Hydrological simulation of the Jialing River Basin using the MIKE SHE model in changing climate

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ABSTRACT

Climate change and human activities have an important impact on the changing environment, leading to significant changes in the basin water cycle process. The Jialing River Basin, the largest tributary of the upper Yangtze River, is selected as the study area. Three different rainfall datasets, the China Meteorological Assimilation Driving (CMAD) dataset, the Tropical Rainfall Measuring Mission data, and gauged observation data, were used as inputs for the MIKE System Hydrological European (MIKE SHE) model. By comparing the simulation results driven by various meteorological data, the applicability of the MIKE SHE model at four stations is evaluated, and the sensitivity and uncertainty of model parameters are analyzed. Meanwhile, the impact of large hydropower stations on the runoff of the Jialing River Basin is assessed, and the influence of human activities on the runoff change is determined. The future climate change of the watershed was analyzed by using the typical representative concentration pathway (RCP) 4.5 and RCP8.5 climate scenarios. Based on the MIKE SHE model, the runoff of the Jialing River Basin in the future climate scenario is predicted, and the corresponding response of the Jialing River Basin is analyzed quantitatively. The results show that the CMAD data-driven model has better Nash–Sutcliffe efficiency and correlation coefficient for each period. By analyzing the influence of the hydropower station on the runoff process at the outlet of the basin, it is found that the hydropower station has a certain regulating effect on the runoff process at the outlet of the basin. In addition, the RCP4.5 scenario is more consistent with the future scenario, indicating that the Jialing River Basin will become colder and drier.

Key words | future climate scenario, hydropower station, MIKE SHE model, rainfall, runoff, uncertainty

HIGHLIGHTS

- By comparing the results of the MIKE SHE model driven by the China Meteorological Assimilation Driving dataset, the Tropical Rainfall Measuring Mission data, and gauged data, the applicability of model parameters of the MIKE SHE model is evaluated, and the sensitivity and uncertainty of model parameters are analyzed.
- The impact of large hydropower stations on the runoff of the Jialing River Basin is assessed, and the influence of human activities on the runoff change is determined.
- Runoff prediction was conducted under two future climate scenarios, and the response of runoff to future climate changes was quantitatively analyzed.

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INTRODUCTION

Climate change triggers global temperature rises, changes in rainfall patterns, and affects the regional water cycle, as well as the hydrological situations of basins (Labat 2004). These hydrological changes affect the ecological environment and biological community of wetlands (van der Valk 2006). Therefore, it is of great significance to study the potential hydrological impact of climate change, which is becoming an increasingly popular topic of interest in the fields of hydrology and water resources (Fung et al. 2015; de Moura et al. 2020).

As a tool to study complex hydrological phenomena, the hydrological model has always been a focus of hydrology research (Dooge 1996). Hence, a number of distributed hydrological models have emerged, including Topography Based Hydrological Model (TOPMODEL) (Beven & Kirkby 1979), variable infiltration capacity (Lohmann et al. 1998), the Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998), and the MIKE System Hydrological European (MIKE SHE) model (Abbott et al. 1986), which have been widely used in practical scientific issues (Immerzeel & Droogers 2008; Dembélé et al. 2020). Particularly, the MIKE SHE model is a distributed hydrological simulation system based on actual physical mechanisms and contains powerful simulation and calculation functions (Abbott et al. 1986; Zhao et al. 2018). Although the MIKE SHE model shows good applicability in different regions of the world (Thompson et al. 2004; Windolf et al. 2011; Sandu & Virsta 2015; Luo et al. 2016), its feasibility to different basin ranges varies. Therefore, it is necessary to carry out specific research work for a given watershed (Song 2019). The uncertainty is an inevitable problem in hydrological simulation. The evaluation methods of hydrological model uncertainty mainly include the Generalized Likelihood Uncertainty Estimation (GLUE) method (Beven & Binley 1992), the Bayesian recursive estimation method (Thieman et al. 2001), and the Monte Carlo method (Vrugt et al. 2008). It is always a challenge for hydrological researchers to estimate the uncertainty of distributed models effectively (Rogers et al. 1985; Burkhart et al. 2021).

In distributed hydrological models, precipitation input data are particularly important for accurate simulation results. Precipitation input data sources mainly include gauged meteorological stations and reanalysis data derived from data assimilation technology (Michaelides et al. 2009). The precipitation data of gauged meteorological stations are often used as the measured data, as the accuracy of the data is very high. However, there are still some problems such as uneven distribution of stations and discontinuous precipitation data. Nevertheless, the reanalysis data can compensate for these shortcomings. Therefore, it has become a common phenomenon that the reanalysis data are used as precipitation input data sources in hydrological models. At present, the commonly used reanalysis data come from the Climate Forecast System Reanalysis (Saha et al. 2005), the Modern-Era Retrospective analysis for Research and Applications (Gelaro et al. 2017), the ERA-Interim (Dee et al. 2011), the Tropical Rainfall Measuring Mission (TRMM) (Rosenfeld 1999), and the China Meteorological Assimilation Driving (CMAD) datasets for the SWAT model (Meng et al. 2017a, 2017b). These rainfall data sources have their own advantages and disadvantages, so they need to be comprehensively evaluated.

In 2016, China established a new precedent for the development of the Yangtze River Economic Belt (Qin et al. 2018). The freshwater resources in the Jialing River Basin account for approximately 17.5% of the total Yangtze River, which is an important component of water resources and an important pillar of economic development in the Yangtze River Basin. Currently, the major problem facing the Yangtze River is frequent flooding, which has greatly hindered the production of agriculture, the balance of ecology, and the stable development of social economy. Furthermore, the frequency of extreme disastrous weather has increased of late, resulting in water environment deterioration and water quality decline (Wang 2015). Moreover, there are several important hydropower stations, such as Bikou, Baozhusi, Tingzikou, and Dongxiguan, in the basin. As a product of human activities in the basin, hydropower stations are a significant factor affecting runoff (Costigan & Daniels 2012; Mcmanamay et al. 2012; Zhang et al. 2015). Therefore, it is necessary to comprehensively explore the impact of these hydropower stations on runoff at the basin outlet and identify the role of human activities on runoff changes. To deepen our understanding, analyzing hydrological processes in this basin
and predicting the runoff under future climate scenarios are particularly important. Furthermore, it is necessary to study and accurately determine the law of the water cycle in the Jialing River Basin, understand the main problems existing in the current basin, and formulate scientific and reasonable strategies to protect the future water environment.

The existing problems are in the study of basin meteorological elements, there is a lack of sustainability analysis on the impact of future climate change on runoff. In previous studies, the selection of precipitation input source driven by a model is very simple. The multi-site calibration scheme is rarely used to calibrate the model. And the runoff simulation results are not analyzed from the level of parameter uncertainty. The impact of human activities on runoff is less analyzed, and the impact of large hydropower stations in the Jialing River Basin on the runoff at the outlet of the basin is rarely discussed. The objectives of this study are (1) to compare the simulation results of the MIKE SHE model driven by three precipitation products (CMADs, TRMM, and gauged meteorological station data), evaluate the model's applicability in the Jialing River Basin, and analyze the sensitivity and uncertainty of the model parameters. (2) To analyze the impact of large hydropower stations in the Jialing River Basin on runoff and to understand the impact of human activities on runoff. (3) To predict under two future climate scenarios (representative concentration pathway (RCP) 4.5 and RCP8.5) using the MIKE SHE model and analyze the response of runoff in the Jialing River Basin to future climate changes. It is necessary to analyze the law of runoff and confluence, understand the hydrological process, and water resource distribution in the basin as they play important roles in water resource management and the formulation of relevant allocation plans. The results of this study will provide reasonable and effective theoretical support for relevant policies and plans and a strong guarantee of economic development.

MATERIALS AND METHOD

Study area

The Jialing River Basin (29°18′–34°30′ N and 102°33′–109°00′ E) originates from the southern side of the Qinling Mountains and has a total length of nearly 1,120 km. Its drainage area is approximately 160,000 km², spreading across four provinces and cities, including Sichuan, Chongqing, Gansu, and Shanxi. The basin primarily includes three major water systems: the Jialing, Fujiang, and Qujiang rivers (Figure 1). Among these, the Fujiang and Qujiang rivers merge into the mainstream of the Jialing River in Hechuan city, which is 100 km away from the urban Chongqing area.

The topography of the Jialing River Basin is complex and diverse. The northwest has high terrain with high mountains and plateaus more than 4 km, while the north is slightly lower with middle-low mountains. The center of the basin has the lowest terrain, with mainly basins and hills, and the southeast is parallel to ridges and valleys. The total altitude difference of the basin is approximately 4,800 m, while the altitude change of the river is approximately 2,300 m. The average drop of the entire Jialing River system is 2.05‰. The upper part of the Jialing River Basin is in the mountainous area. As its channel is very narrow, the streamflow is fast and abundant. There are many large reservoirs in the basin, including the Bikou and Baozhusi hydropower stations, which are in the upper reaches of the Jialing River. Meanwhile, the Tingzikou, Dongxiguan, and Caojie hydropower stations exist in the middle and lower reaches. In addition, the Miaojiaiba reservoir is on the Bailong River, and the Jiangkou reservoir is on the Qujiang River. These large reservoirs, as well as some small reservoirs, regulate and affect the entire Jialing River Basin.

The Jialing River Basin belongs to the subtropical monsoon climate zone. The annual average temperature of the Jialing River Basin is 16.5 °C in the past 55 years. The annual average maximum temperature is 26.2 °C, and the minimum temperature is 4.3 °C (Fu 2019). The distributions of the annual average water surface evaporation and land surface evaporation in the Jialing River Basin vary. Annual water surface evaporation increases from below 800 mm in the middle and lower reaches of the basin to 1,000 mm in the upper mountainous area. Conversely, annual land surface evaporation decreases from 600 to 700 mm in the middle and lower reaches to 400 mm in the upper reaches. The spatial distribution of precipitation in the basin decreases from southeast to northwest. Precipitation mainly occurs from June to September, which accounts for 66% of the total annual precipitation. The annual average
precipitation is 935.2 mm, and the annual maximum and minimum precipitation are 1,283 and 643 mm, respectively. The annual average water production of the Jialing River Basin is $6.99 \times 10^{10}$ m$^3$, which accounts for approximately 17.5% of the total production of the Yangtze River Basin.

**Methodology**

**MIKE SHE model setup**

This study primarily used the coupling of the MIKE SHE model and the MIKE 11 hydrodynamic model to simulate runoff processes in the Jialing River Basin. The MIKE SHE model used herein mainly includes five modules: evapotranspiration, overland flow, saturated flow, unsaturated flow, and rivers and lakes (implemented by coupling with MIKE 11). The data required for the construction of the MIKE SHE model and the relevant parameters of the model are summarized in **Table 1**.

The two-layer water balance method is used to calculate the unsaturated zone of MIKE SHE in the study area. The required data include the distribution of soil types and the hydraulic characteristic parameters of corresponding soil types. This study uses the linear reservoir method to simulate the saturated zone module. Combined with the annual water level of the Beibei hydrological station, the downstream water level boundary is set at 170 m. The Manning coefficient of the reach is set as 30. When the MIKE 11 file of the Jialing River Basin is completed, the corresponding MIKE 11 file is added to the lake module of the rivers in MIKE SHE. The kinetic routing method is selected according to the algorithm.

The meteorological data selected in this study are:

1. Ground observation data from the daily dataset (V3.0) of China's ground climate data from the National Meteorological Information Center of China Meteorological Data Network (http://data.cma.cn/), which includes daily data from 699 benchmark and basic.
weather stations in China since 1951: We mainly selected the precipitation and reference evapotranspiration data of 13 gauged meteorological stations in the Jialing River Basin. According to the location of these stations, the Jialing River Basin was divided into 13 regions using the Tyson polygon method. Each area is controlled by a meteorological station, and the rainfall and reference evapotranspiration of all cells in the area are equal to the data of the control station.

(2) CMAD data from the official website (http://www.cmads.org/): The data sources of the CMAD series include nearly 40,000 regional automation stations of 2,421 National Automation Assessment Centers in China in order to ensure the wide applicability of the CMAD datasets and greatly improve the accuracy of the data. The CMAD dataset version used in this study is CMAD V1.0 with a resolution of 1/3°. According to the site distribution of the CMAD data and the scope of the Jialing River Basin, 182 stations within and around the Jialing River were selected. Similarly, the basin was divided into 182 regions using the Thiessen polygon, wherein each area corresponds to one station.

The data from 2009 to 2015 of three different data sources were selected as the meteorological data input of the model. The spatial distribution of precipitation was selected based on the station location of different data, and the Thiessen polygon was generated using ArcGIS to determine the control range of each station. Because there is no reference evapotranspiration data in the CMAD atmospheric assimilation data or the TRMM data, the reference evapotranspiration data were unified using ground observation data to facilitate a comparison.

### Model calibration

The auto-calibration tool in MIKE SHE was used for a parameter sensitivity analysis and parameter calibration. In this study, 2009–2012 was selected as the calibration period, and 2013–2015 was the validation period. A sensitivity analysis of six model parameters in the hydrological model of the Jialing River Basin was conducted using the auto-calibration tool. A brief description and the parameter sensitivity test rankings are summarized in Table 2. Note that the objective function is the root-mean-square error.
Meanwhile, we selected the daily flow data of four hydrological stations in the basin, including the Beibei station, which is located at the total water outlet of the basin, the Wusheng station, which is located on the mainstream of the Jialing River, and the Xiaoheba and Luoduxi stations, which are located on the tributaries of the Fujiang and Qujiang rivers, respectively. Two schemes were used to calibrate the parameters: a single site as the target and multiple sites as the target, wherein the single site uses the daily flow data of the Beibei station as the target for parameter calibration, and the multiple sites scheme uses the data of four stations simultaneously as the target for parameter calibration.

**GLUE method**

The GLUE uncertainty evaluation method is a commonly used method to quantify the uncertainty of hydrological models. This method can define the likelihood objective function, determine the parameter value range, calculate the likelihood function, perform an uncertainty analysis of the parameters, and determine the limits of the model prediction results. As this method mainly obtains parameter samples using the random sampling method, the spatial distribution of the obtained parameter samples is often different from that of the actual parameters. Hence, only when the number of parameter samples obtained via sampling is sufficient will the sample distribution be near the actual distribution. In addition, the prior distribution of parameters and the selection of the likelihood function are often affected by insufficient prior information and human subjective factors, thereby affecting the simulation results of the model. Furthermore, when the model is running, it often appears as if the simulation effects of the model driven by different parameter groups are similar (‘equifinality’). However, the utilization of the GLUE method overcomes this problem, stopping the model from existing in the local optimal interval (Guo 2018).

**Future scenario analysis**

The scenario analysis method assumes that a certain phenomenon or trend will continue to predict the changes that may be caused by the research object. Recently, scenario analyses have become the main method for evaluating the response of basin runoff to land use/cover and climate change. Future climate scenarios are scientific assumptions regarding the state of the future climate system, which are the key inputs that affect the evaluation results of climate models. A climate model is generally selected according to aerosol and greenhouse gas emission standards. RCPs refer to the estimated collection of greenhouse gas and particulate matter emissions and concentration changes over time under the action of man-made meteorological forcing (Meinshausen et al. 2011), which can predict comprehensive socioeconomic and climate impacts. Several possible RCPs were released by the Fifth Coupled Model Intercomparison Project (CMIP5) in 2013. Different radiative forcing targets were selected for each scenario of RCPs for the year 2100 (Fischer et al. 2010), which mainly includes four types of scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. Herein, we selected two of these future climate models (RCP4.5 and RCP8.5) using the Jialing River Basin as the research area to predict climate change. The MIKE SHE model was used to simulate runoff and quantitatively analyze the future runoff response to climate change in the Jialing River Basin.

A global climate model (GCM) provides global climate change information under different scenarios, including

| Table 2 | Selected calibrated parameters in the MIKE SHE model for the Jialing River Basin |
|---------|----------------------------------|------------------------------|------------------|------------------|
| Parameter | Unit | Description | Sensitivity rank | Range |
| TCI      | d    | Interflow time constant | 5                 | 1–60             |
| TCF1     | d    | Time constant for base flow1 | 1                 | 5–365            |
| SY       |      | Specific Yield | 3                 | 0.1–0.5          |
| C-int    | mm   | Canopy interception | 4                 | 0.5–1            |
| SY2      |      | Specific Yield2 | 2                 | 0.1–0.5          |
| SY1      |      | Specific Yield1 | 6                 | 0.1–0.5          |
near-surface temperature and upper atmosphere field, and is the most important tool for current climate simulations and future scenario predictions (Moss et al. 2010). However, the application of GCM models to the model herein requires a downscaling transformation to regional-scale climate change information. The GCM used herein is the Beijing Normal University Earth System Model (BNU-ESM), which contains data from the high-precision climate model dataset that has been downscaled and error-corrected in the NASA Earth Exchange (NEX) Global Daily Downscaling Projection dataset (https://cds.nccs.nasa.gov/nex-gddp/). Using the self-developed land surface model as the core, the BNU-ESM combines ocean, land, atmosphere, and sea ice component models, including the ESM of the full carbon cycle process, using coupler technology (Wilby et al. 2006). The original BNU-ESM has a larger spatial resolution of 2.8° × 2.8°. However, the NEX center combined statistical downscaling and quantile mapping error correction methods to process the GCM model data, thereby obtaining climate model data with a spatial resolution of 0.25° × 0.25° (Wu et al. 2015). According to the Jialing River Basin, as the data are grid data, 311 grid points of the historical reference period (1986–2005) and forecast period (2021–2040) precipitation data were selected for analysis. To test the credibility of the climate model, we compared the precipitation data calculated by the BNU-ESM in the historical base period (1986–2005) with the data from the gauged meteorological stations. As previously mentioned, the gauged meteorological data are the daily dataset of China’s ground climate data.

Evaluation index of model simulation performance

In this study, several evaluation indicators, including the Nash–Sutcliffe efficiency (NSE), correlation coefficient ($R^2$), and percentage deviation ($P_{\text{bias}}$), were selected to evaluate the simulation performance of the model. The NSE is used to evaluate the quality of the model simulation results. The $R^2$ represents the linear correlation between the simulated and observed values, and the $P_{\text{bias}}$ represents the percentage of the average deviation between the observed and simulated values. The $P_{\text{bias}}$ was mainly used to evaluate the relative deviation of the average trend of the simulated value of the model from the trend of the observed value. The NSE, $R^2$, and $P_{\text{bias}}$ were determined using the following equations:

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}$$  \hspace{1cm} (1)

$$R^2 = \frac{\left[ \sum_{i=1}^{n} (O_i - \bar{O})(S_i - \bar{S}) \right]^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2 \sum_{i=1}^{n} (S_i - \bar{S})^2}$$  \hspace{1cm} (2)

$$P_{\text{bias}} = 100 \times \frac{\sum_{i=1}^{n} (O_i - S_i)}{\sum_{i=1}^{n} O_i}$$  \hspace{1cm} (3)

where $O_i$ is the runoff observation value (m³/s), $S_i$ is the runoff simulation value (m³/s), $\bar{O}$ is the average of the observation value (m³/s), $\bar{S}$ is the average of the simulation value (m³/s), and $n$ is the total amount of observation data (m³/s).

RESULTS AND DISCUSSION

Analysis of simulation results driven by different rainfall inputs

In this study, the daily runoff simulation results of the MIKE SHE model driven by gauged meteorological data, CMAD data, and TRMM data in the Jialing River Basin were compared and analyzed using evaluation indices and flow hydrograph. The applicability of the MIKE SHE model driven by each data source was evaluated. A multi-site calibration scheme was used for the calibration process.

Figure 2 shows the simulated daily runoff process of the model driven by three different precipitation data under the multi-site calibration scheme during the calibration and validation periods of the four stations. In general, the model driven by the gauged meteorological data is closer to the measured value than that driven by the CMAD data for the receding stage simulation. For the flood peak flow simulation, the performance of the model driven by the CMAD data was relatively better than the other data-driven models. Moreover, for the dry season simulation, the performance of the gauged meteorological model was not
Figure 2 | Simulated daily runoff during the calibration (2009–2012) and validation period (2013–2015) of the MIKE SHE model driven by three precipitation input data at (a) Beibei, (b) Wusheng, (c) Xiaoheba, and (d) Luoduxi stations.
stable, and the performance of the CMAD model was relatively better. For the Beibei and Wusheng station simulations, the gauged meteorological data performed very well, wherein the flow process line was close to the actual measured value. However, for the Xiaoheba and Luoduxi stations, the fit between the simulated and measured values was relatively poor. This may be due to the sparse distribution of the gauged meteorological stations, which leads to poor local simulation performance. The difference between the simulated flow process driven by TRMM data and the measured process was more obvious than those driven by the other data.

Table 3 lists the performance of the model during the calibration and validation periods under the multi-site calibration scheme driven by three different precipitation data sources. The evaluation index data showed that during the calibration period, for the Beibei and Wusheng stations, the $R^2$ and NSE values driven by the gauged meteorological data were slightly higher than those driven by the CMAD data, whereas for the Xiaoheba and Luoduxi stations, the performance of the gauged meteorological data was slightly worse than that of the CMAD data. The TRMM data performed slightly better than the gauged meteorological data at the Xiaoheba station, while its performance at the other stations was not as good as those driven by the other data. During the validation period, except for the $R^2$ and NSE driven by the CMAD data at the Wusheng station being slightly lower than the gauged meteorological data, the performance of the CMAD data was generally better than both the gauged meteorological and TRMM data.

At the Xiaoheba and Luoduxi stations, the $R^2$ value driven by CMAD data was greater than 0.8, and the NSE value was above 0.6. In terms of $P_{bias}$, the deviation of the model driven by the gauged meteorological site data was slightly smaller than that of the model driven by the CMAD data. Thus, the performance of the gauged meteorological data at the Beibei and Wusheng stations during the calibration and validation period outperformed the CMAD data. However, the CMAD data-driven model had NSE values above 0.5 and $R^2$ values greater than 0.75 at the four stations during the calibration and validation periods. Furthermore, its performance in the validation period was significantly better than the model simulation performance driven by the gauged meteorological data. The overall performance of the TRMM data in both periods was not as good as that of the other data sources. Therefore, in terms of the model evaluation indices, the model simulation performance driven by CMAD data was generally more stable.

In addition, Figure 2(a)–2(d) shows the flow duration curve of the simulated and observed values for the MIKE SHE model driven by the different precipitation data at four stations. We found that the simulated high-flow (frequency lower than 0.1) and low-flow (frequency higher than 0.9) values of the model driven by gauged meteorological and CMAD data were smaller than the observed values at the Beibei, Wusheng, and Xiaoheba stations. Meanwhile, the simulated middle flow (frequency between 0.1 and 0.9) values of the model driven by gauged meteorological data were closer to the observed values. At the Luoduxi station, the simulated high-flow values driven by the CMAD and gauged data were all smaller than the observed values, while the middle and low flows were relatively closer to the observed values. Moreover, the simulation results using the CMAD data were better than those obtained using the gauged meteorological data. Compared with the other data, there was a significant difference between the simulated values using the TRMM data and the observed values.

Therefore, the simulation results based on the TRMM data were the worst, which may be because the TRMM

| Station | Data  | Calibration period (2009–2012) | Validation period (2013–2015) |
|---------|-------|------------------------------|------------------------------|
|         |       | $R^2$ | NSE | $P_{bias}$ (%) | $R^2$ | NSE | $P_{bias}$ (%) |
| Beibei  | Gauged| 0.85  | 0.66 | 14.7  | 0.84  | 0.69 | 1.8   |
|         | CMADs | 0.83  | 0.63 | 24.7  | 0.85  | 0.72 | 10    |
|         | TRMM  | 0.79  | 0.62 | 1.9   | 0.79  | 0.54 | 17.9  |
| Wusheng | Gauged| 0.83  | 0.63 | 15.6  | 0.80  | 0.63 | 4.8   |
|         | CMADs | 0.83  | 0.61 | 24.3  | 0.78  | 0.59 | 8.6   |
|         | TRMM  | 0.72  | 0.51 | 4.9   | 0.64  | 0.14 | 28.8  |
| Xiaoheba| Gauged| 0.72  | 0.51 | 18.1  | 0.65  | 0.41 | 14.8  |
|         | CMADs | 0.81  | 0.56 | 32.5  | 0.81  | 0.63 | 16.8  |
|         | TRMM  | 0.76  | 0.57 | 5.9   | 0.59  | 0.33 | –6.3  |
| Luoduxi | Gauged| 0.76  | 0.49 | 18.9  | 0.77  | 0.55 | 1.9   |
|         | CMADs | 0.78  | 0.53 | 21.4  | 0.83  | 0.67 | 3.2   |
|         | TRMM  | 0.71  | 0.48 | 4.4   | 0.82  | 0.66 | –22.9 |
data were not corrected with the gauged meteorological data. Thus, its results were obviously high. At the Beibei and Wusheng stations, the simulation results of the MIKE SHE model driven by the gauged meteorological data were better than those of the MIKE SHE model driven by the CMAD data. At the Xiaoheba and Luoduxi stations, the simulation results of the CMAD data were better than those obtained using gauged meteorological data. Furthermore, the CMAD data obtained an $R^2$ above 0.75 and an NSE greater than 0.5 at all four stations during both the calibration and validation periods, and its simulation performance was relatively stable. However, when using the gauged meteorological data for the simulation, the $R^2$ and NSE values of the Luoduxi station during calibration and the Xiaoheba station during validation were not satisfactory. For the Xiaoheba station, the $R^2$ value was only 0.65, and the NSE value was only 0.41. To evaluate the integrity of the basin flow simulation, the subsequent studies all used CMAD data, which had a more stable overall performance.

The CMADS was constructed by using China Land Data Assimilation System (CLDAS) driving field elements as the original data and incorporated Local Analysis and Prediction System/Space-Time Multiscale Analysis System (LAPS/STMAS) technologies. The CMADS data sources include nearly 40,000 national and regional automatic stations, and the CPC Morphing Technique’s (CMORPH’s) global precipitation products are also used for splicing precipitation data (Meng et al. 2017a, 2017b). The CMADS provides high-resolution meteorological data covering the entire East Asia region and can be directly applied to the SWAT and other models, making up for the lack of sparse observation stations and incomplete data series in some regions (Meng & Wang 2017; Meng et al. 2018). The measured data were taken from ‘China Surface Climate Data Daily Data Set (V3.0)’, which has undergone repeated quality control and correction. The dataset only contains more than 800 basic gauge meteorological stations in China, so only 13-gauge stations could be used in this study.

**Uncertainty analysis of MIKE SHE**

In this study, the Monte Carlo sampling method was used to simulate 30,000 groups of uniform distribution parameters that were randomly selected from the prior distribution range of six parameters. The NSE was selected as the objective likelihood function, with a threshold set to greater than 0.5. When the NSE was used as the objective function, 7,243 sets of parameters met the threshold condition. These parameters were called behavioral parameters. Figure 3 shows the correlation graphs of the model behavior parameters with NSE as the objective function. Overall, the high likelihood values of the parameters SY2 (specific yield of the second base flow reservoir) and TCF1 (time constant for base flow 1) were mostly concentrated in the low-value range, and the distribution of TCF1 in the low-value range was more obvious when the NSE was used as the objective function. As TCF1 is a parameter related to the base flow, its obvious distribution may indicate that the NSE is more affected by a lower flow when it is the objective function.

Figure 4 shows the posterior distributions of the parameters calculated using the Bayesian theory when NSE was the objective function. Parameters c_int (canopy interception), SY (specific yield), SY1 (specific yield of the first base flow reservoir), and TCI (interflow time constant) had a basically uniform distribution with a greater uncertainty. The probability density distribution of the SY2 and TCF1 parameters also had a certain trend. Thus, it can be concluded that the c_int, SY, SY1, and TCI parameters have larger fluctuations, a wider range of values, and larger uncertainties,
while TCF1 and SY2 have values that are relatively concentrated with fewer fluctuations and lower uncertainty.

**Influence of hydropower stations on the outflow of the basin**

Climate change and human activities are the main factors affecting basin outflow, wherein the influences of regulation and storage of hydropower stations on the basin outflow are an important component of human activities. In this study, the MIKE SHE model was used to discuss the influence of several large hydropower stations on the outflow of the basin to understand the influence of human activities on the outflow of the Jialing River Basin.

The total regulated storage capacity of various water storage projects in the Jialing River Basin is $4.83 \times 10^9$ m$^3$, which accounts for 8% of the total water resources. The total installed capacity of the hydropower stations built and under construction below Guangyuan on the mainstream of the Jialing River is $1.38 \times 10^6$ kW, accounting for 45.3% of the technological developable capacity of the Jialing River mainstream. The Dongxiguan, Tingzikou, and Caojie hydropower stations have a large installed capacity. Currently, large power stations are being built on the tributaries, including the Bikou, Baozhusi, and Miaojiaba hydropower stations on the Bailong River, and the Jiangkou hydropower station on the Quijiang River. The locations of several large hydropower stations in the basin and their related parameters are shown in Figure 5 and Table 4.

In this study, the flow data of the Baozhusi, Dongxiguan, Tingzikou, and Jiangkou hydropower stations from May 2013 to April 2015 were selected. By considering the
inflow and outflow of the hydropower stations as the outflow condition of the hydraulic structure in the MIKE 11 hydrodynamic model and coupling it with the MIKE SHE model, the flow data at the outlet of the basin were simulated. Through this method, the impacts of the hydropower stations in the basin on the outlet flow were analyzed. To exclude the influence of other factors, the outflow simulated using the MIKE SHE model under the condition of reservoir inflow was regarded as unaffected outflow, and the outflow under the condition of the outflow of the hydropower station was regarded as the outflow affected by the hydropower station. The simulation results are shown in Figure 6. We found that four hydropower stations had a certain effect called ‘peak shaving and dry supplement’ on the runoff process at the basin outlet. The influence of the Dongxiguan hydropower station was the most distinct, which may be because it is closer to the outlet, thereby strengthening its impact.

The impact of the hydropower stations on the outlet runoff of the basin was analyzed using the non-uniform
coefﬁcient of runoff annual distribution \(C_{vy}\), the distribution adjustment coefﬁcient \(C_r\), and the relative change range \(C_m\). These parameters were calculated as follows:

\[
C_{vy} = \sigma / \bar{r} = \sqrt{\frac{1}{12} \sum_{i=1}^{12} (r_i - \bar{r})^2 / \frac{1}{12} \sum_{i=1}^{12} r_i}
\]

\[
C_r = \frac{1}{12} \sum_{i=1}^{12} \psi(i)(r_i - \bar{r}) / \sum_{i=1}^{12} r_i,
\psi(i) = \begin{cases} 
0, & r_i < \bar{r} \\
1, & r_i > \bar{r}
\end{cases}
\]

\[
C_m = Q_{\text{max}} / Q_{\text{min}}
\]

where \(r_i\) is the monthly runoff during the year, \(\bar{r}\) is the average monthly runoff during the year, \(Q_{\text{max}}\) and \(Q_{\text{min}}\) are the maximum and minimum monthly values of average runoff, respectively, and \(C_{vy}\) and \(C_r\) reﬂect the annual distribution of non-uniformity.

The calculation results are listed in Table 5. The ﬁndings show that under the inﬂuence of the Dongxiguan and Tingzikou hydropower stations, the runoff process indices in the two periods fundamentally reduced, indicating that under the inﬂuence of these stations, the runoff process at the outlet of the basin tended to be gentle, and the annual distribution was more uniform. Under the inﬂuence of the Jiangkou hydropower station, the \(C_{vy}\) and \(C_r\) values for each period decreased, whereas the relative variation range of runoff increased. Under the inﬂuence of the Baozhusi hydropower station, the values of \(C_{vy}\) and \(C_r\) increased in the first

![Figure 6](https://example.com/figure6.png)

**Figure 6** | MIKE SHE model simulations of the daily runoff process at the outlet of the basin under the inﬂuence of four hydropower stations.
period and decreased in the second. This shows that the Baozhusi hydropower station has a certain influence on the runoff process, but not for the whole period.

**Prediction of runoff response under climate change**

**Climate models and prediction methods**

Herein, we used the climate data of the BNU-ESM model for prediction modeling, wherein the data of the base period were compared with the data from ground observation stations. The average values of 13 observation points in the Jialing River Basin were obtained according to the Thiessen polygon method, and the data of 311 selected grid points were averaged, also in accordance with the Tyson polygon method. Table 6 lists the absolute error and relative error values of the data calculated by the BNU-ESM relative to the ground observation station data.

Figure 7(a1)–(a3) shows the monthly average values of each dataset during the base period. The monthly average values of the data were very close. The inter-annual process changes of the two data points are shown in Figure 7(b1)–(b3). It can be seen that the precipitation and maximum temperature values of the two sets of data were similar during the inter-annual change process, and the BNU-ESM data of the lowest temperature was slightly lower than that of the ground observation site. The average annual precipitation, and maximum and minimum temperatures of the two data were tested for variance, exhibiting a variance greater than 0.05. Thus, there is no significant difference between the two kinds of data. Therefore, in general, the climate data calculated using the BNU-ESM data meet the prediction and credibility requirements.

**Forecast of future climate change**

Herein, we selected precipitation and temperature data under two climate scenarios (RCP4.5 and RCP8.5). The changes relative to the base period under each scenario were calculated, as summarized in Table 7. The results showed that the annual average precipitation under the RCP4.5 climate scenario had a slight downward trend, while under the RCP8.5 scenario, it had a slight upward trend. Under both climate scenarios, the minimum and maximum temperatures rose relative to the base period, but the temperature under the RCP8.5 climate scenario increased more.

Figure 8 shows the change rate of the climate characteristic values compared with the base period under the scenarios. Except for March and April, the median change rate of the monthly average precipitation under the
RCP8.5 climate scenario was slightly higher than that under the RCP4.5 climate scenario. Meanwhile, in May, July, and December, the median change rate of the monthly average precipitation under the RCP4.5 climate scenario was lower than 0, while that under the RCP8.5 climate scenario was greater than 0. Thus, the average monthly rainfall under the RCP4.5 climate scenario had a decreasing trend compared with the base period, while it has an increasing trend under the RCP8.5 climate scenario. Regarding temperature, the months in which the maximum and minimum temperatures of the climate scenarios changed significantly relative to the base period were mainly concentrated between October and March of the following year.

### Runoff prediction under future climate scenarios

As previously mentioned, the performance of the MIKE SHE model driven by CMAD data was more stable for the four stations in the basin. Therefore, based on the CMAD data-driven multi-site scheme calibration parameters, the MIKE SHE model was used to simulate the daily runoff of the four stations during the base and prediction periods.

The variations in annual average runoff relative to the base period under both climate scenarios were compared, as listed in Table 8. The results show that the annual average runoff of the four stations under the RCP4.5 climate scenario decreased compared with the base period. Conversely,
Figure 8 | Change rates of RCP4.5 and RCP8.5 compared with the climate characteristic values of the base period.
under the RCP8.5 climate scenario, the annual average runoff of the Wusheng station increased compared with the base period, but decreased for the other stations. Figure 9 shows the correlation between annual rainfall and annual average flow for the base period and both scenarios. We found that the rainfall flow correlation in the base period was weak, but the correlation under the two climate scenarios was strong. This may be because the simulation calculation of the MIKE SHE model is discrete to the grid of watershed division, and the average rainfall of the whole basin obtained using the Tyson polygon method makes it difficult to reflect the spatial difference of rainfall during the model calculation.

Figure 10 shows the changing trend of the annual average runoff and annual rainfall at the outlet of the basin, which basically conforms to the rule that runoff increases with increasing rainfall.

Figure 11 shows the monthly average runoff of the four stations in the forecast and base periods. The results show that in the RCP8.5 climate scenario, the Beibei and Wusheng stations had an increasing trend compared with the base period in September. However, in the RCP4.5 climate scenario, the runoff processes of the four stations decreased compared with the base period. At the Xiaoheba and Luoduxi stations, the average runoff in August under the RCP4.5 climate scenario was higher than that under the RCP8.5 climate scenario. In the RCP8.5 climate scenario, although the precipitation of the basin had an increasing trend relative to the base period, the average annual runoff of the outlet station of the basin (Beibei station) was relatively reduced, which does not conform to the rule that the runoff increases with increasing rainfall. Therefore, the simulation of the model under the RCP4.5 climate scenario is more accurate and consistent with future scenarios. Thus, according to this scenario, the Jialing River Basin will be colder and more arid in the future.

**CONCLUSIONS**

From the simulation results driven by three different meteorological data, we found that the performance of the CMAD data at the four stations was relatively stable and the performance of TRMM data was the worst.

By analyzing the influence of several large hydropower stations in the Jialing River Basin on the outlet runoff

| Annual average runoff and relative change in base and forecast periods |
|-------------------------|-----------------|----------------|----------------|
|                         | Annual average runoff (10^4 m^3) | Changes in relative base period (%) |
|                         | Beibei | Wusheng | Xiaoheba | Luoduxi | Beibei | Wusheng | Xiaoheba | Luoduxi |
| Base period             | 408    | 165     | 77.3     | 105     |        |         |         |         |
| RCP4.5                 | 393    | 204     | 73.5     | 101     | -3.65  | -2.8    | -4.92   | -4.32   |
| RCP8.5                 | 403    | 188     | 68.2     | 92.4    | -1.36  | 13.95   | -11.69  | -12.14  |

**Table 8**

![Figure 9](http://iwaponline.com/jwcc/article-pdf/12/6/2495/934575/jwc0122495.pdf) | Correlation diagram of rainfall and runoff in the base period and climate scenarios.

![Figure 10](http://iwaponline.com/jwcc/article-pdf/12/6/2495/934575/jwc0122495.pdf) | Correlation diagram of rainfall and runoff in the base period and climate scenarios.
process, we found that the Tingzikou and Dongxiguan hydropower stations made the outlet runoff process gentler and the distribution more even throughout the year. The Jiangkou hydropower station had a moderating effect on the runoff process but had little influence on the runoff variation. Meanwhile, the Baozhusi hydropower station had a certain influence on the runoff process trend, but its impact was not continuous. One shortcoming of this study is that our influence analysis only involved the 2-year runoff processes of four hydropower stations. If the data conditions permit, an analysis of more hydropower stations should be carried out over a longer period.
The BNU-ESM data were selected, and two climate scenarios were adopted to predict the precipitation and maximum and minimum temperatures of the basin. It was found that the precipitation under the RCP4.5 scenario had a downward trend relative to the base period, while under the RCP8.5 scenario, it had a slight upward trend relative to the base period. The maximum and minimum temperatures of both climate scenarios rose. Under the RCP8.5 scenario, the runoff at the Beibei and Wusheng stations showed an increasing trend in September compared with the base period. Under the RCP4.5 scenario, the runoff processes of the four stations were reduced compared with the base period. At the Xiaobha and Luoduxi stations, the average runoff in August under the RCP4.5 scenario was higher than that under the RCP8.5 scenario. Even though the precipitation in the basin under the RCP8.5 scenario increased and the outlet runoff decreased, this phenomenon does not conform to the law that the runoff increases with increasing precipitation. It can be concluded that the RCP4.5 scenario had better agreement with the future scenario, suggesting that the Jialing River Basin will be colder and drier in the future.

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DATA AVAILABILITY STATEMENT

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

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