Hydrological Projections under CMIP5 and CMIP6
Sources and Magnitudes of Uncertainty

Yi Wu, Chiyuan Miao, Louise Slater, Xuewei Fan, Yuanfang Chai, and Soroosh Sorooshian

ABSTRACT: Projections of future hydrological conditions rely largely on global climate models, but model performance varies greatly. In this study, we investigated projected changes in runoff ($R$), precipitation ($P$), evapotranspiration (ET), and soil moisture (SM) based on the fifth and sixth phases of the Coupled Model Intercomparison Project (CMIP5 and CMIP6) and quantified the uncertainties of their projected changes on annual and seasonal scales. The results indicate that all four hydrological variables show an increase over most of the global land: annual projections of $R$, $P$, ET, and SM from CMIP6 increase in 72%, 81%, 82%, and 66% of the global land area, respectively, under a high emissions scenario during the period 2080–99 relative to 1970–99. We estimated the uncertainties in CMIP6 from different sources on an annual scale and found that model uncertainty dominates the total projected uncertainties during the twenty-first century [76% ($R$), 73% ($P$), 89% (ET), and 95% (SM) in the 2090s], and the contribution of internal variability decreases with time. The low-latitude regions have the greatest uncertainty in hydrological projections. In CMIP6, the uncertainty of projected changes in $P$ contributes the most to the uncertainty of projected changes in $R$, with a contribution of 93% on annual scale, followed by ET and SM. Overall, the performances of the CMIP5 and CMIP6 models are similar in terms of hydrological changes and the composition of their uncertainties. This study provides a theoretical reference for the further improvement and development of hydrological components in global climate models.

SIGNIFICANCE STATEMENT: Previous studies concerning future hydrological changes have predominantly focused on trends in future drying or wetter conditions but often ignored or discounted obvious disparities in model performance across distinct regions. The purpose of this study is to investigate future hydrological changes, quantify the agreement among CMIP6 models regarding these changes, and then decompose the sources that contribute to the discrepancies in hydrological projections. This study has the potential to strengthen the reliability of hydrological components in global climate models, thereby contributing to more accurate future projections of global water conditions.

https://doi.org/10.1175/BAMS-D-23-0104.1
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Supplemental material: 10.1175/BAMS-D-23-0104.2
In final form 20 September 2023
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Water is an essential resource for achieving many of the sustainable development goals (SDGs) (Tortajada 2020), and so accurate estimation and effective management of water resources can help contribute to the attainment of these goals (Bleischwitz et al. 2018; Miao et al. 2022). The fundamental reason for the renewable nature of water resources is the existence of the hydrological cycle (Oki and Kanae 2006), which keeps the total amount of water in the Earth system constant. The hydrological cycle regulates the climate and influences the redistribution of energy and water on Earth (D’Odorico et al. 2019), while shaping the rich and varied natural landscapes of the planet. Recently, several regions of the world have been dealing with disasters caused by extreme hydrometeorological events, including floods in most of Asia and parts of central Europe (Kundzewicz et al. 2019), heat waves and droughts in Russia (Hunt et al. 2021), mudslides and landslides in China (Xiao et al. 2022), and severe droughts in sub-Saharan Africa (Kamali et al. 2018). Future hydrological changes are likely to directly affect agricultural irrigation (Yazdi et al. 2019) and hydropower generation (Zhao et al. 2021) and will also greatly influence economic and social development and people’s livelihoods globally. However, reasonable projection of hydrological changes and extreme hydrologic events requires that we obtain information about the future magnitudes of hydrological variables with low uncertainty.

Projections of future hydrological conditions depend largely on the outputs of global climate model (GCM) simulations. Recently, new simulations from the latest state-of-the-art climate models participating in phase 6 of the Coupled Model Intercomparison Project (CMIP6) have become available (Eyring et al. 2016). Many studies have already been conducted on future hydrological changes based on CMIP6 (Gao et al. 2021; Zhao and Dai 2022). However, their results are limited by the large uncertainties arising from the GCMs, and the large discrepancies in the simulation of hydrological changes. High uncertainty in precipitation has been confirmed (Hawkins and Sutton 2011; Lehner et al. 2020; Zhou et al. 2020), and uncertainty in projected runoff is even larger than uncertainty in precipitation (Lehner et al. 2019). Although previous studies have analyzed the uncertainty in hydrological projections (Bosshard et al. 2013; David et al. 2019; Gourley and Vieux 2006; Lehner et al. 2019), the sources of uncertainty have rarely been quantified. Hawkins and Sutton (2009) proposed a method of uncertainty decomposition based on variance decomposition, and they divide projection uncertainty into three sources: internal variability (natural fluctuations produced by absence of any radiative forcing of the planet), model uncertainty (variations in the responses of different models to the same radiative forcing), and scenario uncertainty (a given model exhibits notable differences under various emission scenarios). Emissions scenarios have evolved from representative concentration pathways (RCPs) to shared socioeconomic pathways (SSPs) as climate models have evolved. The RCPs describe likely future levels of greenhouse gases and other factors in the atmosphere that could alter the amount of solar energy captured by Earth (known as “radiative forcing” and measured in watts per square meter). The SSPs are the result of a separate modeling effort that looks at how factors such as
population, economic growth, education, urbanization, and the rate of technological development determine levels of greenhouse gas emissions. This uncertainty decomposition method has been applied to crop models (Ramirez-Villegas et al. 2017), water scarcity (Greve et al. 2018), glacier mass (Marzeion et al. 2020), and other situations (Miao et al. 2023; Wu et al. 2022). Further development of this method provides a theoretical basis for the quantification of uncertainty in hydrological projections.

Precipitation, evapotranspiration, soil moisture, and runoff are four essential components of the hydrological cycle; changes in the first three components can lead to regional runoff changes, ultimately impacting water availability in an area (Berghuijs et al. 2017; Wu et al. 2020). Many past studies have focused on the main factors affecting runoff changes (Hou et al. 2018; Hu et al. 2020; Liu et al. 2019) by estimating the sensitivity of runoff to temperature, precipitation, potential evaporation, and other factors (Berghuijs et al. 2017; Gou et al. 2022). These factors can contribute directly to the diversity and complexity of runoff simulations, resulting in large uncertainty among runoff projections. Existing studies have also pointed out that narrowing uncertainty in runoff changes is crucial (Lehner et al. 2019), and an important prerequisite for that is to conduct an attribution analysis to find the main influencing factors. However, it is still unclear which of the hydrological variables is most responsible for the uncertainty in runoff projections. Therefore, the attribution of uncertainty in runoff simulations needs to be further explored.

This study aims to 1) investigate future changes in runoff ($R$), precipitation ($P$), evapotranspiration (ET), and soil moisture (SM) relative to the historical period at annual, JJA (June–August), and DJF (December–February) scales; 2) decompose the uncertainty of projected changes in $R$, $P$, ET, and SM into internal variability, model uncertainty, and scenario uncertainty at annual, JJA, and DJF scales; 3) quantify the sensitivity of projected uncertainty in $R$ to projected uncertainty in $P$, ET, and SM; and 4) compare the above results for CMIP5 and CMIP6.

Data and method

Data. In this study, we obtained data on the following four major hydrological variables from CMIP5 and CMIP6: monthly total runoff outputs (“mrro” in CMIP), precipitation (“pr” in CMIP), total soil moisture content [“mrso” in CMIP, corresponding to the mass per unit area (summed over all soil layers) of water in all phases], and evapotranspiration [calculated by surface upward latent heat flux (“hfls”) in CMIP]. We standardized all variables to the same unit (mm). All the models are listed in Tables S1 and S2 in the online supplemental material. The historical simulations are from 1950 to 2014 for CMIP6 (1950–2005 for CMIP5) and future projections are from 2014 to 2099 for CMIP6 (2006–99 for CMIP5) (available at https://esgf-node.llnl.gov/search/cmip5/ and https://esgf-node.llnl.gov/search/cmip6/). The CMIP5 emissions scenarios in the Scenario Model Intercomparison Project (O’Neill et al. 2016) that are used in this study include three representative concentration pathways (RCP2.6, RCP4.5, and RCP8.5), and from CMIP6, we include three shared socioeconomic pathways scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5). For CMIP5 and CMIP6, the models that included all three scenarios were collected. We selected only the first ensemble member “r1i1pi(f1)” for each model, under each scenario. The method of calculating the internal variability (i.e., whether we used one or more ensemble members for each model) had little effect on the results (Yip et al. 2011). All model outputs were regridded to a common 1° × 1° grid because the spatial resolution of different models varies greatly.

Method. We calculated the accumulated amount of $R$, $P$, ET, and SM at annual, JJA, and DJF scales. We considered 1970–99 as the baseline period, and for the future, we considered 2030–49 to be near term, 2050–69 to be medium term, and 2080–99 to be long term. Our study
focused on global land overall (excluding Antarctica and Greenland) and six continents—Africa (AFR), Asia (ASI), Oceania (OCE), Europe (EUR), North America (NAM), and South America (SAM). First, we calculated relative changes in hydrological variables during the future periods (2030–49, 2050–69, and 2080–99) with respect to the baseline period (1970–99), rather than absolute changes; for the specific calculation formula, see Text S1 in the supplemental material. Second, we quantified the model agreement, and this refers to consistency in the direction of change in hydrological variables (Text S2). We also defined high model agreement to be when two-thirds or more of the models change in the same direction. Next, following Hawkins and Sutton (2009), the uncertainty of the four hydrological variables was decomposed into three parts (the specific decomposition steps are detailed in Text S3).

Finally, sensitivity analysis was conducted based on the total uncertainty of projected changes in $R$, $P$, ET, and SM obtained above. Using multiple linear regression with the least squares method, we took the uncertainty of projected change in $R$ as the dependent variable and the uncertainties of projected changes in $P$, ET, and SM as the independent variables. The multivariate linear model is as follows:

$$U_R = \varepsilon_0 + \varepsilon_P \times U_P + \varepsilon_{ET} \times U_{ET} + \varepsilon_{SM} \times U_{SM} + \omega,$$

where $U_R$, $U_P$, $U_{ET}$, and $U_{SM}$ are the total uncertainties of projected changes in $R$, $P$, ET, and SM, respectively; $\varepsilon_P$, $\varepsilon_{ET}$, and $\varepsilon_{SM}$ are the sensitivity coefficients of $U_R$ to each factor ($U_P$, $U_{ET}$, and $U_{SM}$, respectively); $\varepsilon_0$ is the intercept of the regression fit, and $\omega$ is the residual. Regression equations were established at the JJA, DJF, and annual scales. In addition, we used the $F$ test to carry out a significance test on the regression equation to determine whether the influence of the explanatory variable ($U_P$, $U_{ET}$, and $U_{SM}$) on the explained variable ($U_R$) was significant at the 95% confidence level.

Here we used the sensitivity ratio to represent the relative contributions of $U_P$, $U_{ET}$, and $U_{SM}$ to $U_R$. For example, the relative contribution of $U_P$ to $U_R$ is calculated using

$$\text{Contribution}_P = \frac{\varepsilon_P}{\varepsilon_P + \varepsilon_{ET} + \varepsilon_{SM}}.$$  

The calculated contribution can vary from close to zero (indicating that this factor has no effect on $U_R$) to close to one (the sensitivity of this factor is much greater than the sensitivity of the other two factors).

Results

Relative changes in hydrological projections. The four hydrological variables show a projected increase under CMIP6 SSP5-8.5 over most of the global land surface at annual and seasonal scales (Fig. 1). We found that 72% of the global land surface shows increased annual runoff from CMIP6 at annual scale, and over 50% and 73% of the area shows increased runoff in JJA and DJF, respectively, under SSP5-8.5. The greatest changes in runoff (by more than 80%) are found in the Middle East, South Asia, central Africa, and Argentina. The regions with decreasing runoff (by more than 40%) are the Mediterranean region, southern North America, the Amazon, southern Africa, and southeastern and southwestern Australia. We also found greater spatial variability in the projections of DJF runoff than in JJA. As the emissions scenario changes (from SSP1-2.6 to SSP2-4.5 to SSP5-8.5), the proportion of global land exhibiting increased annual runoff becomes larger—from 67%–70% to 72%, respectively (Figs. S1 and S2 in the supplemental material); the increases and decreases in runoff also tend to become larger in magnitude with the rise in greenhouse gas emissions.
For precipitation, evapotranspiration, and soil moisture, similar results to the changes in runoff are shown in Fig. 1. It is noteworthy that a larger proportion of the global land exhibits increases in annual precipitation (81%) and evapotranspiration (82%) under SSP5-8.5 compared to runoff changes. The projected change in soil moisture under SSP5-8.5 is notably smaller than the changes in the other three hydrological variables; it varies by less than 20% in most parts of the globe. The proportion of the global land surface where soil moisture increases is also low relative to other hydrological variables—only 66%, 57%, and 68% at annual scale, in JJA, and in DJF, respectively. When compared with the baseline period, the changes in future spatial distribution of the four hydrological variables are significant under SSP5-8.5 ($p < 0.01$). The areas where these variables increase or decrease are generally consistent, except in Australia. In addition, the high latitudes of the Northern Hemisphere in JJA show reduced runoff but increased precipitation, evapotranspiration, and soil moisture.
Uncertainty in hydrological projections. The four hydrological variables show high model agreement annually in most regions and over more than 50% of global land (Fig. S3). For projected changes in $R$, $P$, ET, and SM during the period 2080–99 relative to the baseline period, 64%, 76%, 81%, and 57%, respectively, of the regions show high model agreement under SSP5-8.5. Areas with high model agreement for projected changes in $R$, $P$, and ET are relatively similar, mainly in the Sahara Desert, southern Africa, southern South America, Western Australia, and the high latitudes of the Northern Hemisphere. A notable difference is that the range of model agreement for projected changes in $P$ and ET extends to most of Asia, compared to projected changes in $R$. In contrast, the model agreement for projected changes in SM is relatively low; only the Amazon, central Africa, the Mediterranean region, and a few other areas show relatively high agreement. Model agreement for the hydrological variables except for ET generally increases from low- to high-emissions scenarios at the annual scale over the globe and most continents. Model agreement for projected changes in $P$ and ET is relatively high, exceeding 80% in some continents, such as Asia, Europe, and North America. We also found a greater proportion of regions with high model agreement in DJF than in JJA (Figs. S4 and S5).

The uncertainty in hydrological projections was also explored, and the proportions of uncertainty in hydrological changes contributed by the three different sources (internal variability, model uncertainty, and scenario uncertainty) are presented in Fig. 2. For the four hydrological variables, the contribution of internal variability decreases with time, while the contribution of scenario uncertainty increases, and the contribution of model uncertainty increases and then decreases at annual scale over the globe. Model uncertainty is the dominant source of uncertainty in most years of the twenty-first century, while scenario uncertainty plays a growing role at the end of the century. A notable difference among the four variables is that the scenario uncertainty is lower for SM compared with the other three hydrological variables. It is worth noting that the proportion of internal variability at the beginning of the century is greater for DJF ($R$: 53.1%, $P$: 55.4%, ET: 39.9%, SM: 17.6%) than for JJA ($R$: 48.6%, $P$: 43.0%, ET: 24.1%, SM: 17.4%). The proportion of scenario uncertainty at the end of the century is also larger for DJF ($R$: 31.9%, $P$: 42.8%, ET: 30.8%, SM: 5.9%) than for JJA ($R$: 4.3%, $P$: 1.6%, ET: 2.3%, SM: 2.3%), which is consistent with results at the continental scale. From a regional perspective, in the long-term future, most continents are dominated by model uncertainty, followed by scenario uncertainty, with internal variability contributing the least. Long-term future internal variability plays an important role in the uncertainty of hydrological projections on annual and seasonal scales for Australia compared to other continents.

Looking at the spatial variation in hydrological projection uncertainty, we found that the total uncertainty, model uncertainty, and scenario uncertainty increase from the near-term to the long-term projections at annual scale, while internal variability is constant (Fig. 3). We found that model uncertainty dominates ($R$: 76.07%, $P$: 68.46%, ET: 82.23%, SM: 90.35% of total uncertainty in long term) in most global regions over time, and scenario uncertainty is the smallest source of uncertainty ($R$: 0.76%, $P$: 1.29%, ET: 0.78%, SM: 0.67% of total uncertainty) at annual scales in the near term, but it does increase over time, and the most pronounced increases occur in tropical low-latitude regions. Among the four hydrological variables, the projected change in ET has the smallest uncertainty. Overall, the regions with larger uncertainty are relatively consistent among hydrological variables except SM. The regions with greatest uncertainty for annual projected changes in $R$, $P$, and ET are tropical low-latitude areas, such as northern South America, southern Africa, the Southeast Asian islands, and northern Australia. It should be noted that the uncertainty of projected change in SM estimates is large, exceeding 9,000 mm² (where the magnitude was calculated as the variance, so the unit is square mm).
in most regions of the globe except North Africa. At the seasonal scale, the magnitude and range of uncertainty are larger for JJA than for DJF (Figs. S6 and S7).

**Sensitivity analysis of uncertainty.** Based on the uncertainties of projected changes in \( R \), \( P \), ET, and SM (expressed as \( U_R \), \( U_P \), \( U_{ET} \), and \( U_{SM} \) respectively) obtained in the previous subsection, we calculated the sensitivities of \( U_R \) to \( U_P \), \( U_{ET} \), and \( U_{SM} \) (Fig. 4) in order to better understand which other key hydrological element’s uncertainty has the greatest influence on \( U_R \). The annual-scale sensitivity of \( U_R \) to \( U_P \) is positive for 79% of the global land surface and positive for more than 66% of the land at seasonal scale. However, the sensitivity of \( U_R \) to \( U_P \) at seasonal scale in the high latitudes of the Northern Hemisphere is mainly negative. The sensitivity of \( U_R \) to \( U_{ET} \) is positive in about half of global regions and negative in half, but the proportion of the positive sensitivity is larger. The sensitivity of \( U_R \) to \( U_{SM} \) at seasonal scale in the high latitudes of the Northern Hemisphere is mainly negative, which is consistent with that of precipitation. The sensitivity of \( U_R \) to \( U_{SM} \) is the lowest among the three, and the sensitivity coefficient is less than 0.4 in most areas.

**Fig. 2.** The proportion of uncertainty for CMIP6 projected changes in \( R \), \( P \), ET, and SM over the global land at the annual scale, for JJA, and for DJF during the period 2000–99. The corresponding bar charts in the right column show regional results at annual scale (the left-hand bar for each region), for JJA (the center bar), and for DJF (the right-hand bar) over the continents (AFR: Africa, ASI: Asia, OCE: Oceania, EUR: Europe, NAM: North America, SAM: South America) in the long term (2080–99).
Fig. 3. Uncertainties in CMIP6 projected changes in $R$, $P$, ET, and SM and their main sources at annual scale over global land during the near term (2030–49) and long term (2080–99) relative to the baseline period (1970–99). The number in the lower-left corner of each panel in the three rightmost columns is the proportion of uncertainty.
CMIP5 versus CMIP6. Extending the analysis described in the previous subsections, in this subsection we compare the results from CMIP5 and CMIP6. From relative changes in hydrological variables (Fig. 5), the probability of detection (POD) values (i.e., fraction of agreement of detected hydrological changes; increase, decrease, or neutral) are above 0.6 (for the specific calculation formula, see Text S4). The future projections of precipitation and evapotranspiration by CMIP5 and CMIP6 models have high agreement in the direction of change, with high POD values (greater than 0.8, or even 0.9, at annual scale). However, the future projections of the two generations of climate models for soil moisture are less consistent, and the POD value is less than 0.7. The annual-scale POD values are larger than the seasonal-scale values, which means models from CMIP5 and CMIP6 have better consistency in simulating annual hydrological variables than seasonal variables. There is no obvious change in the POD values among different emissions scenarios.

For runoff and precipitation, the proportion of areas with high model agreement under RCP8.5 in CMIP5 (R: 68%, 47%, 70%; P: 79%, 65%, 74% at annual, JJA, and DJF time scales, respectively) is slightly higher than under SSP5-8.5 in CMIP6 (R: 64%, 41%, 69%; P: 76%, 59%, 72%) (Figs. S3, S4, S5, and S8). Under the high-emission scenarios, for evapotranspiration and soil moisture, the proportion of areas with high model agreement under
SSP5-8.5 in CMIP6 (ET: 81%, 72%, 82%; SM: 57%, 55%, 65% for the annual, JJA, and DJF time scales, respectively) is higher than that under RCP8.5 in CMIP5 (ET: 71%, 56%, 74%; SM: 46%, 52%, 50%) (Figs. S3, S4, S5, and S8). For both CMIP5 and CMIP6, regions with high model agreement are basically consistent: the areas with high model agreement for projected changes in $R$, $P$, and ET are mainly located in the middle and high latitudes of the Northern Hemisphere and southern Africa, whereas areas with high model agreement for soil moisture are the Mediterranean region, southern South America, and southern Africa (Figs. S3, S4, S5, and S8). Compared with CMIP5, CMIP6 achieves higher model agreement in hydrological simulations in some regions such as the Amazon and the Sahara Desert. Both generations of models show higher model consistency under high emissions scenarios across the globe and for most continents (Fig. S9). The uncertainty in hydrological projections from CMIP5 and CMIP6 is compared in Fig. S10. We found that the results of CMIP5 and CMIP6 are relatively consistent, but the uncertainty in CMIP6 is larger than in CMIP5, especially in the long-term period. The uncertainty in projected change in $P$ is greatest at annual scale, and the uncertainty of projected change in SM is greatest at seasonal scale.

Overall, the characteristics of the proportioning of uncertainty in the two generations of models are basically the same (Fig. S11): from the near-term period to the long-term period, the contributions of internal variability and model uncertainty gradually decrease, while the contribution of scenario uncertainty gradually increases. For both CMIP5 and CMIP6, model uncertainty remains the most important source of uncertainty over the globe and for individual continents. However, the proportion of uncertainty associated with internal variability in the near term and the proportion associated with scenario uncertainty in the long term are greater in CMIP5 compared to CMIP6. From a regional perspective, internal variability plays a more important role in uncertainty projections in Australia compared to other continents in both CMIP5 and CMIP6. For Africa and South America, the scenario uncertainty of the four hydrological variables is less in CMIP5 than in CMIP6 in each period.

<table>
<thead>
<tr>
<th>Probability of Detection</th>
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<tbody>
<tr>
<td><strong>R-Near term</strong></td>
</tr>
<tr>
<td>0.71 0.61 0.66 0.76 0.61 0.64 0.74 0.61 0.66</td>
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<tr>
<td><strong>R-Medium term</strong></td>
</tr>
<tr>
<td>0.76 0.61 0.67 0.75 0.63 0.64 0.77 0.62 0.67</td>
</tr>
<tr>
<td><strong>R-Long term</strong></td>
</tr>
<tr>
<td>0.72 0.60 0.63 0.79 0.63 0.67 0.79 0.63 0.63</td>
</tr>
<tr>
<td><strong>P-Near term</strong></td>
</tr>
<tr>
<td>0.92 0.85 0.87 0.90 0.81 0.87 0.90 0.82 0.87</td>
</tr>
<tr>
<td><strong>P-Medium term</strong></td>
</tr>
<tr>
<td>0.93 0.84 0.86 0.91 0.84 0.86 0.92 0.83 0.87</td>
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<tr>
<td><strong>P-Long term</strong></td>
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<tr>
<td>0.92 0.81 0.87 0.91 0.82 0.86 0.91 0.83 0.87</td>
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<tr>
<td><strong>ET-Near term</strong></td>
</tr>
<tr>
<td>0.91 0.87 0.87 0.87 0.83 0.85 0.89 0.83 0.85</td>
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<tr>
<td><strong>ET-Medium term</strong></td>
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<tr>
<td>0.92 0.87 0.86 0.91 0.88 0.85 0.91 0.85 0.86</td>
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<tr>
<td><strong>ET-Long term</strong></td>
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<tr>
<td>0.92 0.88 0.87 0.92 0.89 0.87 0.92 0.85 0.86</td>
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<tr>
<td><strong>SM-Near term</strong></td>
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<tr>
<td>0.64 0.63 0.63 0.65 0.63 0.64 0.64 0.62 0.65</td>
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<tr>
<td><strong>SM-Medium term</strong></td>
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<td>0.63 0.63 0.62 0.65 0.64 0.65 0.65 0.63 0.67</td>
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<tr>
<td><strong>SM-Long term</strong></td>
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<tr>
<td>0.63 0.63 0.63 0.64 0.65 0.65 0.65 0.63 0.67</td>
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Fig. 5. The probability of detection (POD) of projected changes in $R$, $P$, ET, and SM from CMIP5 and CMIP6. Low-, medium-, and high-emissions scenarios in CMIP5 and CMIP6 are, respectively, RCP2.6 and SSP1-2.6, RCP4.5 and SSP2-4.5, and RCP8.5 and SSP5-8.5. POD values of 0.85 and above are marked with white font.
The contribution of scenario uncertainty is higher in DJF relative to JJA over the globe and most continents (Figs. S12 and S13).

According to the spatial pattern of the sensitivity coefficients, CMIP5 and CMIP6 behave similarly (Fig. 4 and Fig. S14). However, at annual scale, the proportion of areas with positive sensitivity of $U_R$ to $U_P$ and $U_{SM}$ is higher in CMIP5 ($\varepsilon_P$: 87%, $\varepsilon_{SM}$: 59%) relative to CMIP6 ($\varepsilon_P$: 79%, $\varepsilon_{SM}$: 55%), while the proportion of areas with negative sensitivity of $U_R$ to $U_{ET}$ is greater in CMIP5 (66%) than in CMIP6 (48%). In terms of regional sensitivity coefficients (Fig. S15), the sensitivity of $U_R$ to $U_P$ and $U_{SM}$ is always positive over the globe and most continents, while the sensitivity of $U_R$ to $U_{ET}$ is predominantly negative at annual scale and positive at seasonal scale, varying from continent to continent. The sensitivity coefficients of CMIP5 and CMIP6 during 2000–99 are basically consistent at annual scale, except for in Australia, Europe, and North America. Moreover, the magnitude of annual sensitivity of $U_R$ to $U_P$ and $U_{ET}$ is much larger in CMIP5 than in CMIP6. At seasonal scale, the characteristics of the sensitivity coefficients of $U_R$ are somewhat different. For JJA, the sensitivity of $U_R$ to $U_{SM}$ is greater in CMIP6 than in CMIP5. We also notice that seasonal sensitivity of $U_R$ to $U_{ET}$ is negative in Africa, South America, and Australia, unlike other continents. Overall, the relative contribution of $U_P$ to $U_R$ is most important, followed by that of $U_{ET}$, and the contribution of $U_{SM}$ to $U_R$ is minimal for most continents, except for a few areas (Fig. 6). The relative contributions of sensitivity in the two generations of models have some differences. The relative contribution of sensitivity from $U_P$ to $U_R$ is greater in CMIP6 (93%) than in CMIP5 (61%) over the global land surface, while the contribution of sensitivity from $U_{ET}$ is greater in CMIP5 (34%) than in CMIP6 (2%).

Discussion

**Historical performance of hydrological simulations.** The evaluation results of historical climate model simulations can indicate the reliability of their future simulations. Many previous studies have evaluated historical simulation performance of hydrological variables. Du et al. (2022) found that the CMIP6 models outperform the CMIP5 models in simulating historical precipitation patterns. These GCMS generally overestimate global precipitation over land, with the exception of southeast Asia and tropical rain forest climate regions (Li et al. 2022). Most CMIP6 models overestimate ET, and the estimates of different models vary greatly (Wang et al. 2021). The runoff from CMIP6 has also been substantially overestimated over the globe and most basins, and this phenomenon is more prominent in arid and semiarid areas (such as the Murray–Darling and Nile basins) (Guo et al. 2022). Compared
with CMIP5 models, CMIP6 models have less uncertainty in global runoff simulation (Guo et al. 2022). Hou et al. (2023) confirmed that using multimodel ensembles is an effective way to reduce uncertainty regarding trends in mean annual magnitude and annual runoff trend. The majority of models provide consistent and capable simulations of soil moisture over the globe, but they perform poorly over extremely arid regions (Qiao et al. 2022). Furthermore, spatial resolution is not the primary limiting factor for CMIP6 soil moisture simulations.

**Mitigation potential of future warming.** We found consistent reductions in the magnitudes of hydrological variables under future emissions scenarios in some regions, such as the Mediterranean and the Amazon (Fig. 1), which are similar to reductions reported in prior studies (Cook et al. 2020; Zhao and Dai 2022). Model agreement in terms of runoff and soil moisture is relatively high in these regions, whereas the projected decline in annual evapotranspiration is not relatively robust (Fig. S3). The decreasing magnitude in evapotranspiration in the Mediterranean and Amazon regions is relatively slight, and the model consistency for evapotranspiration projections is relatively low in these regions, which are therefore likely to be at risk of drought in the context of future global warming. Therefore, local governments should take preventative measures to alleviate the occurrence of droughts and so protect agricultural production and fragile communities. We also found that as the emissions scenario changes (from low to high emissions), regions that are expected to become drier are projected to become even drier, regions expected to become wetter become even wetter, and spatial heterogeneity further increases. This suggests that the low-emissions scenario would be beneficial in mitigating future drought conditions in drier regions, while the high-emissions scenario is more likely to enhance the need for agricultural irrigation and water projects in drought-prone areas. Moreover, recent studies have shown that the equilibrium climate sensitivity of the latest generation of CMIP6 models is greater than in CMIP5 models (Meehl et al. 2020; Zelinka et al. 2020), which means that CMIP6 models might be more sensitive to the increase in CO₂. This could possibly lead to an increased risk of drought under conditions represented in CMIP6 simulations.

**Uncertainty of hydrological projections.** Various methods and indicators have been developed to quantify model consistency (Knutti and Sedláček 2013). We assessed the agreement across models in the ensemble using a similar approach to previous studies, like Cook et al. (2020), who incorporated both sign and magnitude of change, and obtained similar results to ours. The uncertainties in the four hydrological variables have similar patterns of variation over time: for all four variables, model uncertainties are the dominant source of uncertainty in the twenty-first century, and the contribution of internal variability decreases with time, while scenario uncertainty plays a more important role at the end of the century (Fig. 2). These findings are consistent with previous research (Hawkins and Sutton 2009, 2011; Lehner et al. 2020; Zhou et al. 2020). The model uncertainties in CMIP6 hydrological projections at annual scale and for JJA and DJF in the 2090s are notably larger than those from CMIP5 (Fig. S10). This result indicates that although CMIP6 has undergone improvements compared with CMIP5 (Eyring et al. 2016), the addition of more complex processes also introduces greater uncertainty (Wei et al. 2021). The inclusion of models from both CMIP5 and CMIP6 in our study potentially impacts the outcomes, although overall, the disparity in the number of utilized models is minimal. Notably, for both annual and seasonal scales, scenario uncertainty is always the smallest source of uncertainty over most regions of the globe (Fig. 3, Figs. S6 and S7). This reflects the fact that differences in emissions scenarios do not appear to have a major influence on the future projection of hydrological variables (Sharafati and Pezeshki 2020). The regions with the greatest uncertainty in various hydrological variables are low-latitude tropical regions (Fig. 3, Figs. S6 and S7),
since the tropics are the regions with the greatest precipitation and evapotranspiration, and the hydrological cycle there is relatively strong (Ma et al. 2018; Stephens et al. 2018), leading to the larger uncertainties in hydrological simulations.

**Attrition of runoff uncertainty.** The simulation of runoff in climate models depends on many factors, starting with near-surface atmospheric variables. The results discussed earlier suggest that uncertainties in precipitation simulations may have a substantial impact on the simulation of runoff in coupled Earth system models (ESMs); however, uncertainties in runoff simulations do not depend exclusively on precipitation. The parameterization scheme of the land surface model is another important source of uncertainty in runoff simulation. Different land surface models, even when driven by the same atmospheric forcing data, may produce large uncertainties in the runoff output—consider, for example, that the 24 CMIP6 and 22 CMIP5 members used in our study share 12 and 14 land surface models, respectively (Tables S1 and S2)—and this may be one of the reasons for the differences in runoff simulations among the models.

We also attempted to interpret the contributions of uncertainty in other hydrological variables ($U_P$, $U_{ET}$, $U_{SM}$) to uncertainty in runoff changes ($U_R$). Above, we noted that $U_P$ is always the main source of $U_R$ over global land at the annual scale (Fig. 6). Although runoff changes are tied closely to precipitation changes (so $U_R$ depends mainly on $U_P$), the impact of $U_{ET}$ on $U_R$ is nonnegligible. We speculate that the large variations in precipitation in summer (JJA for Northern Hemisphere; DJF for Southern Hemisphere) make it more difficult for individual models to simulate precipitation, leading to greater uncertainty in runoff. In contrast, in winter (DJF for Northern Hemisphere; JJA for Southern Hemisphere), the changes in evapotranspiration are weak (Kleine et al. 2020) and snowfall is likely to be the main source of runoff over many regions (Feng et al. 2022); precipitation in CMIP outputs includes both liquid and solid phases, so uncertainty in snowfall simulation may contribute to the greater uncertainty.

**Conclusions**

In this study, we investigated the characteristics of changes in runoff ($R$), precipitation ($P$), evapotranspiration ($ET$), and soil moisture ($SM$) based on CMIP5 and CMIP6, and we quantified uncertainties in these hydrological variables at annual and seasonal (JJA and DJF) scales. We also explored the contributions of uncertainties in three hydrological variables ($U_P$, $U_{ET}$, $U_{SM}$) to uncertainty in runoff change ($U_R$). Finally, we compared the results from using CMIP5 and CMIP6. We find the following:

1) The four hydrological variables showed an increase over time from CMIP6 for most of the global land. Annual runoff, precipitation, evapotranspiration, and soil moisture from CMIP6 under SSP5-8.5 increase across 72%, 81%, 82%, and 66%, respectively, of global land regions in the long term relative to the baseline period. Hydrological projections are found to be increasing over most of the global land surface, with some decreases in the Mediterranean region, southern North America, the Amazon, southern Africa, and southeastern and southwestern Australia.

2) Regarding the contributions of uncertainty in these variables from CMIP6 on an annual scale, model uncertainty is the dominant source of uncertainty [76% ($R$), 73% ($P$), 89% ($ET$), and 95% ($SM$) in the 2090s], while the contribution of internal variability decreases with time [from 48% to 2% ($R$), from 42% to 2% ($P$), from 46% to 2% ($ET$), and from 17% to 1% ($SM$)] during the twenty-first century, and scenario uncertainty plays a more important role at the end of the century than it does in the early years of the century. The regions with greatest uncertainty for annual runoff, precipitation, and evapotranspiration are tropical low-latitude areas.
3) In CMIP6, the uncertainty of projected change in $P$ contributes overwhelmingly to the uncertainty of projected change in $R$, with a contribution of 93% at annual scale, 73% for JJA, and 89% for DJF, followed by the contribution of uncertainty in ET. The performance of CMIP5 and CMIP6 projections is generally consistent. Although plenty of existing studies have demonstrated that the ensemble mean results of CMIP6 perform better than CMIP5 in hydrometeorological simulations, the uncertainties of projected changes in runoff and precipitation from CMIP6 are larger than those in CMIP5.

**Acknowledgments.** This work was supported by the Second Tibetan Plateau Scientific Expedition and Research Program (STEP) (2019QZKK0405), the National Natural Science Foundation of China (42041006), the State Key Laboratory of Earth Surface Processes and Resource Ecology (2022-ZD-03), and the Fundamental Research Funds for the Central Universities. L. S. is supported by UKRI (MR/V022008/1) and NERC (NE/S015728/1). We acknowledge the World Climate Research Programme, which, through its Working Group on Coupled Modeling, coordinated and promoted CMIP5 and CMIP6. We thank the climate modeling groups listed in Tables S1 and S2 for producing and making available their model output. The authors declare no conflicts of interest relevant to this study.

**Data availability statement.** The involved CMIP5 models and CMIP6 models are listed in Tables S1 and S2 in the supplemental material. The data from CMIP5 and CMIP6 models can be accessed at https://esgf-node.llnl.gov/projects/cmip5/ and https://esgf-node.llnl.gov/projects/cmip6/.
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