Projecting the impacts of climate change on streamflow in the upper reaches of the Yangtze River basin

Danyang Gao, Ting Chen, Kebi Yang, Jiye Zhou and Tianqi Ao

ABSTRACT

The study of climate change impacts on streamflow in small-middle basins within the Upper Yangtze River Basin (UYRB) is not paid enough attention. This paper projected future streamflow changes in the Laixi River basin (LRB), a small-middle basin in the UYRB, during 2041–2100 under RCP2.6, RCP4.5 and RCP8.5 by coupling SDSM and SWAT. The results indicate that the temperature and precipitation in the LRB show a fluctuating upward trend, and the change is most severe under RCP8.5. The increase of maximum temperature is larger than that of minimum temperature. The precipitation changes in May to September are relatively greater than in other months, while temperature is the opposite. More importantly, the streamflow is projected to rise gradually during the whole period. Under RCP2.6, increases of streamflow in the 2050s are greater than in the 2080s, while it is the opposite under RCP4.5 and RCP8.5. The increase in high flow from May to August is expected to be significantly higher than the low flow from September to April. Although the study is focused on the LRB, the results gained can provide a reference for other small-middle basins in the UYRB and all basins experiencing subtropical monsoon humid climate.

Key words | CanESM2, Laixi River basin, SDSM, subtropical monsoon humid zone, SWAT

HIGHLIGHTS

- It is the first study to project climate impacts on streamflow in the Laixi River basin (LRB).
- We do not focus on the whole Upper Yangtze River Basin (UYRB) (1,000,000 km²) but pay attention to a small-middle basin (3,240 km²) within it.
- We focus on streamflow response in a subtropical monsoon humid climate basin.
- This paper coupled SDSM and SWAT.
- Comparative analysis of differences between the LRB and the UYRB were discussed.

INTRODUCTION

Climate change may change the spatial and temporal distribution of water resources, thereby affecting the hydrological cycle system (Hoyer & Chang 2014; Michel-Guillou 2014; Sample et al. 2016; Deb et al. 2018; Islam et al. 2018). Ultimately, such hydrological changes will lead to a negative impact on ecology, society and economy (Talib & Randhir 2017; Jin et al. 2018; Gelete et al. 2019; Wan et al. 2020). With global warming, climate change due to a large number of natural and anthropogenic processes has become one of the important factors hindering sustainable development. Therefore, projection on the impact of climate change due to climate change is a crucial issue for water resource management.
change on the hydrology, especially the prediction of future streamflow, has become a booming research area (Abubakari et al. 2019; Bao et al. 2019; Bhatta et al. 2019; Gebrechorkos et al. 2019; Luo et al. 2019; Vandan et al. 2019; Gaur et al. 2020).

Numerous previous studies have estimated the climate change impact on streamflow in different watersheds with different climate types around the world. Pandey et al. (2019) assessed the climate change impacts on the hydrological system in a snow-fed watershed in Western Nepal which experience plateau monsoon climate. Op de Hipt et al. (2018) investigated the effect of climate change on catchment hydrology in a West African watershed which belongs to a tropical desert climate zone. Fonseca & Santos (2019) simulated the potential effects of climate change on the hydrology in the Tâmega River basin, northern Portugal, experiencing a Mediterranean climate. Meaurio et al. (2017) assessed the climate change impact on river discharge in the Bay of Biscay, a transition zone of the European Atlantic region, which is a marine climate zone.

However, most of the previous studies did not pay enough attention to climate change impact on future streamflow of small-middle basins in a subtropical monsoon humid climate zone. It is distributed on the east coast of the subtropical continent, most typical in parts of the Yangtze River in China. Affected by monsoon activity and the topographic effects of the Tibetan Plateau, climate change in basins within the Yangtze River Basin experiencing this climate type becomes more complicated. Therefore, studying the future climate response on streamflow in this climate type basin is of great significance to the formulation of sustainable development strategies for China to cope with climate change. Furthermore, it can also provide a reference for water resource planning for other subtropical monsoon humid areas.

As the longest river in China and the third longest river in the world, the Yangtze River plays a key role in the socioeconomic development of China (Zhang et al. 2009). Because the water resources of the upper Yangtze River Basin (UYRB) account for about 40 and 15% of the Yangtze River and China, respectively, the changes of the streamflow in the UYRB may cause serious life and property loss. Therefore, many scholars paid attention to the impact of climate change on the streamflow process in the UYRB. Cao et al. (2013) and Wang et al. (2015) studied the spatial and temporal distribution characteristics of water resources in the upper reaches of the Yangtze River under the IPCC SRES emission scenarios. The results show that the streamflow is expected to decrease due to a decline of the precipitation. Su et al. (2016) studied the streamflow variation in the UYRB under different typical RCPs of the Coupled Model Inter-comparison Project Phase5 (CMIP5) climate model, and found that the annual streamflow will increase with the increase of projected precipitation during the 21st century. Wang et al. (2019) used the variable infiltration capacity (VIC) model and eight general circulation model (GCM) outputs from CMIP5 to calculate the streamflow changes under RCP4.5 and RCP8.5. The results show that the high flow, low flow and mean annual streamflow will decrease, while precipitation and temperature are expected to increase. Yang et al. (2019) projected that streamflow will increase in the future period (2031–2060) under RCP8.5 in the UYRB.

As one can see, the conclusions of future streamflow trends of these studies are contradictory. In addition to the impact of differences in methods and data used in these studies, this may also be because the whole upper region of the Yangtze River Basin which experiences not only subtropical monsoon humid climate but also plateau mountain climate, the mixed climate types greatly increase the uncertainty of the climate change impact projection, and lead to inconsistent streamflow response conclusions.

Most previous studies focused only on the whole UYRB but ignored the future streamflow changes study in small-middle basins within it. The spatial distribution of climate elements and streamflow in the UYRB is uneven; overall changes of the UYRB smooth out the local changes in small-middle basins. So, local streamflow changes under future scenarios in these basins are not clear, which is bad for local water management.

Therefore, in this study, the Laixi River basin (LBR) which only belongs to the subtropical monsoon humid climate zone in the UYRB, is chosen as the research area. We aim to estimate the variation characteristics of future precipitation, temperature and streamflow in the subtropical monsoon humid climate zone, and project the change trends of a single climate zone within the UYRB. It is hoped that this study will be useful for rationally planning water resources in the LRB for sustainable development as well.
as water security, and provide a reference for the subtropical monsoon humid zone to cope with future climate change. There are four-fold objectives in this study: (1) to investigate the adaptability of Soil and Water Assessment Tool (SWAT) in simulating the streamflow in the subtropical monsoon humid zone, (2) to investigate the adaptability of Statistical DownScaling Method (SDSM) in downscaling temperature and precipitation in the subtropical monsoon humid climate zone, (3) to project future precipitation and temperature (2041–2100) in the LRB under low, medium and high concentration pathway (RCP2.6, RCP4.5 and RCP8.5) of Canada’s second-generation Earth System Model (CanESM2) and (4) to assess the impacts of projected changes in precipitation and temperature on the streamflow process in the LRB.

**MATERIALS AND METHODS**

**Study area and data**

The Laixi River is located in the upper reaches of the Yangtze River in the southwest of China. It originates from Bayan Mountain in Dazu, Chongqing, and flows through Sichuan Province and finally into the Tuojiang River. The basin area is 3,240 km² with the main stream 195 km long. There are four meteorological stations and one discharge gauging station in the basin. The basin location and station distribution are shown in Figure 1.

The data required for the SWAT model in this study include the digital elevation model (DEM) of 30-m resolution, the soil use data of the Harmonized World Soil Database and the 2010 land use data from the Data Center for Resources and Environmental Science of the Chinese Academy of Science (http://www.resdc.cn). Daily climate data (2003–2012) were collected from four meteorological stations, including precipitation, maximum and minimum temperature, wind speed, relative humidity and solar radiation. Besides, monthly streamflow data of the Fuji discharge gauging station in 2003–2012 were used for the calibration and validation of the model.

To build the SDSM model, NCEP reanalysis data, historical meteorological data and GCM data are needed. The GCM used in this paper is CanESM2 provided by the Canadian Centre for Climate Modeling analysis (http://www.cccsn.ec.gc.ca). The NCEP reanalysis data sets are from the National Centers for Environmental Prediction (https://www.ncep.noaa.gov).

The historical meteorological data include daily precipitation, daily maximum and minimum temperature from 1980 to 2017 which is same time series as NCEP reanalysis data. The low, medium and high concentration pathways (RCP2.6, RCP4.5 and RCP8.5) of CanESM2 under CMIP5 were selected to forecast the future climate in the LRB. The predictor variables for CanESM2 were downloaded from the following website: http://ccds-dscc.ec.gc.ca/page=pred-canem2.

**Hydrological modeling using SWAT**

The SWAT model is a semi-distributed, continuous in time and basin-scale model. It is developed to predict the impact of management practices on water, sediment and agricultural chemical yields in large-scale basins. Besides, it has already been widely used to study the impacts of climate change on streamflow.

It divides the entire watershed into multiple sub-basins and forms them into several different types of basic units – hydrological response units (HRUs). As the smallest hydrological calculation unit of the model, HRUs are constituted of only one soil type and land use type. The meteorological data such as daily precipitation, maximum and minimum temperatures, wind speed, relative humidity and solar radiation are input for the simulation of the hydrological cycle.

SWAT utilizes water balance equation (1) for the hydrological simulation (Ghoraba 2015). The streamflow of each HRU is simulated separately, and finally, the streamflow of the entire basin is summarized.

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_{\text{day}} - Q_{\text{surf}} - E_a - W_{\text{seep}} - Q_{\text{gw}}) \quad (1)$$

where $SW_0$ and $SW_t$ are the initial and final soil moisture content, $R_{\text{day}}$, $Q_{\text{surf}}$ and $E_a$ are the quantities of precipitation, surface streamflow and evapotranspiration, respectively, $W_{\text{seep}}$ is the content from the bottom of the soil profile to the vadose zone, and $Q_{\text{gw}}$ is the amount of return flow. All parameters have units in mm and $t$ is time (days). $i$ represents the parameter value for a day.
In this study, we used Arc-SWAT (Olivera et al. 2006) to establish the SWAT streamflow model of the LRB. In order to better represent the heterogeneity, the DEM was used to extract the water system and divide the basin into sub-basins, and the HRUs in each sub-basin were further divided based on land use, soil and slope. After inputting daily historical climate data (2003–2012) from four meteorological stations into this model, potential evapotranspiration (PET) was simulated using the Penman–Monteith formula (Monteith 1965, 1981), and the surface streamflow was estimated by the SCS streamflow curve method.

There are a huge number of parameters in the SWAT model, and the simulation results of different watersheds are inconsistent in sensitivity to different parameters. Model calibration is the parameterization of a given set of conditions, thereby reducing the uncertainty of prediction (Arnold et al. 2012). With an initial list of 30 parameters, the global sensitivity analysis in the SWAT-CUP program (Abbaspour 2007) was used for defining the rank, then the top 15 sensitive parameters were selected for parameter optimization using the SUFI-2 algorithm (Abbaspour et al. 2007). The global sensitivity analysis was evaluated using the t-stat and the p-value, larger t-stat and smaller p-value present greater sensitivity of parameters. The top 15 sensitive parameters to streamflow are listed in the results Section 4.1.

Coefficient of determination ($R^2$) and Nash–Sutcliffe efficiency (NSE) were used in this study to check model performance. $R^2$ indicates the fit between the model predictions
and observed data, ranging from 0 to 1, where 0 indicates no correlation and 1 represents perfect correlation. NSE values can range from $-\infty$ to 1 and indicate the match between simulated output and the observed data along a regression line with slope equal to 1 (Arnold et al. 2012; Deb et al. 2019; Deb & Kiem 2020). Ideally, an NSE value of 1 presents a perfect fit.

**Meteorological modeling using SDSM**

The SDSM model is coupled with a multiple linear regression and weather generator (Wilby et al. 2002) to downscale by establishing a statistical relationship between the large-scale climate predictors shared by the GCM and NCEP reanalysis data and the observed data (e.g. precipitation and temperature).

When the SDSM model simulates precipitation, it firstly uses large-scale climate predictors to simulate the precipitation probability (Equation (2)) in a certain day, and then simulates the precipitation yield (Equation (3)) on that rainy day.

\[
W_i = a_0 + \sum_{j=1}^{n} a_j x_j + a_{i-1} W_{i-1} \tag{2}
\]

where \(W_i\) and \(W_{i-1}\) are the probability of precipitation on the \(i\)th day and the \(i-1\)th day, respectively, \(x_j\) is the extracted \(j\)th prediction factor, and \(a_0, a_{i-1}\) and \(a_j\) are regression coefficients.

The occurrence of precipitation is determined by a random number \(r\) \((0 \leq r \leq 1)\) that conforms to a uniform distribution. If \(r \leq W_i\), it is considered that precipitation will occur on that day. When precipitation events occurring on a certain day are determined, the multivariate exponential regression function will be used to simulate the precipitation yield of that day

\[
R_i = \exp(\beta_0 + \sum_{j=1}^{n} \beta_j x_j + \varepsilon_i) \tag{3}
\]

where \(R_i\) is the precipitation yield on the \(i\)th day, \(\beta_0\) and \(\beta_j\) are regression coefficients, \(x_j\) is the extracted \(j\)th prediction factor, and \(\varepsilon_i\) is the error.

The main steps to use the SDSM model include predictand quality control, screening of downscaling predictors, model calibration, weather generator and model evaluation. Most of the raw observed meteorological data collected from meteorological stations might have missing or inaccurate values. For that matter, quality control should be carried out to identify missing data, outliers and suspected imperfect data (Gulacha & Mulungu 2017) and improve the quality of model output (Wilby & Dawson 2007).

Screening predictor variables is most important for building statistical models (Wilby et al. 2002; Huang et al. 2010). The selection of variables is based on correlation analysis, partial correlation analysis and scatter plot of SDSM 5.2 software between sets of predictors (Table 1) and single predictand (precipitation, maximum temperature or minimum temperature in this case). The selected predictor variables need to have physical meaning and are weakly correlated or unrelated.

**Table 1** Alternative predictor shared by GCM and NCEP reanalysis data

<table>
<thead>
<tr>
<th>Predictor code</th>
<th>Description</th>
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<th>Description</th>
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<tbody>
<tr>
<td>p500</td>
<td>500 hPa Geopotential height</td>
<td>p_th</td>
<td>1,000 hPa Wind direction</td>
</tr>
<tr>
<td>p8_v</td>
<td>850 hPa Meridional velocity</td>
<td>p5_f</td>
<td>500 hPa Wind speed</td>
</tr>
<tr>
<td>s500</td>
<td>500 hPa Specific humidity</td>
<td>p5_z</td>
<td>500 hPa Vorticity</td>
</tr>
<tr>
<td>Shum</td>
<td>1,000 hPa Specific humidity</td>
<td>p8_f</td>
<td>850 hPa Wind speed</td>
</tr>
<tr>
<td>p5_u</td>
<td>500 hPa Zonal velocity</td>
<td>p5_zh</td>
<td>500 hPa Divergence</td>
</tr>
<tr>
<td>p_u</td>
<td>1,000 hPa Zonal velocity</td>
<td>p8_z</td>
<td>850 hPa Vorticity</td>
</tr>
<tr>
<td>p5_v</td>
<td>500 hPa Meridional velocity</td>
<td>p_f</td>
<td>1,000 hPa Wind speed</td>
</tr>
<tr>
<td>s850</td>
<td>850 hPa Specific humidity</td>
<td>temp</td>
<td>Screen (2 m) Air temperature</td>
</tr>
<tr>
<td>P_v</td>
<td>1,000 hPa Meridional velocity</td>
<td>p8zh</td>
<td>850 hPa Divergence</td>
</tr>
<tr>
<td>p8_u</td>
<td>850 hPa Zonal velocity</td>
<td>p_z</td>
<td>1,000 hPa Vorticity</td>
</tr>
<tr>
<td>mslp</td>
<td>Mean sea level pressure</td>
<td>p8th</td>
<td>850 hPa Wind direction</td>
</tr>
<tr>
<td>p850</td>
<td>850 hPa Geopotential height</td>
<td>p_zh</td>
<td>1,000 hPa Divergence</td>
</tr>
<tr>
<td>p5th</td>
<td>500 hPa Wind direction</td>
<td>prep</td>
<td>Precipitation</td>
</tr>
</tbody>
</table>
The model calibration takes user-specified predictand along with a set of predictors, and the parameters of multiple linear regression equations are calculated by an optimization algorithm. Then, the model structure can be specified as monthly, seasonal or annual sub-models as well as conditional for temperature and unconditional for precipitation.

In this study, the annual sub-model was chosen to estimate the output for all months of a year. The 38 years’ historical data were divided into two periods. The first half (1980–1998) 19 years of daily observed data were used to calibrate, and the second half (1999–2017) was used to validate. The coefficient of determination ($R^2$) and standard error (SE) of the regression model were calculated to evaluate the model performance during the calibration period, while $R^2$ and regression analysis were used during the validation period.

**Future climate scenario generation and streamflow simulation**

CanESM2 can better simulate the precipitation and temperature in China (Sun et al. 2015). It couples atmospheric-ocean models, terrestrial plant models and carbon-cycle models for terrestrial and ocean interactions. The terrestrial carbon-cycle model in CanESM2 is primarily used to simulate carbon-to-atmosphere exchanges between the land and the atmosphere. The carbon-cycle model for terrestrial and ocean interactions is based on the Canadian terrestrial ecosystem model and can simulate all major terrestrial ecological processes.

The CanESM2 data were input into the SDSM model which has been calibrated and validated, and the future meteorological data of the meteorological stations in the LRB under RCP2.6, RCP4.5 and RCP8.5 were output, respectively. Then, the Tyson polygon method was adopted to calculate the surface precipitation in the LRB and weight the average temperature to the entire basin. Two representative time periods, 2041–2070 (2050s) and 2071–2100 (2080s), were selected to compare the changes of precipitation and temperature between the climate scenario and the baseline (historical observation, 1980–2017). Then, the future streamflow changes of the LRB were simulated in the SWAT model with the input future climate data generated by the SDSM.

**Uncertainty assessment of the streamflow projection**

The future meteorological data input to the hydrological model are from the output of GCM, so the uncertainty factors of GCM should be taken into account. Meanwhile, due to the uncertainty factors of the hydrological model itself, the streamflow uncertainty will also be affected. Therefore, the uncertainties originating from the selection of the emission scenarios, CanESM2 and SWAT model were analyzed here.

In order to investigate the uncertainty of the emission scenarios (RCP2.6, RCP4.5 and RCP8.5), the range of maximum and minimum bounds between different simulations (precipitation, temperature and streamflow) was compared. Root-mean-square error (RMSE) between model simulation and observed meteorological data was calculated to analyze the uncertainty of CanESM2. The SUFI-2 algorithm was used to evaluate the uncertainty of the SWAT model through P-factor (the percentage of observed data within 95% uncertainty interval) and R-factor (the ratio of average distance and standard deviation between upper and lower limits of 95PPU). P-factor = 1 and R-factor = 0 present a completely ideal simulation result.

**RESULTS AND DISCUSSION**

**Performance evaluation of SWAT**

The DEM was used to divide the watershed into 21 sub-basins, and each area ranged from 27.8 to 324.1 km² with an average of 149 km². Taking into account model accuracy and computational efficiency, combined with land use data, soil use data and slope, the basin was further divided into 106 HRUs. Based on the historical monthly streamflow data of the Fuji Hydrological Station, the SWAT model was calibrated and validated. Three years (2003–2005) were selected as a warm-up period to eliminate the error of the initial condition when the model is running. The period from 2006 to 2009 was chosen for the model calibration while 2010–2012 was chosen for the model validation.

The top 15 sensitive parameters of the parameter sensitivity analysis were calibrated, and the optimal value is shown in Table 2. The threshold depth of the water in the
shallow aquifer required for return flow to occur (GWQMN), groundwater delay (GW_DELAY) and soil evaporation compensation factor (ESCO) are the top 3 in the rank, indicating that the LRB is sensitive to the exchange of surface water and groundwater as well as climate change.

The coefficient of determination $R^2$ and Nash coefficient NSE in the calibration period are 0.91, 0.87, and 0.84, respectively, in the validation period, indicating that the SWAT model has good applicability in the LRB. The comparison of observed data and simulated values during calibration period and validation period are shown in Figure 2. The simulation results show that the simulated streamflow trend is basically consistent with the observed value, and the flow process is well fitted.

The simulated peaks of the streamflow are slightly less ideal. The simulated peak values of the calibration period are larger than the observed peak in 2006, 2008 and 2009. Meanwhile, in July 2007, the simulated peak is underestimated when observed streamflow reaches highest value. In the validation period, the observed data in 2012 show two abnormal peaks. But, the SWAT model does not simulate the peak well in September. The observed streamflow peak in September may be because reservoirs upstream discharged water to regulate storage capacity.

From the analysis of monthly streamflow distribution, the LRB is clearly distinguished between the wet season and the dry season. June to September is the peak period of the LRB. The streamflow usually reaches its peak in July, then gradually declines. The watershed enters the dry season in October and lasts until May of the next year. During both periods, the simulation results of the dry season in the regular are better than those in the wet season.

### Performance evaluation of SDSM

#### Statistical analysis during calibration and validation

The coefficient of determination $R^2$ of the maximum and minimum temperature are more than 0.7, the maximum temperature can reach 0.814, and the minimum temperature reaches 0.752 (Figure 3), suggesting that the selected predictor variables can better explain the temperature, and the
simulation performance of the maximum temperature is slightly better than the minimum temperature. In contrast, the $R^2$ of simulated precipitation for each site is relatively low, ranging from 0.333 to 0.607 (Figure 3). Due to the complexity of spatial and temporal distribution, the statistical relationship between precipitation and predictor needs to be established through intermediate variables. The SE of the temperature of each station is about 2, the highest does not exceed 2.9, whereas the SE of precipitation is between 0.446 and 0.692 (Figure 3), indicating that the model can

Figure 2 | Monthly simulation results of streamflow during calibration (2006–2009), a) and validation (2010–2012), b).

Figure 3 | Statistical feature value of forecasting elements in each station during the calibration period.
accurately simulate precipitation to a certain extent. In summary, the SDSM model has a good simulation performance, which can well simulate the correlation between selected predictor variables and forecasting predictant, and can be used to generate the future climate scenarios.

Through regression analysis between daily precipitation simulated and observed values (Figure 4), it can be seen that the slope of the trend line fitted during the validation period of each meteorological station ranges from 0.6292 to 0.8492, with an average value of 0.7004. From the perspective of $R^2$, all values in each station are between 0.3497 and 0.4533. The slope in Rongchang Station is the highest, while the $R^2$ is smallest. The $R^2$ at Dazu Station is the highest, which indicates a better performance of precipitation simulation.

The slope between the simulated and observed maximum temperature during the model validation period is relatively high, ranging from 0.8967 to 0.9635 (Figure 5). All of the $R^2$ in each station are between 0.9199 and 0.9342. The slope and the $R^2$ at Longchang Station are relatively lower compared with that of other stations. The simulation performance of the SDSM model in maximum temperature at Dazu Station and Luxian Station are better.

![Figure 4](http://iwaponline.com/jwcc/article-pdf/doi/10.2166/wcc.2020.082/820272/jwc2020082.pdf)

**Figure 4** | Scatter plots of simulated and observed daily precipitation in each station during validation period: (a) Dazu Station, (b) Longchang Station, (c) Luxian Station and (d) Rongchang Station.
The slope between the simulated and observed minimum temperature during the model validation period is similar to that of maximum temperature, ranging from 0.8789 to 0.9488 (Figure 6). The highest $R^2$ value is in Luxian Station, at 0.9411. In contrast, the simulation performance in Longchang Station is not as good as that of other stations, with the slope of 0.8789 and $R^2$ of 0.9069.

Regression analysis of the simulated temperature with observed records shows good agreement for the validation period. In contrast, the simulation performance of precipitation is slightly worse. Overall, the SDSM model of the LRB is more accurate in the simulation of temperature than precipitation simulation. This may be because the precipitation is a conditional process and affected by the complexity of temporal–spatial distribution, the statistical relationship needs to be established through intermediate variables.

From a station perspective, the simulation of both precipitation and temperature in Dazu Station and Luxian Station is good. Precipitation simulation in Rongchang Station is not good, while temperature simulation in Longchang Station is slightly worse than other stations.

Figure 5 | Scatter plots of simulated and observed daily maximum temperature in each station during validation period: (a) Dazu Station, (b) Longchang Station, (c) Luxian Station and (d) Rongchang Station.
Comparison of observation and simulation

Comparisons of the simulated temperature with observed records show good agreements for the validation period (Figure 7). The simulated and the observed maximum temperature curves fit best, and the peak simulation is good. There are many underestimates of the peak of the minimum temperature. In contrast, the simulation performance of precipitation is slightly worse. In 1985, 1990–1991, 2002, 2005–2006 and 2012–2013, the simulated and the observed values are quite different, but the general trend of precipitation change can still be simulated.

Analysis of future meteorological changes

Annual meteorological changes

It can be seen from Figure 8 that the precipitation and temperature show a significant increase from 2041 to 2100. The increase under RCP8.5 is the most obvious, while the
precipitation and temperature under RCP2.6 show the slowest increase. The average increases of precipitation are 9.87, 10.32 and 10.47% in the 2050s, and 11.73, 13.36 and 18.37% in the 2080s for RCP2.6, RCP4.5 and RCP8.5, respectively.

Under RCP2.6, the upward trend of precipitation prediction in the 2050s is more obvious than in the 2080s. Meanwhile, the trends of precipitation do not change much during 2041–2100 under RCP8.5, and change slowly under RCP4.5.
The average increases of maximum temperature are 0.33, 0.39 and 0.49 °C in the 2050s, and 0.42, 0.56 and 1.06 °C in the 2080s for RCPs 2.6, 4.5 and 8.5, respectively. The minimum temperature shows an average increase of 0.21, 0.22 and 0.28 °C in the 2050s, and 0.28, 0.34 and 0.51 °C in the 2080s for RCPs 2.6, 4.5 and 8.5, respectively.

Figure 8 | Projected annual changes of (a) precipitation, (b) maximum temperature and (c) minimum temperature in LBR under different climatic scenarios.
It can be seen that the change of maximum temperature in the future period is larger than the change of minimum temperature. The maximum temperature rises faster in the 2080s than that in the 2050s in three concentration pathways. On the contrary, the minimum temperature rises faster only under RCP8.5 in the 2080s, the trends of 2050 and 2080s basically remain level under RCP2.6 and RCP4.5 scenarios.

Monthly meteorological changes

From the perspective of monthly rate of change (Figure 9), precipitation is projected to increase in most months. The changes in May to September are relatively greater than in other months. The decrease of monthly average precipitation is only shown in January to March, October and November of 2041–2070. In most scenarios, the changes of monthly average precipitation from October to April over 2071–2100 are at the same level as over 2041–2070, while the monthly average precipitation from May to September in 2071–2100 increased even more than in 2041–2070.

Monthly average temperature over 2041–2070 and 2071–2100 in every month shows an increasing trend. But, the inter-monthly changes of temperature are opposite to monthly precipitation variation. The increases in May to September are less than in October to April. The changes of monthly average temperature from October to April over 2071–2100 are greater than over 2041–2070 in most scenarios. The inter-monthly trend of maximum temperature and minimum temperature is basically the same, but the increase of maximum temperature is more drastic.

Analysis of future streamflow changes

Annual streamflow changes

Under RCP4.5 and RCP8.5 scenarios, the streamflow in the LRB is projected to rise gradually (Figure 10). The streamflow increases by 4.68 and 5.73% on average from 2041 to 2070, and the average increase during 2071–2100 is about 5.55 and 7.71%, indicating that the change of annual mean streamflow in the 2080s is larger than in the 2050s. Meanwhile, the increase rate in the 2080s is faster than in the 2050s.

The increase of streamflow under RCP4.5 and RCP8.5 is mainly due to increased projected precipitation. Besides, the rise of minimum temperature will cause precipitation to fall as liquid water and the absence of snow and ice on the ground, which will reduce the loss of conversion from precipitation to streamflow. The fast growth rate of streamflow in the 2080s may be because projected precipitation will increase more dramatically in the 2080s.

Under the RCP2.6 scenario, the streamflow increased by 4.65% on average in 2041–2070, the rate of increase basically remains stable, and by 4.54% in 2071–2100, showing a downward trend. Contrary to the situations under RCP4.5 and RCP8.5, the average increase of the streamflow in the 2080s is smaller than in the 2050s.

The different trend in the 2080s under RCP2.6 may be because the increase of projected precipitation cannot compensate for the evaporation caused by rising temperatures. Slight increase of streamflow under RCP2.5 may be due to the lack of significant changes in projected temperature and precipitation.

The streamflow fluctuates and shows considerable changes in the 2080s, which may be related to the climate oscillation. It generates the peak of extreme conditions of temperature and precipitation; the streamflow will fluctuate more than ever.

Monthly streamflow changes

It can be seen from Figure 11 that the monthly average streamflow is projected to increase in most months. The decreases are only shown in January, February and November, which might be because precipitation in some scenarios is projected to decrease during these months. The increasing change of high flow in May to August is more evident than that of low flow in September to April. This might be because precipitation is projected to increase dramatically in May to August and temperatures will increase less from May to August than in other months, resulting in less evaporation.

Relative to the 2050s, it is projected that the mean value of monthly streamflow will show an increase in most scenarios during the 2080s. High flow in May to August during the 2080s shows a remarkable increase under RCP8.5,
Figure 9 | Projected monthly changes of (a) precipitation, (b) maximum temperature and (c) minimum temperature in the two future periods under different climatic scenarios.
while it is expected to slightly decrease under RCP2.6. On the contrary, low flow in September to April in the 2080s is projected to grow compared with the 2050s under three RCPs.

Uncertainty analysis of the streamflow projection

The maximum and minimum change bounds of precipitation, temperature and streamflow associated with different emission scenarios using CanESM2 are shown in Table 3. The range of precipitation change under RCP2.6 is smallest, at 7.69%. The biggest precipitation change is under RCP8.5, with 15.42%. The ranges of maximum temperature change are between 0.29 and 1.09 °C under three scenarios. The minimum temperature change is slightly lower than maximum temperature counterpart, ranging from 0.26 to 0.49 °C. The average range between the maximum and minimum annual streamflow change under three scenarios is 4.59%, among which the minimum range is 3.18% of RCP4.5. In general, the degree of uncertainty of RCP2.6, RCP4.5 and RCP8.5 is small.

The RMSE between the observed and simulated values from CanESM2 is shown in Table 4. The RMSE of precipitation data is less than 12.74. The uncertainty of
The CanESM2 simulation in maximum temperature is smaller than that in minimum temperature. The RMSE of maximum temperature is between 2.13 and 2.97 while ranging from 2.45 to 3.31 in minimum temperature. All of the RMSE values are in acceptable ranges.

The P-factor of the SWAT model during the calibration and validation period is 0.89 and 0.87, respectively, and the R-factor is 0.57 and 0.61, respectively. The uncertainty of SWAT simulation in the calibration period is relatively small. In general, the P-factor and R-factor during calibration and validation periods can meet the criteria of low uncertainty, and the simulation results of the SWAT model are applicable.

Table 3 | Comparison of maximum and minimum bounds of different simulation under three emission scenarios

<table>
<thead>
<tr>
<th>Emission scenarios</th>
<th>Precipitation change</th>
<th>$T_{\text{max}}$ change</th>
<th>$T_{\text{min}}$ change</th>
<th>Streamflow change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min (%) Max (%)</td>
<td>Min (°C) Max (°C)</td>
<td>Min (°C) Max (°C)</td>
<td>Min (%) Max (%)</td>
</tr>
<tr>
<td>RCP2.6</td>
<td>7.00 14.69</td>
<td>0.26 0.55</td>
<td>0.14 0.40</td>
<td>2.64 6.86</td>
</tr>
<tr>
<td>RCP4.5</td>
<td>7.26 17.10</td>
<td>0.26 0.77</td>
<td>0.12 0.48</td>
<td>3.68 6.86</td>
</tr>
<tr>
<td>RCP8.5</td>
<td>7.62 23.04</td>
<td>0.30 1.39</td>
<td>0.21 0.70</td>
<td>4.27 10.64</td>
</tr>
</tbody>
</table>

Table 4 | RMSE between CanESM2 simulation and observation

<table>
<thead>
<tr>
<th>Station</th>
<th>RMSE</th>
<th>Precipitation</th>
<th>Maximum temperature</th>
<th>Minimum temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dazu</td>
<td>10.12</td>
<td>2.33</td>
<td>2.45</td>
<td></td>
</tr>
<tr>
<td>Luxian</td>
<td>12.87</td>
<td>2.13</td>
<td>2.62</td>
<td></td>
</tr>
<tr>
<td>Rongchang</td>
<td>13.42</td>
<td>2.76</td>
<td>2.80</td>
<td></td>
</tr>
<tr>
<td>Longchang</td>
<td>12.74</td>
<td>2.97</td>
<td>3.31</td>
<td></td>
</tr>
</tbody>
</table>

Comparative analysis with studies in the UYRB

Su et al. (2016) found that the total streamflow will increase by 10.7–21.4% under RCP8.5 during the 2050s in the upper Yangtze River. Qin et al. (2019) calculated that the annual mean flow would increase by about 7, 3.9 and 7.8%, respectively, in three RCPs during 2050–2069, and 8, 12.2 and 15.3%, respectively, during 2080–2099. However, almost every annual mean streamflow from this study in the same scenarios and similar period is smaller than the projection from previous study in the UYRB. The difference of changes may be because their study area (the UYRB) also contains the Tibet Plateau which belongs to a plateau mountain climate zone. The increase of temperature there will melt glaciers and snow, causing the total streamflow to change dramatically. The change of streamflow in the subtropical monsoon humid climate watershed may not be particularly significant compared with other basins in the UYRB.

The differences with previous studies in the UYRB indicate that the studies in the whole upper reaches of the Yangtze River smooth out the spatial differences, which is not good for water resources planning in small-middle basins. Results of the LRB in the UYRB in this paper can reflect the dynamic changes of local water resources response to climate change in a small-middle basin within the UYRB.

Therefore, this research is of great significance for local government to manage local water resources and offer a reference for other similar small-middle basins within the UYRB. Meanwhile, the LRB only experiences subtropical monsoon humid climate, and the future streamflow projection in this paper can also offer a reference for sustainable water resource management under future scenarios in other basins with the same climate.

CONCLUSIONS

This study assessed the future climate change impact on streamflow in a typical subtropical monsoon humid climate watershed – the LBR. The SDSM model was applied to calculate the precipitation and temperature under RCP2.6, RCP4.5 and RCP8.5 scenarios of CanEMs2. The SWAT model was established to simulate current streamflow and assess the streamflow response during two typical periods (2050s and 2080s) based on the projected future climate.

The SWAT model has good applicability in the LRB. The model parameters $R^2$ and NSE are 0.91 in the calibration period, and 0.87 and 0.84, respectively, in the
validation period. Through parameters sensitivity analysis, ESCO is ranked higher, indicating that the LRB is sensitive to the climate change.

Using the SDSM model to carry out statistical downscaling of the LRB, the study found that the model can well simulate the correlation between selected predictor variables and forecasting predictand, and can be used to generate the future precipitation, maximum temperature and minimum temperature, and the simulation effect on temperature is better than the precipitation simulation effect.

Under three climate scenarios in the future, the annual variation of precipitation, maximum temperature and minimum temperature show a fluctuating upward trend. The maximum temperature increases by 0.33–0.46 °C in the 2050s and 0.42–1.06 °C in the 2080s, and the minimum temperature increases by 0.21–0.28 °C in the 2050s and 0.28–0.51 °C in the 2080s. The change of the maximum temperature is larger than the minimum temperature change. There is also an increase of precipitation, by 9.87–10.47% in the 2050s and 11.73–18.37% in the 2080s. The changes of both precipitation and temperature are most severe under RCP8.5 and slowest under RCP2.6.

In terms of the monthly rate of change, precipitation and temperature will increase in most months. The change of precipitation from May to September is relatively larger than that of other months, while the change of temperature is opposite. In the 2080s, the monthly average precipitation from May to September is expected to increase more than in the 2050s. On the contrary, the monthly average temperature change from October to April in the 2080s was mostly greater than in the 2050s. The monthly trend of maximum temperature and minimum temperature is basically the same, but the maximum temperature will increase more.

Under three concentration pathways, the estimated streamflow in the LRB is projected to rise gradually during the whole period, by 9.19, 10.23 and 13.44%, respectively. Under RCP2.6, the increase of streamflow in the 2050s is greater than in the 2080s. On the contrary, the situation is exactly the opposite under RCP4.5 and RCP8.5, the increase of streamflow in the 2080s is more dramatic. Besides, the increase rate under RCP2.6 is basically unchanged in the 2050s, then gradually decreases in the 2080s. Under RCP4.5 and RCP8.5, the growth rate is faster in the 2080s than in the 2050s.

The monthly average streamflow is expected to increase in most months, and the increase change of high flow is more obvious than that of low flow. Compared with the 2050s, the monthly average streamflow shows an upward trend under most scenarios in the 2080s. High flow in the 2080s will increase significantly under RCP8.5 and is expected to decrease slightly under RCP2.6. In contrast, under the three RCPs, low flow is expected to increase in the 2080s compared with the 2050s.

The uncertainties originating from the selection of the emission scenarios, CanESM2 and SWAT model can be accepted. The degree of uncertainty of RCP2.6, RCP4.5 and RCP8.5 is small. All RMSE values between the observed and simulated results from CanESM2 are in acceptable ranges. The P-factor and R-factor during calibration and validation periods show low uncertainty.

Compared with other studies in the whole UYRB, future changes in streamflow in the LRB are not as large as those in the UYRB. The absence of streamflow from melting snow may be the main reason for the difference.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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