Impact of Climate Change on Reservoir Flood Control in the Upstream Area of the Beijiang River Basin, South China

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ABSTRACT

One of the potential impacts of global warming is likely to be experienced through changes in flood frequency and magnitude, which poses a potential threat to the downstream reservoir flood control system. In this paper, the downscaling results of the multimodel dataset from phases 3 and 5 of the Coupled Model Intercomparison Project (CMIP3 and CMIP5, respectively) were coupled with the Variable Infiltration Capacity (VIC) model to evaluate the impact of climate change on the Feilaixia reservoir flood control in the Beijiang River basin for the first time. Four emissions scenarios [A1B and representative concentration pathway (RCP) scenarios RCP2.6, RCP4.5, and RCP8.5] were chosen. Results indicate that annual distribution and interannual variability of temperature and precipitation are well simulated by the downscaling results of the CMIP3 and CMIP5 multimodel dataset. The VIC model, which performs reasonably well in simulating runoff processes with high model efficiency and low relative error, is suitable for the study area. Overall, annual maximum 1-day precipitation in 2020–50 would increase under all the scenarios (relative to the baseline period 1970–2000). However, the spatial distribution patterns of changes in projected extreme precipitation are uneven under different scenarios. Extreme precipitation is most closely associated with extreme floods in the study area. There is a gradual increase in extreme floods in 2020–50 under any of the different emission scenarios. The increases in 500-yr return period daily discharge of the Feilaixia reservoir have been found to be from 4.35% to 9.18% in 2020–50. The reservoir would be likely to undergo more flooding in 2020–50.

1. Introduction

Because of human activity, atmospheric concentrations of some of the greenhouse gases are increasing, and most climatologists believe this is causing significant climate change. The global average surface temperatures are expected to increase by 1.1°–6.4°C in the twenty-first century (Meehl et al. 2007). Projected increases in global temperatures are expected to affect the hydrological cycle, to make the spatiotemporal distribution of rainfall more uneven, and to increase the frequency and magnitude of flood and drought events (Chen et al. 2012). Accordingly, the effect of climate change on hydrological regimes has recently become a hot research topic in the hydrological and meteorological fields.

The application of global climate models (GCMs) to predict future climate is a topical issue in climate change...
research. GCMs are considered as the most essential and feasible tools, which could supply useful information for global or large scales. Furthermore, GCM outputs may be converted by downscaling methods into reliable estimates of regional-scale climate variables (e.g., temperature and precipitation), which serve as the input for hydrological models. Over the past few years, the hydrological models driven by the output from GCMs have been extensively applied to assess the effect of future climate change on regional water resources (Guo et al. 2009; Yu and Wang 2009; Chen et al. 2012; Harding et al. 2012; G. Q. Wang et al. 2012, 2013) and floods (Loukas et al. 2004; Kay et al. 2006; Dankers and Feyen 2008; Smith et al. 2014).

Water conservation facilities are an important step in the water cycle, and their operating conditions with climate change attract ever-increasing attention. Burn and Simonovic (1996) found that climate change has a potentially important influence on reservoir operations. Dibike and Coulibaly (2005) coupled a hydrological model and GCM to assess the impacts of future climate change on reservoir inflow in Canada by using two statistical downscaling techniques. Li et al. (2010) investigated potential impacts of future climate change on operation performance of the Shellmouth reservoir in a North American prairie watershed based on a hydrological-reservoir water dynamics model. Chen et al. (2007) used a two-parameter water balance model to analyze the runoff of the Danjiangkou reservoir in response to future climate change predicted by GCMs. In general, the reservoir used for flood control is very sensitive to the upstream flood peak. Frequent extreme flooding events are likely to affect the design of reservoir flood control standards and to pose a threat to the safety of the reservoir and property security in the downstream area. Investigation of upstream regulation and trends of extreme floods in the future is of great significance for disaster prevention and reduction of reservoir damage.

The Feilaixia reservoir is the largest water conservation hub project used for flood control in the Guangdong Province, south China. It is an important part of the flood control engineering of the Beijiang River basin and plays an important role in flood control for the city of Guangzhou and other areas located in the downstream area of the Beijiang River basin. Because of the effect of climate warming, extreme rainfall events have recently been occurring more frequently in the upstream area of the Beijiang River basin (Wu et al. 2014), causing significant damage to property and affecting the operation of the Feilaixia reservoir. Although it is clearly imperative to assess the impact of climate change on the safety of the Feilaixia reservoir flood control measures, relevant data are lacking. In this study, downscaling results from phases 3 and 5 of the Coupled Model Intercomparison Project (CMIP3 and CMIP5, respectively) multimodel datasets were coupled with the Variable Infiltration Capacity (VIC) model to evaluate the impact of climate change on the Feilaixia reservoir flood control for the first time. The results can serve as a reference point for planning and management of flood control in the study area.

2. Study area and data

a. Study area

The study area is located in the upstream Feilaixia reservoir (called the Feilaixia catchment, shown in Fig. 1) in the upstream basin of the Beijiang River in south China. It has a drainage area of 34,097 km² and accounts for 73% of the Beijiang River basin. The basin terrain has a north–south inclination. It is an important water source for Guangdong Province, one of the most developed areas of China. The region is located in the tropical and subtropical climate zones, which have sufficient climate conditions (e.g., precipitation and humidity) responsible
for the frequently occurring flood disasters. The runoff in the flood season (April–September) accounts for about 70%–80% of the annual runoff. Regional rainstorms often occur in the downstream catchment area, and the upstream high-speed water flows easily cause floods (Wu et al. 2014). The Feilaixia reservoir, built in 1998 and having a total capacity of 1.904 billion m$^3$, is mainly used for flood control, navigation, and power generation. The flood design standard of the Feilaixia reservoir is 500-yr flood and the flood check standard is 5000-yr flood (Huang et al. 2007). The Hengshi hydrological station is the discharge station of the Feilaixia reservoir and is located 5 km upstream (Fig. 1).

b. Data

Considering the data sequence length and spatial distribution of stations, daily hydrological data from 28 stations (27 rainfall stations and 1 discharge station) and daily temperature data from 4 temperature stations were used in this study (Fig. 1). Data from all stations spanned the period 1969–2011. The hydrological data were provided by the Hydrology Bureau of Guangdong Province, China, and the temperature data were provided by the China Meteorological Data Sharing Service System, National Meteorological Information Center, China Meteorological Administration (http://cdc.cma.gov.cn/home.do).

In addition, the Shuttle Radar Topography Mission (SRTM) data with a resolution of 90 m were used for the digital elevation model (DEM), which is provided by International Scientific and Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences. Vegetation coverage datasets were obtained from the University of Maryland (UMD), College Park, which provided information on global land classification at a 1-km resolution (Hansen et al. 2000). The classification of soil texture at a resolution of 1 km was based on the Harmonized World Soil Database (HWSD) provided by the Food and Agriculture Organization of the United Nations and the International Institute for Applied Systems Analysis (www.iiasa.ac.at/web/home/research/modelsData/HWSD/HWSD.en.html).

c. CMIP3 and CMIP5 multimodel dataset

CMIP is a standard experimental protocol for studying the output of coupled ocean–atmosphere GCMs. CMIP3 and CMIP5 are available from the World Climate Research Programme’s (WCRP) Working Group on Coupled Modelling (WGCM). CMIP3 consists of climate model output from past, present, and future climate simulations collected by the Program for Climate Model Diagnosis and Intercomparison (PCMDI) for 2005 and 2006. The research based on this dataset has provided much of the new material underlying the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4; www-pcmdi.llnl.gov/ipcc/about_ipcc.php). Compared to CMIP3, CMIP5 has involved a much more coordinated approach to climate modeling experiments resulting in uniform inputs (atmospheric greenhouse gas, ozone concentrations, aerosols, etc.), standardized outputs, and a more systematic storage of the results (Smith et al. 2013). Analyses of these results underpinned the IPCC Fifth Assessment Report (AR5; www.ipcc.ch/report/ar5/). Accordingly, climate models provided by CMIP3 and CMIP5 have been widely used in the assessment of worldwide climate change (Kim et al. 2008; Lloyd et al. 2009; Thibault et al. 2010; Harding et al. 2012; Jiang and Tian 2013; Dirmeyer et al. 2013; Smith et al. 2013).

Thus, 11 CMIP3 and 13 CMIP5 models were used (Table 1). The simulation data used in this study include the CMIP3 20th Century Climate in Coupled Models (20C3M) simulation and the CMIP5 historical simulation for the 1970–2000 period and the CMIP3 Special Report on Emissions Scenario (SRES) scenario A1B (Nakićenović et al. 2000) and the CMIP5 representative concentration pathway (RCP) scenarios RCP2.6, RCP4.5, and RCP8.5 (van Vuuren et al. 2011) for the 2020–50 period.

3. Methodology

a. Downscaling techniques

To generate local climate conditions such as precipitation and temperature from GCMs, statistical downscaling models (SDMs) are normally used. On the basis of observed data, the SDMs define empirical relationships between the large-scale variable fields (e.g., climate model outputs) and local-scale surface conditions (Tisseuil et al. 2010). The relationships can then be used to estimate changes in local hydrological measures such as precipitation and temperature, based on future projections from GCMs outputs. In this study, generalized additive models (GAMs; Hastie and Tibshirani 1990; Vrac et al. 2007; Yang et al. 2012) and Bayesian model averaging (BMA; Yang et al. 2012) were used to relate synoptic large-scale atmospheric predictors to catchment-scale climate variables based on analysis of historical data. The method is described as follows.

First, large-scale atmospheric variables (predictors) from GCMs were interpolated to the sites of the study area by using the bilinear interpolation method. GAMs were used to fit the spatial–temporal precipitation and temperature models to individual ensemble member forecasts. In this case, the interpolation results on the
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<tr>
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sites from each GCM were used as predictor variables in the GAMs; the observed data (monthly temperature and precipitation) at multiple sites were used for calibration and validation of the GAMs. Local-scale simulated sequences of the twentieth century and future climate change scenarios for each GCM were then generated by the GAMs, which can be considered as model output bias correction. Second, local-scale results from all the GCMs output were weighted averaged to generate the mixture model using BMA. The mixing weights were estimated using the expectation maximization (EM) algorithm (McLachlan and Krishnan 2008). Third, a stochastic weather generation method was employed to temporally disaggregate the monthly downscaled climate projections into daily weather forcings required by the VIC model. According to the observed monthly temperature and precipitation sequences, the calibration weather years (1969–2011) were subdivided into four categories: hot-wet, hot-dry, cold-wet, and cold-dry (Raff et al. 2009). On the basis of the above four categories, the multiple downscaling simulations of daily temperature and precipitation were then generated for each scenario. In this case, the simulation set size was arbitrarily set to a specified number of simulated samples of daily values. Finally, the multiple simulated samples of daily temperature and precipitation at the site scale were interpolated to a high-resolution grid (e.g., $0.25^\circ \times 0.25^\circ$) of the study area by using the bilinear interpolation method.

In this study, on the basis of observed data from 27 rainfall stations and 4 temperature stations, monthly large-scale climate data from 11 CMIP3 and 13 CMIP5 models were downscaled to daily data (precipitation and temperature) with a resolution of $0.25^\circ \times 0.25^\circ$ in the Feilaixia catchment. Each scenario consists of 50 simulated samples.

b. VIC model

The VIC model (Liang et al. 1994, 1996a,b, 1999; Lohmann et al. 1998; Liang and Xie 2001) is a macroscale physical hydrological model based on the spatial distribution grid, which can produce a time series of the runoff, base flow, evapotranspiration, soil moisture, and snow water equivalent for each grid cell. Saturation and infiltration excess runoff-yield mechanisms; subgrid-scale soil heterogeneity; and spatial variabilities of infiltration, precipitation, and vegetation are partially considered in the model when simulating water and energy budgets at the land surface.

As a typical land surface hydrological model, the VIC model has been extensively applied to simulate runoff, the effect of climate change on water resources, land–atmosphere coupling, and soil moisture (Nijssen et al. 1997; Cherkauer and Lettenmaier 1999; Wu et al. 2007; Guo et al. 2009; Wu et al. 2011; Harding et al. 2012). Besides, this model has been successfully applied in the Zhujiang River basin and performs well in simulations of streamflow (Xie et al. 2007; G. Q. Wang et al. 2012; Xiao et al. 2013). In this study, on the basis of the $0.25^\circ \times 0.25^\circ$ spatial resolution for each grid, the VIC model (VIC 4.1.2.b; www.hydro.washington.edu/Lettenmaier/Models/VIC/index.shtml) with a calculation time length of one day is only used to simulate the water balance in the study area. The flow chart of the VIC model in the Feilaixia catchment

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<td>MIROC-ESM-CHEM</td>
<td>Model for Interdisciplinary Research on Climate, Earth System Model, Chemistry Coupled</td>
<td>AORI, NIES, JAMSTEC</td>
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<td>MIROC-ESM</td>
<td>Model for Interdisciplinary Research on Climate, Earth System Model</td>
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area is shown in Fig. 2. In addition, the Dag Lohmann model (Nijssen et al. 1997) is used as the routing model, which transports the gridcell surface runoff and base flow produced by VIC within each grid cell to the outlet of that grid cell and then into the river system.

4. Results

a. Adaptability analysis of CMIP3 and CMIP5 multimodel dataset

To increase the credibility of future predictions with coupled climate models, it is essential to evaluate the models’ ability of simulation (McAvaney et al. 2001). In this study, the simulation accuracy of the downscaling results of the CMIP3 and CMIP5 multimodel dataset was tested by comparing observed and simulated values in the baseline period (1970–2000).

A comparison of 50 simulated samples of monthly temperature and precipitation and their observations in the Feilaixia catchment is shown in Fig. 3 ($R^2$ inside the figure is the correlation coefficient of the average of 50 simulated samples and observations). As shown in Fig. 3, observed and simulated values fit the 1:1 line well for most samples, especially for monthly temperature. Moreover, a strong correlation is found between simulated and observed temperatures, as well as between simulated and observed precipitation (the smallest value of $R^2$ is 0.8711), which indicates that the annual distribution of the simulated values is consistent with that of the observed ones. Overall, the simulation accuracy of monthly precipitation for CMIP5 is slightly lower than that for CMIP3. As observed from the above analysis, the downscaling results of the CMIP3 and CMIP5 multimodel dataset suitably simulate the annual distribution of temperature and precipitation.

Observed and simulated daily temperature and precipitation in the Feilaixia catchment are shown in Figs. 4 and 5, respectively. As shown in Fig. 4, the downscaling results of the CMIP3 and CMIP5 multimodel dataset simulate the temperature range well and suggest good simulation performance with respect to interannual variability. Comparing Fig. 4 with Fig. 5, it can be seen that the simulation accuracy of the precipitation is slightly lower than that of the temperature, which reflects the uncertainty in the precipitation forecasting of the climate models. Furthermore, the simulated values of the precipitation for CMIP5 are slightly bigger than those for CMIP3 in some years (Fig. 5). Although strong rainfall features could not be accurately represented for a few years, the simulated results are in good agreement with observations in most cases, and the interannual variability of precipitation is well simulated as a whole. The above finding indicates that the downscaling results of the CMIP3 and CMIP5 multimodel dataset are suitable for the study area.

b. Assessment of the VIC model

While running the VIC model, several hydrological parameters need to be calibrated: the infiltration shape parameter $B$; the soil depth of layers 1 ($d_1$), 2 ($d_2$), and 3 ($d_3$); and the three base flow–related parameters $D_m$, $D_s$, and $W_s$. The Nash–Sutcliffe efficiency coefficient (NSE) and relative error (RE) are used to evaluate the efficacy of the simulation. The VIC model parameters and error statistics for the simulation forced with
observed temperature and precipitation data are listed in Tables 2 and 3, respectively. Simulated and observed daily discharges and maximum $k$-day ($k = 1, 3, 7, 15$) discharges at the Hengshi hydrological station are shown in Figs. 6 and 7.

As shown in Table 3, all NSEs exceed 0.92 and the REs are less than 3%, indicating that the VIC model is highly accurate in the study area. From Fig. 6 it can be seen that the VIC model can accurately simulate runoff processes, with a high simulation precision of the flood peak in the flood season. Furthermore, the maximum discharges of $k$ day ($k = 1, 3, 7, 15$) are well simulated by the VIC model (Fig. 7). Thus, the use of such a model to assess the impact of climate change on flooding in the study area is deemed appropriate.

c. Changes in extreme precipitation for 2020–50

Floods are one of the most common hazards predominantly caused by extremely intense rainfall events in south China, especially in this study area, which has a north–south terrain inclination that easily triggers floods. Thus, an analysis of the changes in extreme precipitation events under different scenarios (A1B, RCP2.6, RCP4.5, and RCP8.5) is of great significance. In this section, the spatial distribution patterns of changes in projected extreme precipitation are analyzed using the inverse distance weighting (IDW) interpolation method.

Figure 8 displays the spatial distribution patterns of changes in projected annual maximum $k$-day precipitation ($k = 1, 3, 7, 15$) under the A1B, RCP2.6, RCP4.5, and RCP8.5 scenarios. As shown in Fig. 8, the main impression is that the spatial changes in projected annual maximum $k$-day precipitation are uneven under different scenarios. Under the A1B scenario, the annual maximum $k$-day precipitation is projected to increase in most parts of the study area. Furthermore, the greatest increments will primarily occur in the downstream area of the Feilaixia catchment, increasing by approximately 80.7%–107.3% in 1-day precipitation, 75.9%–99.4% in 3-day precipitation, 42.3%–58% in 7-day precipitation, and 16.4%–30.8% in 15-day precipitation. Compared to the A1B scenario of the CMIP3, different spatial patterns of the changes in projected annual maximum $k$-day precipitation are shown under the RCP2.6, RCP4.5, and RCP8.5 scenarios of the CMIP5. Under the RCP2.6...
scenario, the maximum 1-, 3-, and 7-day precipitation show positive trends in most parts of the study area, especially in the middle part of the region. However, the maximum 15-day precipitation shows negative trends in most parts of the study area.

The spatial patterns of the changes in projected annual maximum $k$-day precipitation under the RCP4.5 and RCP8.5 scenarios show similar characteristics. In this case, increases in projected annual maximum $k$-day precipitation are scattered in the region, mainly in the northeast and some areas in the west. By contrast, decreases in projected annual maximum 3-, 7-, and 15-day precipitation are shown in most parts of the study area. Figure 9 shows the box plots of annual maximum $k$-day precipitation ($k = 1, 3, 7, 15$) in the Feilaixia catchment under the baseline and future scenarios. As illustrated in Fig. 9, annual maximum 1-day precipitation would be likely to increase under all the scenarios. Under the A1B scenario, there are increasing trends in the average of annual maximum $k$-day precipitation. Under the RCP2.6 scenario, the increases in annual maximum 1- and 3-day precipitation and decreases in annual maximum 7- and 15-day precipitation are projected to occur in the coming few decades. In contrast, except for annual maximum 1-day precipitation, annual maximum 3-, 7-, and 15-day precipitation may experience negative trends under the RCP4.5 and RCP8.5 scenarios. From the above analysis, it is quite evident that annual maximum 1-day precipitation would be likely to increase in the study area, which may increase the intensity of extreme floods in the future.

### Table 2. Parameters of the VIC model in Feilaixia catchment.

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<th>Parameter</th>
<th>Physical interpretation</th>
<th>Value</th>
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<tr>
<td>$B$</td>
<td>Exponent of variable infiltration curve</td>
<td>0.4</td>
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<tr>
<td>$D_S$</td>
<td>Fraction of $D_m$ in which nonlinear base flow occurs</td>
<td>0.7</td>
</tr>
<tr>
<td>$D_m$</td>
<td>Max daily base flow (mm)</td>
<td>20</td>
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<tr>
<td>$W_S$</td>
<td>Fraction of max soil moisture in the lower soil layer for which nonlinear base flow occurs</td>
<td>0.8</td>
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<tr>
<td>$d_1$</td>
<td>Thickness of the first soil layer (m)</td>
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<tr>
<td>$d_2$</td>
<td>Thickness of the second soil layer (m)</td>
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<tr>
<td>$d_3$</td>
<td>Thickness of the third soil layer (m)</td>
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FIG. 4. Observed and simulated daily temperature in the Feilaixia catchment during 1970–2000: (a) CMIP3 and (b) CMIP5. Light gray lines indicate the 50 simulated samples. Black lines indicate observations.

FIG. 5. As in Fig. 4, but for precipitation.
Changes in monthly precipitation and discharge for 2020–50

In general, rainfall is the main cause of floods for a basin in south China, and the monthly discharge and flood peak flow are strongly correlated (Guo 1995). Thus, the monthly discharge in the flood season (April–September) can represent the characteristic variations of floods in the Feilaixia catchment.

The changes in projected monthly precipitation and discharge under the A1B, RCP2.6, RCP4.5, and RCP8.5 scenarios based on the average of 50 simulated samples are shown in Fig. 10. It is found that the projected changes in monthly precipitation are most closely associated with those in monthly discharge under any of the different emission scenarios. Furthermore, there are clear differences between the CMIP3 and CMIP5 results. Under the A1B scenario, increasing trends in monthly discharge dominate for most months of the year and occur primarily in the flood season months of June, July, and September. By contrast, opposite changes are found under the scenarios of the CMIP5 multimodel dataset. Almost all the monthly runoffs are projected to decrease under the RCP2.6, RCP4.5, and RCP8.5 scenarios. An increase is only found in August runoff under the RCP2.6 scenario. This finding indicates an uncertainty in future projections related to the flood risks caused by monthly precipitation.

e. Effect of climate change on the peak discharge

Understanding floods (occurrences, mechanisms, characteristics, and regularities) is of great importance for design and management of water conservation hub projects, especially for the reservoirs used in flood control. This section discusses the frequency of the maximum peak discharge and changes in extreme floods of the Feilaixia reservoir under the A1B, RCP2.6, RCP4.5, and RCP8.5 scenarios. To estimate the probability of the peak discharge levels, the Pearson type III (P-III) distribution was fitted to the annual maximum peak discharge. The parameters of the P-III distribution were estimated by the linear moment method (Hosking and Wallis 1997).

Comparison of observed annual maximum daily discharge and annual maximum peak discharge is shown in Fig. 11. This figure shows that there is a strong correlation between the annual maximum daily discharge and annual maximum peak discharge, indicating that the annual maximum daily discharge closely reflects the variation characteristics of the peak discharge in the study area.

The P-III frequency distribution of annual maximum daily discharge based on 50 samples and P-III frequency distribution of the average of 50 samples of annual maximum daily discharge under the RCP4.5, RCP2.6, A1B, and RCP8.5 scenarios are shown in Figs. 12 and 13, respectively. The peak flow is predicted to increase for most samples under the future scenarios, especially under the RCP2.6 scenario (Fig. 12). According to the P-III frequency distribution in Fig. 13, the positive trends in the
annual maximum daily discharges ($p < 2\%$) are found for all the future scenarios, especially for the RCP4.5 and RCP2.6 scenarios. The increase in 500-yr return period floods under the RCP4.5, RCP2.6, A1B, and RCP8.5 scenarios has been found to be 9.18%, 7.61%, 4.58%, and 4.35%, respectively (Table 4). The results clearly imply that extreme floods of the Feilaixia reservoir would be likely to become more frequent and more intense in 2020–50.

The annual maximum discharges for selected durations (3, 7, and 15 days) under the A1B, RCP2.6, RCP4.5, and RCP8.5 scenarios are shown in Fig. 14. Similar to the changes in annual maximum precipitation in Fig. 9, increasing trends are projected for the average of annual maximum 3-, 7-, and 15-day discharges under the A1B scenario. Under the RCP2.6 scenario, there are increasing trends in annual maximum 3- and 7-day discharges and no obvious changes in annual maximum 15-day discharges. In contrast, no obvious changes in annual maximum 3-, 7-, and 15-day discharges are found under the RCP4.5 and RCP8.5 scenarios. Thus, the above analysis indicates that flood intensity (the flood lasts more than 3 days) in the Feilaixia reservoir would be likely to increase under the A1B and RCP2.6 scenarios, which may have a negative impact on the reservoir flood control.

5. Discussion

The results discussed above suggest that climate change would be likely to result in increased extreme floods (e.g., maximum 1-day discharge) in the study area under the future scenarios, which is similar to previous studies for many regions around the world, including Europe (Lehner et al. 2006; Dankers and Feyen 2008), Bangladesh (Mirza et al. 2003), Germany (Muller-Wohlfeil et al. 2000), the United Kingdom (Reynard et al. 2001), Canada (Roy et al. 2001), Australia (Schreider et al. 2000), Iran (Khazaei et al. 2012), and other regions in China.
The results of this study are somewhat in line with the results by Xiao et al. (2013), who investigated the flood response to climate change in the Zhujiang River basin during 2011–40 and found that extreme floods in the Beijiang River basin were likely to increase under the RCP4.5 scenario. In addition, the increasing trends in past flood frequency and intensity for the study area have been confirmed (L. N. Wang et al. 2012; Wu et al. 2013), which is also consistent with our study.

In this study, the VIC model was forced using daily data of maximum and minimum temperatures and precipitation, which is a common practice in many studies showing the calibration and validation of the model in selected basins worldwide (e.g., Xie et al. 2007; Saurral 2010; G. Q. Wang et al. 2012; Xiao et al. 2013). In the VIC model, daily estimations of evapotranspiration (ET) are achieved by using information on relative humidity, wind speed, and long- and shortwave incoming radiation (Bohn et al. 2013). However, Pierce et al. (2013) found that this approach can result in opposite humidity trends for GCMs, which would affect the simulated runoff under the future scenario. Thus, in future research, it will be necessary for us to force the VIC model with humidity and radiative data taken from the GCMs and discuss the potential implications on the simulated discharges of future scenarios.

In general, our study suggests a similar increase in projected extreme floods of the study catchment for both CMIP3 and CMIP5 multimodel ensembles. However, there are important differences between the CMIP3 and CMIP5 results in this study. For example, the spatial distribution patterns of changes in projected extreme precipitation show different characteristics (Fig. 8), and the changes of monthly precipitation and discharges for CMIP3 and CMIP5 multimodel ensembles are almost opposite (Fig. 10). Actually, the CMIP3 simulations of the twenty-first century are forced with emissions scenarios from the SRES, whereas the CMIP5
simulations of the twenty-first century are driven by the RCPs. Therefore, the differences between the SRES and RCPs may contribute to a discrepancy of the simulation of precipitation in this study. Some previous studies (e.g., Lutz et al. 2013; Gulizia and Camilloni 2014) also indicated that the precipitation simulated by both CMIP3 and CMIP5 global climate models exhibited some differences. In addition, uncertainty in predictions of future climate may also have potentially serious influence on the results, especially for extreme events (e.g., extreme precipitation and floods), which can result in huge differences between the CMIP3 and CMIP5 results. In general, there are many sources of uncertainty in climate projections. These include future greenhouse gas concentrations in the atmosphere, insufficient information from research and simulations of climate systems, the sensitivity of climate model systems, and natural variability (Qin et al. 2005; Foley 2010). Kundzewicz et al. (2010) indicated that climate model uncertainties play the dominant role in the near term and the uncertainties due to the selection of emission scenarios become increasingly significant over longer time horizons. Liu et al. (2013) investigated three uncertainty sources (emission scenarios, GCM structure, and downscaling techniques) in the modeling of hydrological impacts of climate change on projected flood frequencies of the Zhujiang River and found that the range of relative change and dominance among the three uncertainty sources vary with the lead time and return period.

In this study, although four emission scenarios are incorporated into multimodel ensembles to lower the uncertainty of future climate projections, the results are not fully representative as some sources of uncertainty are not investigated here. For example, the GCM initial conditions, statistical downscaling methods, the hydrological model structure, and the hydrological parameterization, which are not discussed in this study, will be of primary concern for future investigations.

6. Conclusions

In this work, we thoroughly discussed the changes in projected flooding of the Feilaixia reservoir under the A1B, RCP2.6, RCP4.5, and RCP8.5 scenarios, on the basis of simulations with the VIC model driven by the downscaling results of the CMIP3 and CMIP5 multimodel output. The CMIP3 and CMIP5 multimodel dataset for each scenario were downscaled to 50 simulated samples of daily precipitation and temperature datasets with a resolution of 0.25° × 0.25° in the Feilaixia catchment by using a statistical downscaling method. The results reveal that the downscaling results of the CMIP3 and CMIP5 multimodel dataset can accurately simulate the annual distribution and interannual variability
of temperature and precipitation in the study area. The simulation accuracy of the precipitation is slightly lower than that of the temperature. The simulation accuracy of monthly precipitation for CMIP5 multimodel dataset is slightly lower than that for CMIP3 multimodel dataset. The simulated values of daily precipitation for CMIP5 multimodel dataset are slightly bigger than those for CMIP3 multimodel dataset in some years. The VIC model performs well in simulating runoff processes in the study area, with a high simulation precision of the flood peak in the flood season. The NSE values for the simulation forced with observed temperature and precipitation are above 0.92, and the RE values were less than 3%. The VIC model is a suitable tool to assess the impact of climate change on future flooding in the study catchment.

In the future (2020–50), annual maximum 1-day precipitation would be likely to increase under all the scenarios. However, the spatial distribution patterns of changes in projected extreme precipitation are uneven under different scenarios. Extreme precipitation is projected to increase in most parts of the study area under the A1B and RCP2.6 scenarios. By contrast, the increases in projected annual maximum precipitation under the RCP4.5 and RCP8.5 scenarios are only scattered in some small parts of the study area. There are big differences in the changes of mean monthly discharge between CMIP3 and CMIP5 multimodel dataset. Increasing trends in the projected mean monthly discharge dominate for most months of the year under the A1B scenario, whereas almost all the monthly discharges are

<table>
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<th>RCP2.6</th>
<th>RCP4.5</th>
<th>RCP8.5</th>
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<td>5000</td>
<td>3.96</td>
<td>10.61</td>
<td>12.64</td>
<td>6.87</td>
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FIG. 13. The P-III frequency distribution of the average of 50 samples of annual max daily discharge under the A1B, RCP2.6, RCP4.5, and RCP8.5 scenarios at the Hengshi hydrological station. (a) The A1B and (b) the RCP2.6, RCP4.5, and RCP8.5 scenarios.

FIG. 14. Annual max discharges for selected durations (3, 7, and 15 days) at the Hengshi hydrological station under the A1B, RCP2.6, RCP4.5, and RCP8.5 scenarios. (a) The A1B and (b) the RCP2.6, RCP4.5, and RCP8.5 scenarios. The central mark is the median, the small square inside the box is the average, the box edges are the 25th and 75th percentiles, and the whiskers extend to the 1st and 99th percentiles.
projected to decrease under the RCP2.6, RCP4.5, and RCP8.5 scenarios.

Future scenario simulations show mixed signals in terms of predicted flooding for the next several decades. However, the average of the 50-sample simulations tend to suggest a gradual increase in extreme floods of the Feilaixia reservoir in 2020–50 under any of the different emission scenarios. The increases in 500-yr return period daily discharge under the A1B, RCP2.6, RCP4.5, and RCP8.5 scenarios have been found to be from 4.35% to 9.18%. Annual maximum 3- and 7-day discharges are projected to increase under the A1B and RCP2.6 scenarios. In contrast, no obvious changes in annual maximum 3-, 7-, and 15-day discharges are found under the RCP4.5 and RCP8.5 scenarios. Overall, extreme floods of the Feilaixia reservoir would be likely to become more frequent and intense in the next several decades. These results should be taken with care, since GCMs are still a bit inaccurate at representing the actual climate, and there are also some sources of uncertainty need to be considered, which would result in different streamflows from those simulated in this paper.

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