially from CRU observations due to the large cold biases shown in Europe (figure 1).

We next compare the spatial patterns of linear trends during 1901-1940 (period 1), 1941-1970 (period 2) and 1971-2014 (period 3), calculated using observational data and the CMIP6 multi-model mean simulations (figure 3). A more detailed look at the performance of individual CMIP6 models during the three periods is shown in figures S12–S14. Overall, the CMIP6 mean can capture the trends of global surface temperatures shown by the observational data during the three subperiods (warming in period 1, cooling in period 2 and rapid warming in period 3) but with less spatial variability compared with the observations. During period 1, CRU and UDEL reveal that there was a fast warming trend in annual temperatures over the high latitudes of the northern hemisphere; however, the CMIP6 ensemble mean underestimates the observed warming trends

by \sim 0.1 °C–0.5 °C per decade. A closer look at the trends of individual models (figure S12) shows that some models (e.g. UKESM1-0-LL, CNRM-ESM2-1, CNRM-CM6-1, CAMS-CSM1-0 and BCC-CSM2-MR) do not simulate a warming trend similar to that seen in the observations but instead show a cooling trend in these regions. For low latitudes of the northern hemispheres and southern hemispheres, the CMIP6 mean broadly shows a significant warming trend, whereas the observed warming trend is not significant in many regions. During period 2, the CMIP6 mean underestimates the cooling trend in high latitudes of the northern hemisphere by \sim 0.2 °C-0.7 °C. Contrary to the cooling trend of observations, IPSL-CM6A-LR, CNRM-CM6-1, CNRM-ESM2-1, CESM2 and CAMS-CSM1-0 exhibit warming trends in high latitudes of the northern hemisphere (figure S13). EC-Earth3, EC-Earth3-Veg and BCC-CSM2-MR show warming trends in high latitudes of North America, while FGOALS-g3 and GFDL-ESM4 show warming trends in high latitudes of Asia and Europe. The CMIP6 mean does not reflect the observed warming trend in some regions of middle-to-low latitudes (northern South America, Australia and western and central Asia). However, the warming trends of these regions are reproduced in some individual models with warm biases. The CMIP6 mean and the individual models can reasonably capture the observed trend patterns with slight overestimation of less than 0.2 °C during period 3. CAMS-CSM1-0 shows weak underestimation in most regions of the global land, whereas the simulations from UKESM1-0-LL show noticeable overestimation in high latitudes of the northern hemisphere (figure S14).



Figure 4 further shows the model behavior of regional average trends simulated by the CMIP6 models over global land and each continent during the three subperiods. The results suggest that large biases of CMIP6 models are present in Asia, Europe and North America in all subperiods, which correspond to the biases in high latitudes of the northern hemisphere drawn from the previous findings in figure 3. With respect to the relative performance of the individual models, we found that (1) EC-Earth3 and FGOALS-g3 shows overestimation, while UKESM1-0-LL, CNRM-ESM2-1, CNRM-CM6-1 and BCC-CSM2-MR shows underestimation during period 1; (2) CNRM-CM6-1, CNRM-ESM2-1 and IPSL-CM6A-LR underestimates the cooling trend, while MRI-ESM2-0 and UKESM1-0-LL overestimates the cooling trend during period 2; and (3) Most models show overestimation, especially CESM2-WACCM, CESM2, CNRM-ESM2-1, CanESM5 and UKESM1-0-LL, while CAMS-CSM1-0 shows underestimation during period 3. The magnitude of the multi-model mean generally shows higher consistency with observations than for the majority of the CMIP6 models.

3.2. Temporal climatological means and trends

After investigating the spatial performance of the CMIP6 GCMs in relation to the observations, we also looked at their temporal performance. Figure 5 shows the time series of the annual mean temperature anomalies over the global land surface and each individual continent for the 16 GCMs, along with the observations for 1901–2014.

As shown in figure 5, the observational time series (CRU and UDEL) of temperature anomalies over the global land surface and for each individual continent exhibit good agreement, especially after the 1950s, which is probably due to the increase in meteorological stations after the 1950s. Both sets of observations and the CMIP6 results show positive trends in temperature during the historical period. The warming trends seen in the multi-model ensemble mean are closer to the CRU results, but greater than the trends seen in both CRU and UDEL observations over the global land surface and the continents other than Asia (in Asia, CRU > CMIP6 mean > UDEL). We quantified the inter-model uncertainty with the mean values and standard deviation from the multi-year





average of 16 CMIP6 models, shown in figure S15. Comparatively, the CMIP6 models show more uncertainty in Europe (-0.05 ± 0.31), North America (-0.06 ± 0.21) and Asia (-0.03 ± 0.18), and slightly lower uncertainty in Australia (-0.12 ± 0.08), Africa (-0.11 ± 0.07) and South America (-0.13 ± 0.06) during 1901–2014 (figure S15(a)). In each subperiods, and especially before the 1970s, the uncertainties for Europe are the largest (figures S15(b)–(d)).

To analyze the annual cycle of the mean climate over the global land surface and for each individual continent, figure 6 presents box plots of monthly mean temperatures from the 16 CMIP6 models. The monthly variability of the CMIP6 models is consistent with the observations, but there are still some biases, varying with the season. From a global perspective, the median values of the 16 models are close to the observed values in months JJA (June–July–August), but they slightly underestimate the temperatures in MAM (March–April–May), SON (September–October–November) and DJF (December–January–February). The remarkable consistency between CMIP6 models and observations in JJA is also apparent in the northern hemisphere (Europe, Asia and North America). For these three continents, the performance of the CMIP6 models in other seasons is basically the same as the performance over the global land, except for an overestimation during DJF in Asia and a slight overestimation during SON in Europe. In Africa, which spans



both hemispheres, the observed values are above the 75th quantile or the median of the box plots in MAM, SON and DJF, reflecting the fact that most of the CMIP6 models underestimate temperatures in these three seasons. In JJA, by contrast, the observed values are below the 25th quantile or the median of the box plots, showing overestimation and a few outliers. However, for South America, the models largely underestimate temperatures in JJA and May, and observations are close to the median of the model results in the rest of the seasons, which indicates better performance than in JJA. The observations consistently falling below the median or even the 25th quantile of the models in Australia, indicating that most models are overestimating temperature throughout the year. There are large impacts of clouds on the radiation budget and the hydrological cycle, and even small changes in cloud properties could have

a significant impact on climate (Lauer and Hamilton 2012, Grise and Polvani 2014). In regions that are relatively dry, with high incoming solar radiation (such as Australia), the large errors in surface downwelling solar radiation caused by clouds could dry out the surface, resulting in initial bias of the surface temperature simulations in CMIP6.

4. Temperature projections for the 21st century

To assess consistency among GCM projections of the future, we have divided the 21st century into three different periods—near term (2025–2049), mid-term (2050–2074) and long term (2075–2099) —and looked at four scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5). The multi-model ensemble



mean has been constructed to analyze the projected changes.

The spatial distributions of the changes in annual mean temperature relative to 1979-1999 over the global land surface for the near-, mid- and long-term periods of the 21st century under the four scenarios are shown in figure 7. The results show that there will be continued warming over the global land surface. In the simulations, the greatest absolute temperature increases occur over northern Europe, northern Asia and north-central North America, while weaker warming occurs in South America, Africa, Australia and Southeast Asia. However, lower latitudes display considerably smaller natural climate variability than high latitudes, which impedes the identification of clear changes in warming signal (Mahlstein et al 2012). Following the approach proposed by Hawkins et al (2020; Text S1), we calculated the signal-to-noise ratio (SNR) of climate warming under the SSP5-8.5 scenario during 1901-2099 and found that tropical regions are experiencing the largest SNR of warming under the forced change (figure S16). For the nearterm period (2025-2049), the different forcing pathway scenarios do not lead to dramatically different temperature responses, with temperature increasing less than 4 °C in most areas. By the end of the 21st century (2075-2099), the warming in Europe, North America and north-central Asia is 2 °C–4 °C, while that in most of South America, Africa, Australia and

Southeast Asia is less than 2 °C under the SSP1-2.6 scenario. Compared with SSP1-2.6, ubiquitous temperature increases of 1 °C–1.5 °C and 2 °C–3.5 °C are apparent under the SSP2-4.5 and SSP3-7.0 projections, respectively. Additionally, under the SSP5-8.5 scenario, the increase exceeds 3 °C–5 °C over most of the global land surface, and it exceeds 8 °C over high latitudes of northern hemisphere. The midterm period (2050–2074) of the 21st century can be viewed as a transition period during which the different temperature responses under weaker and stronger forcing pathway scenarios become increasingly noticeable.

To further investigate the spatial patterns of temperature changes in future scenarios, figure 8 shows the multi-model-averaged temperature trends and carries out the statistical significance test in each grid cell. For the near-term (2025-2049) period of the 21st century, all the scenario experiments exhibit significantly increasing temperatures over the global land surface. The warming trend in the southern hemisphere is weaker than that in the northern hemisphere. Under the scenarios of SSP1-2.6, SSP2-4.5 and SSP3-7.0, temperatures in most regions increase by 0.2 °C-0.8 °C per decade. For SSP5-8.5, the temperature increase in most regions over the global land surface is more than 0.4 °C per decade, and the fastest warming is in the high-latitude regions of the northern hemisphere, with a trend of more than



Figure 8. Spatial distributions of annual mean temperature trends over the global land surface in near-term (2025–2049), mid-term (2050–2074) and long-term (2075–2099) periods of the 21st century under the SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios. The histograms represent the regional averages for the global land surface and each continent (A = Global, B = Africa, C = Asia, D = Europe, E = North America, F = South America and G = Australia). The stippling shows 95% level of significance.



Figure 9. Time series of annual mean temperature anomalies for the multi-model mean (gray = historical, green = SSP1-2.6, blue = SSP2-4.5, red = SSP3-7.0 and purple = SSP5-8.5), CMIP6 mean (black) and the observations (orange) over the global land surface and for each individual continent. The shaded areas are the spreads of the 5th to the 95th percentiles of the annual mean temperature.



1 °C per decade. Most of Africa, South America and Australia show a relatively small warming trend of 0.4 °C-0.6 °C per decade. For the mid-term period (2050–2074), the warming trend starts to slow down under the scenarios of SSP1-2.6 and SSP2-4.5, due to the stabilization of the SSP1-2.6 and SSP2-4.5 forcings during this time period. Temperature under the SSP1-2.6 scenario increases less than 0.2 °C per decade in most areas, but only a few areas pass the trend significance test at 95% confidence interval, and there is a weak cooling trend in Greenland and the Sahara. However, the warming trends of SSP3-7.0 and SSP5-8.5 continue to increase in comparison with the near-term period, with warming trends greater than 0.4 °C per decade or 0.6 °C per decade, respectively. By the end of the 21st century (2075–2099), under the SSP1-2.6 scenario, the global temperature began to show a decreasing trend, except for in some parts of central East Asia and central North America,

while Europe shows the largest decreasing. Compared with the two earlier periods, the temperature in most regions slowly increases below 0.4 °C per decade under the SSP2-4.5 scenario. By contrast, the rapid temperature increases under the scenarios of SSP3-7.0 and SSP5-8.5 reached the maximum of the three periods.

Temporal evolution from 1901 to 2099 of the annual mean temperature anomalies derived from multi-model mean over the global land surface and each individual continent are shown in figure 9, together with their inter-model spreads. The SSP5-8.5 scenario exhibits the largest increasing trend, at a rate of 7.20 °C/100 yr globally. Continued increases in annual mean temperature also can be seen under the SSP3-7.0, SSP2-4.5 and SSP1-2.6 scenarios, at a rate of 5.50 °C/100 yr, 3.22 °C/100 yr and 1.18 °C/100 yr globally, respectively. According to projected temperature changes for the different

continents under the four scenarios, the changes of the warming curves in the different scenarios are roughly consistent with the changes projected for global land. Asia and North America show a greater warming trend than that of the global warming in all four scenarios. For SSP1-2.6, the warming trend stays within 1.5 °C/100 yr for all continents. Under the SSP5-8.5 scenario, the warming trends in North America, Asia and Europe are \sim 7 °C–8.5 °C/100 yr, while those in Africa, South America and Australia also exceed 6 °C/100 yr.

Probability density distributions are often used to illustrate how changes in the variability, skewness or shape of the distribution of climate variables in the real world may change in a changing climate (Stott et al 2016, Zhang and Zhao 2018). Each subplot in figure 10 shows the estimated probability density distributions from the CMIP6 mean under the different scenarios, for the historical (1901-2014) and future (2015-2099) period, displayed as normalized curves of annual, DJF and JJA mean temperature over the whole global land and six continents. Relative to the historical curves, from SSP1-2.6 to SSP5-8.5, the curves become flatter, combined with a reduced peak, increased spread and a mean value shift to the right for the global land, which implies large increases in the frequency and magnitude of warm extremes over the global land in the future. Similar results can also be found with DJF and JJA mean temperature under the different scenarios. Further, we notice that these changes in DJF are greater than in JJA for Asia, North America and Europe, which suggests larger increases in the frequency of extremes during DJF in these regions.

5. Summary and concluding remarks

Based on the simulations of 16 climate models from the CMIP6 set of experiments during the period of 1901–2099, the models' performance in simulating the historical temperature over the global land surface was assessed and the projected temperature changes for the 21st century were then investigated. The major results are summarized below.

Most CMIP6 models reproduced the spatial pattern of climatological annual mean temperature over the global land surface well (correlation coefficient typically >0.98), but with large variability across models and regions. Further, The CMIP6 mean capture the trends of global surface temperatures shown by the observational data during the periods 1901– 1940 (warming), 1941–1970 (cooling) and 1971– 2014 (rapid warming). As has also been noted from previous studies for CMIP5 (Kumar *et al* 2013), both generations of CMIP models have limited capability to capture the spatial variability of the observed trends. Among these three periods, the CMIP6 mean produces trend patterns that are most consistent with observations during 1971–2014. However, the CMIP6 mean underestimates the observed trends (warming trend during 1901–1940, cooling trend during 1941–1970) in high latitudes of the northern hemisphere.

The temperature time series of observations and model results over the global land surface and each individual continent exhibit good agreement, with more inter-model uncertainty in Europe, North America and Asia. Kumar *et al* (2014) found that CMIP5 models show a warm bias with respect to reanalysis data sets for almost all regions during months JJA. The bias seems improved in CMIP6, especially for the three continents in the northern hemisphere, although there is still a warm bias in Africa and Australia and a cold bias in South America.

Future temperature projections show that there will be continued warming over the global land surface. By the end of the 21st century, the global temperature is projected to increase under the different scenarios by 1.18 °C/100 yr (SSP1-2.6), 3.22 °C/100 yr (SSP2-4.5), 5.50 °C/100 yr (SSP3-7.0) and 7.20 °C/100 yr (SSP5-8.5). Spatially, the annual mean temperatures show a strong (moderate) warming in the high (middle) latitudes of the northern hemisphere and weaker warming in the tropics and the southern hemisphere. Similar results have also been seen in the future warming distribution projections of CMIP5 (Feng et al 2014). For the near term (2025–2049), all the scenarios exhibit significant increases over the global land surface. But the warming trends start to slow down under the SSP1-2.6 and SSP2-4.5 scenarios during the period 2050-2074 and even show a decreasing trend under the SSP1-2.6 scenario during 2075-2099. This indicates the effectiveness of anticipated climate mitigation and adaptation strategies, while largely reflecting the design of the SSP-RCP scenarios in terms of socioeconomic development and radiative forcing projections: SSP1-2.6 has consistent downward trajectories, and SSP2-4.5 results peak in 2040 and then decrease in magnitude (Thomson et al 2011, van Vuuren et al 2011, 2017, Fricko et al 2017, Gidden et al 2019). The SSP3-7.0 and SSP5-8.5 scenarios exhibit a steady increase in annual temperature during the 21st century. Under the highest emission scenario (RCP8.5) in CMIP5, Feng et al (2014) found 3 °C-10 °C of warming over the global land area by the end of the 21st century. But for SSP5-8.5 in CMIP6, the warming in most regions increases by 4 °C–12 °C, which may be due to the higher climate sensitivity compared with previous versions of CMIP5 (Flynn and Mauritsen 2020, Zelinka et al 2020). Furthermore, from SSP1-2.6 to SSP5-8.5, the frequency and magnitude of the warm extremes would largely increase over the global land in the future. Our analysis here provides a preliminary understanding of the new generation of CMIP6 models, providing a foundation for future research on CMIP6.

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Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-node.llnl.gov/projects/cmip6 https:// crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/ and https://www.esrl.noaa.gov/psd/data/gridded/data. UDel_AirT_Precip.html.

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