Simulation effect evaluation of single-outlet and multi-outlet calibration of Soil and Water Assessment Tool model driven by Climate Forecast System Reanalysis data and ground-based meteorological station data – a case study in a Yellow River source

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ABSTRACT

It is the research hotspot in the field of hydrology to apply the climate model and its downscaling data into hydrological simulations, and it is very important to evaluate the accuracy of its data. In this study, the accuracy of Climate Forecast System Reanalysis (CFSR) was evaluated from two perspectives: statistical evaluation and hydrological evaluation. In the hydrological evaluation, the applicability of CFSR in the Soil and Water Assessment Tool (SWAT) model of the Yellow River source area was studied. The results show that CFSR temperature data at the source of the Yellow River is consistent with the measured temperature data, and CFSR precipitation data overestimates precipitation. In the Yellow River source runoff simulation, the SWAT model driven by CFSR can obtain satisfactory simulation results. It does not reduce the simulation accuracy at the total outlet of the basin under the multi-outlet calibration method. It also considers the spatial differences of hydrological characteristics of each sub-basin and improve the simulation accuracy of the sub-basin simulation.

Key words | CFSR, multi-outlet calibration, single-outlet calibration, SWAT model, Yellow River source

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HIGHLIGHTS

- Simulation effect of SWAT model was evaluated.
- Accuracy of precipitation and temperature data of CFSR data set was evaluated.
- Simulation effects of SWAT model and multi-outlet calibration method were compared.
- The CFSR data did not achieve good simulation effect.
- The spatial difference of the sub-basin was taken into account in the multi-outlet calibration method.

INTRODUCTION

The global climate system has been undergoing significant changes since the 1900s, and the increasingly intense human activities affect the process of hydrological cycles to varying degrees (Yang *et al.* 2020). Therefore, the hydrological cycle and the vulnerability of water resources against the backdrop of climate changes have become a focus of hydrological research. Hydrological modeling, which is based on mathematical principles and hydrometeorological data to simulate the complex hydrological cycles in nature, is a necessary and important method for hydrological research (Ouermi

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et al. 2019). Building a hydrological model driven by ground-based meteorological station (GMS) can provide a strong support for simulation of regional water cycles. High-precision and high-quality meteorological data can reduce the uncertainty of the model, thereby increasing the accuracy of simulation and prediction results (Barnett et al. 2008).

Conventional methods of hydrological research use the meteorological data collected from GMS to drive the hydrological model to simulate hydrological cycles and perform flood forecasting (Arnold et al. 1998; Golmohammadi et al.2014). However, limited by financial investment and monitoring technology, GMS is rare and unevenly distributed. In remote areas and inaccessible rivers, the lack of GMS leads to challenges in collecting effective meteorological data and subsequent hydrological modelling. To solve this problem, scholars all over the world have used the output data of the climate models and their downscaling data in large-scale hydrological simulations and achieved good results (Smith & Kummerow 2013). However, due to the low resolution of climate models and reanalysis data, large deviations occur when these data are applied to simulation of regional climate change with complex underlying surface features (Liu et al. 2017). Therefore, in hydrological response research, it is important to study the application effect and sensitivity of different meteorological reanalysis data and climate model products in the Soil and Water Assessment Tool (SWAT) model. At present, the China Meteorological Assimilation Driving Datasets (CMADS) for the SWAT model established by Meng Xianyong is widely used in China (Meng & Wang 2017). The application of this data set in several basins in China shows that its simulation results are better than those achieved by the conventional method, which is based on data from GMS. Nowadays, the CMADS has become a mature data set for hydrological studies. On the other hand, the Climate Forecast System Reanalysis (CFSR) data set, developed by the National Centers for Environmental Information (NCEI) of the U.S., has shown in recent years that its simulation effect is as good or better than that of data from GMS. However, some scholars point out that this data set fails to deliver good simulation results in certain regions, especially the tropical basins. They suggest that CFSR data be used in regions where conventional GMS are available.

The SWAT model is a semi-distributed hydrological model developed by the U.S. Department of Agriculture. It is mainly used to simulate and evaluate the hydrological situation and water quality changes of basins under various management measures and climate changes. To judge whether the SWAT model is applicable to a basin, it is necessary to calibrate the parameters of the model first. At present, the SWAT model parameter calibration methods mainly include single-station calibration and multi-station calibration. The method of single-station calibration is to set a total basin outlet, and the parameters are assumed the same throughout the whole basin (Thavhana et al. 2018). This method ignores the uniqueness of sub-basins, and thus the calibrated parameters cannot describe the characteristics of the corresponding sub-basin. On the other hand, the multi-station calibration method can show the spatial differences among sub-basins and improve the simulation accuracy of each sub-basin without impairing the simulation accuracy at the whole basin (Yu et al. 2014).

To this end, this paper takes the source of the Yellow River as the research area and evaluates the CFSR data set from two aspects: statistical evaluation and hydrological evaluation. In hydrological evaluation, CFSR data is used to drive the SWAT model. To reasonably evaluate product characteristics and reduce the impact of hydrological model calibration methods on product performance, runoff is simulated under single-outlet and multiple-outlet scenarios, and the simulation accuracy is evaluated.

RESEARCH AREA AND MATERIALS

Overview of the research area

Originating from Zhaqu of Chahasila Mountain in the Bayan Kala Mountains of Qinghai–Tibet Plateau, the Yellow River from eastwards through nne provinces in China before entering the Bohai Sea. The catchment area above Tangnaihai Hydrological Station is the source of the Yellow River (Figure 1). The catchment area covers $12.2 \times 10^4\,km^2$, accounting for 16.2% of the total area of the Yellow River Basin. The geographical range is 95° 30′–103° 30′E and 32°10 ′–36°05N. The terrain is high in the west and low in the east, with the lowest altitude of 2,546 m and the highest altitude of

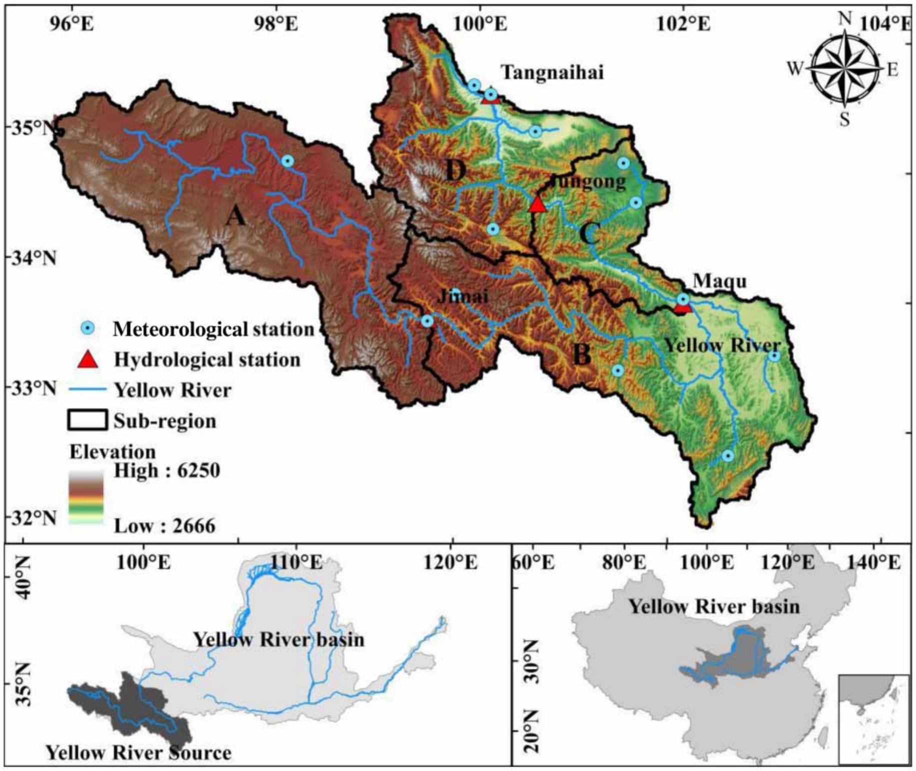

Figure 1 | Meteorological stations, hydrological stations and their control sub-regions in the source area of the Yellow River.

6,282 m (the Aemye Ma-chhen Range). The source area belongs to the sub-cold and semi-arid area in the plateau, with a high temperature in the southeast and a low temperature in the northwest, and the annual precipitation of between 287.49 mm and 754.36 mm decreases from southeast to northwest. There are many tributaries, well-developed glacial landforms, and more than 40 glaciers of various sizes. The source area is 1,959 km long, and the natural runoff is 20.52 billion m^3.

Spatial data

The spatial data, digital elevation digital elevation model (DEM) data, land use and soil data, and DEM data required for the present study were obtained from ASTER GDEM with a resolution of 30 m (Li & Zhao 2018). The land use data was from 2010 and 2015 and was obtained from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences, with an accuracy is 30 m. Soil data was from the Chinese soil data set based on the Harmonized World Soil Database (HWSD).

Hydrometeorological data

In hydrological models, meteorological data input is the key factor affecting the result of runoff simulation. GMS required for the SWAT model includes daily precipitation, temperature, relative humidity, wind speed, and solar radiation (Zhang et al. 2005). In this research, SWAT models were driven by two data sets: GMS data set and CFSR data set. The GMS data set is derived from the China Meteorological Data Network. GMS data from nine GMS, including Xinghai, Dari, and Henan, which are located in the source area of the Yellow River, were selected as input into the SWAT model with a time span from 1997 to 2013. On the other hand, CFSR data, a third-generation analytical product developed by the NCEI of the USA, is a global, highly variable, coupled atmospheric–ocean–land–sea surface–sea ice system designed to provide best estimates of these coupling states over the period. In the present study, data from 260 CFSR stations in the source area ranging from 95°30′–103°30″ E and 32°10′–36°05′ N were used, with a spatial resolution of 38 km and a time span from 1997 to 2013.

RESEARCH METHOD

Construction and evaluation method of SWAT model

The SWAT model is a semi-distributed hydrological model developed by the U.S. Department of Agriculture in the 1990s. The model is mainly used to simulate and evaluate the hydrological process and water quality changes of basins under various management measures and climate change conditions. The simulation of the hydrological process is divided into two parts: simulation of the land surface water cycle and the confluence calculation. The water cycle process simulated by the model follows the water balance equation:

$$SW_t = SW_0 + \sum_{t=1}^{t} (R_i - Q_i - ET_i - W_i - QR_i) \tag{1}$$

where SW_t represents the final soil water content (mm), SW_0 represents the initial soil water content, t is time (day), R_i represents precipitation (mm), Q_i represents the surface runoff (mm), ET_i represents evaporation (mm), and W_i and QR_i represent water content (mm) entering the aeration zone and regression flow (mm), respectively.

Tangnaihai Hydrological Station was set as the basin outlet of the source of the Yellow River, and 54 sub-basins were divided by the SWAT model. After reclassifying the land-use types in the source area according to the SWAT land-use classification system, six types of land-use were obtained. Based on the Chinese soil data set in HWSD, 26 soil types in the source area were extracted and the required soil parameters were calculated using Soil–Plant–Air–Water (SPAW) (Jiang *et al.* 2018).

The correlation coefficient (R^2), the Nash–Sutcliffe model efficiency (NSE) coefficient and Percent Bias (PBIAS) were selected to evaluate the performance of the SWAT model in simulating runoffs. The specific calculation formula is as follows:

$$R^2 = \left[\frac{\sum_{i=1}^{n} (O_i - S_i)(S_i - \overline{S})}{\left(\sum_{i=1}^{n} (O_i - \overline{O})^{0.5}\right)\left(\sum_{i=1}^{n} (S_i - \overline{S})^{2}\right)^{0.5}} \right] \tag{2}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \overline{O})^2} \tag{3}$$

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n} (O_i - S_i) \times 100}{\sum_{i=1}^{n} O_i} \tag{4}$$

where O_i is the measured runoff sequence, S_i is the simulated runoff sequence, $\bar{O}$ is the measured average runoff, $\bar{S}$ is the simulated average runoff, and n is the series length. It is generally considered that if $R^2 > 0.6$, NSE > 0.5, and PBIAS is <25%, the performance of the model to simulate daily runoff is satisfactory. In monthly runoff simulation, if $R^2 > 0.7$, NSE > 0.55 and PBIAS is <25%, the performance of the monthly runoff model is considered to be satisfactory (Moriasi *et al.* 2015).

Evaluation on CFSR data

In order to fully quantify the accuracy of CFSR data, continuous statistical indexes were used to assess the accuracy of monthly temperature and precipitation of CFSR data set. The correlation coefficient (CC), mean error (ME), root mean square error (RMSE), and mean bias error (MBE) were selected as evaluation indexes in the present study. CC represents the degree of linear correlation between CFSR and GMS data; ME and RMSE represent the average error of CFSR data; and MBE describes the systematic bias of data (Hu *et al.* 2014; Tan *et al.*2015). The formulas for calculating each index are as follows:

$$\mathrm{CC} = \frac{\sum_{i=1}^{n} (G_i - \bar{G})(O_i - \bar{O})}{\sum_{i=1}^{n} (G_i - \bar{G}) \sum_{i=1}^{n} (O_i - \bar{O})} \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (G_i - O_i)^2}{n}} \tag{6}$$

$$\mathrm{ME} = \frac{\sum_{i=1}^{n} (O_i - G_i)}{n} \tag{7}$$

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n}(O_i - G_i)}{\sum_{i=1}^{n} O_i} \quad (8)$$

where G_i is the temperature/precipitation data in CFSR; O_i is the temperature/precipitation data in GMS; $\bar{G}$ is the average temperature/precipitation data in CFSR; $\bar{O}$ is the average temperature/precipitation data in GMS; and n is the data length.

Simulation method

Single-outlet simulation

Single-outlet simulation means that the model only has one outlet for the calibration of the model's parameters, so that the model parameters of the entire basin are consistent. Specific implementation steps, from upstream to downstream, sequentially rate the hydrological stations. When the Tangnaihai Hydrological Station is calibrated, the parameter values of all sub-basins in the source area of the Yellow River are consistent.

Multi-outlet simulation

Multiple-outlets are set in the basin and each sub-basin can be regarded as a single-outlet. The variation of parameters in each sub-basin is related to the hydrological characteristics of the sub-basin. Even if the same parameters are used, their changes in each sub-basin are inconsistent. First, as shown in Figure 1, area A is calibrated using the Jimai Hydrological Station to obtain a set of optimal parameters for the area. When calibrating the Maqu Station, the control drainage area at this time is A + B, but the parameters of area A have been calibrated at the Jimai Station. The parameters of area A are not changed, and only area B is calibrated. Then, when calibrating the Jungong Hydrological Station, its control basin area is A + B + C, the previous A and B have been calibrated, the parameters are unchanged, and only are C is calibrated. calibrating The Tangnaihai Hydrological Station, which controls the basin area A + B + C + D, is then calibrated. Similarly, A, B, and C do not need to be rated, only area D needs calibrated. Finally, the parameters of the four sub-regions A, B, C, and D are different.

RESULTS AND DISCUSSION

Parameter sensitivity analysis

The SWAT model contains many parameters that affect the results of runoff simulation. Calibrating all parameters can lead to excessive uncertainties and excessive parameters. Therefore, parameter sensitivity analysis is required to improve the efficiency and accuracy of calibration. The global sensitivity analysis of SWAT calibration and uncertainty program (SWAT-CUP) is used to analyze all parameters that affect the runoff. According to t-stat and *P*-value, the greater the absolute value of t-stat and the closer the *P*-value to 0, the more sensitive the parameters are to the model. In this study, 12 parameters with high sensitivity are selected for model calibration (Table 1).

Evaluation on data accuracy

Valuation of temperature and precipitation data

In order to assess the accuracy of CFSR temperature data in the source area of the Yellow River, GMS data were used to verify the accuracy of CFSR data. In this paper, hydrometeorological data from nine GMSs were used to drive the SWAT model. We chose four representative stations, and selected CFSR stations with similar coordinates based on their latitude and longitude for evaluation. The CC, RMSE, ME, and MBE were used as evaluation indexes. The specific evaluation results are shown in Table 2.

Table 2 reveals that the CC value of the CFSR temperature data at four stations is close to the ideal value 1, which indicates that the CFSR temperature data is closely related to the GMS temperature data. ME values at the highest temperatures at all stations were positive and MBE values were >0, indicating that CFSR data underestimated

Table 1 | Results of model sensitivity analysis

Parameter	Parameter significance	GMS t-stat	GMS P-value	GMS Ranking	CFSR t-stat	CFSR P-value	CFSR Ranking
SMTMP	Average slope length	10.85	0.000	1	5.59	0.000	3
CN2	Soil Conservation Service runoff curve number	−5.79	0.000	2	−4.35	0.000	4
SMTMP	Melting temperature	−5.55	0.000	3	−10.66	0.000	1
SFTMP	Rain-snow boundary temperature	−5.25	0.000	4	−6.37	0.000	2
ALPHA_BF	Baseflow recession constants	−4.10	0.000	5	−3.70	0.000	6
GWQMN	Return threshold of shallow groundwater	4.05	0.000	6	4.05	0.000	5
SOL_K	Soil saturated hydraulic conductivity	−2.90	0.003	7	−2.90	0.003	7
CH_K2	Effective hydraulic conductivity in main river channel	2.79	0.005	8	2.79	0.005	8
GW_REVAP	Reevaporation coefficient of shallow groundwater	2.53	0.011	9	2.53	0.011	9
CH_N2	N value of Manning's formula in river channel	2.13	0.033	10	2.13	0.033	10
EPCO	Compensation coefficient of plant transpiration	2.02	0.043	11	−2.02	0.043	11
SURLAG	Hysteresis coefficient of surface runoff	1.76	0.078	12	1.76	0.078	12

Table 2 | CFSR data evaluation

		Maqin (3451003)	Dari (339997)	Maqu (3391022)	Hongyuan (3291025)
Highest temperature	CC	1	1	0.99	0.98
	RMSE	6.9	5.5	3.3	4.1
	ME	5.9	4.5	1.7	2.8
	MBE	0.63	0.57	0.17	0.25
Lowest temperature	CC	1	0.99	0.99	0.98
	RMSE	4.12	3.45	3.2	5.05
	ME	−1.2	0.44	−1.5	−3.29
	MBE	0.18	−0.07	0.49	0.72
Precipitation	CC	0.59	0.45	0.44	0.49
	RMSE	5.1	3.71	5.2	4.7
	ME	−1.9	0.038	−1	−0.75
	MBE	−1.35	0.024	−0.67	−0.38

Note: The corresponding CFSR station number in brackets represents the meteorological station.

the temperature. The average ME of the lowest temperatures at four stations were above 0, and the MBE mean >0, indicating that CFSR data overestimated the lowest temperatures.

As for precipitation data, the CC values of the daily CFSR data at all four stations were more than 0.4, which indicates that a weak correlation between CFSR precipitation data and GMS precipitation data. The mean values of ME and MBE of CFSR data from four stations are <0, which indicates that CFSR data overestimated four meteorological precipitation data in the source area of the Yellow River.

Evaluation of accuracy of the SWAT model

Single-outlet simulation

According to the actual measured hydrological data sequence and in order to make all the hydrological processes at the initial stage of the simulation go from the initial state to the equilibrium state, a 3-year warm-up period was set. The years 2000–2009 was set as the model calibration period and 2010–2013 as the validation period. Using the combination of the SUFI-2 optimization algorithm in SWAT-CUP2012 and manual calibration, the 12 main parameters in the model were calibrated. Figure 2 shows the runoff simulation results during the model calibration period (2000–2013).

Figure 2 shows that the simulation results of the SWAT model constructed by GMS data have a high fitting degree, while the SWAT model constructed by CFSR data has a lower fitting degree. At the same time, from the index evaluation results of the four stations in Table 3, it can be seen that values of R^2 and NSE of the SWAT model constructed by GMS data are generally above 0.75, and PBIAS is <16.1% in the calibration and validation period, and the simulation results of this model are satisfactory. On the other hand, it can be seen that the R^2 of the model built by CFSR in the calibration period is above 0.68, the NSE value is above 0.65, and the PBIAS coefficient is lower than 10.4%. Except for the Jimai Station, the R^2 and NSE of the other stations during the validation period are both greater than 0.75, which indicates that the simulation results of the SWAT model driven by GMS are basically satisfactory. However, regardless of the kind of data the model is based on, the simulation results in the downstream are obviously better than those in the upstream, mainly because the regulation and storage functions of lakes were not considered in this study. There are two large lakes in the upper reaches of the source area of the Yellow River–Zhaling Lake, and Eling Lake, which have a regulating and storing effect on runoff. According to existing studies, the retention and regulation of the two lakes make the annual runoff distribution of the Yellow River, along with the source of the Yellow River, more uniform (Li *et al.* 2001). However, the study found that the runoff from the Huangheyan Hydrological Station only accounted for 19%, 6%, 5%, and 4% from Jimai, Maqu, Jungong, and Tangnaihai, respectively. Therefore, the influence from Zhaling Lake and Eling Lake on the runoff to the lower Yellow River gradually decreases. In general, the SWAT model results constructed with GMS data are better than those using CFSR data in the source area of the Yellow River.

Multi-outlet simulation

In this paper, considering the geographical location of hydrological stations and effective hydrological data, the source area of the Yellow River is generalized into four sub-regions (Figure 1), and the hydrological stations at the outlet of each region are set as the calibration points of the region. From upstream to the outlet of the basin, the hydrological stations are successively Jimai (A), Maqu (B), Jungong (C), and Tangnaihai (D). The four stations constitute nine multi-outlet calibration situations (Table 4), and

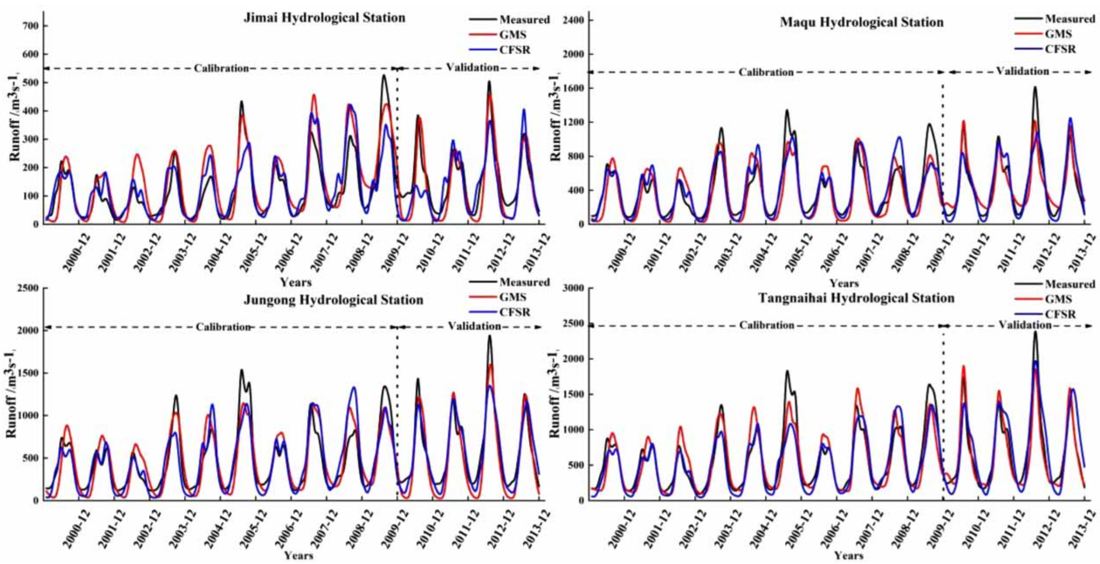

Figure 2 | GMS and CFSR calibration results in the single-outlet.

Table 3 | Evaluation results of single-outlet simulation effect

		GMS			CFSR		
Period	**Station**	**R^2**	**NSE**	**PBIAS %**	**R^2**	**NSE**	**PBIAS %**
Calibration period (2000–2009)	Jimai	0.75	0.65	−20.1	0.68	0.65	−7.2
	Maqu	0.76	0.72	10.9	0.72	0.71	−0.9
	Jungong	0.74	0.73	−0.2	0.73	0.71	2.7
	Tangnaihai	0.77	0.76	3.2	0.79	0.77	10.4
Validation period (2010–2013)	Jimai	0.79	0.68	15.4	0.59	0.60	16.9
	Maqu	0.88	0.86	−1.8	0.75	0.75	1.5
	Jungong	0.86	0.80	16.1	0.81	0.80	4.7
	Tangnaihai	0.90	0.89	6.2	0.77	0.75	−6.4

Table 4 | Multi-outlet calibration situation

Situation	Calibration station	Comparable station
2 control stations	Jimai/Maqu	Maqu
3 control stations	Jimai/Maqu/Jungong	Jungong
4 control stations	Jimai/Maqu/Jungong/Tangnaihai	Tangnaihai

the calibration results are compared with the single-outlet calibration.

According to Figure 3, the simulation results are slightly worse than the single-outlet simulation results. The difference is mainly manifested in the overestimation of peak flow in 2000 and 2003 and the flow process is advanced. However, during the verification period, the multi-outlet calibration method is generally better than the single-outlet calibration method, and the simulation results fit the measured runoff process line to a higher degree. From the evaluation indicators of the model in Table 5, it can be seen that during the calibration period, both R^2 and NSE indicators are significantly reduced, especially at the Maqu Station, R^2 is reduced by 18%, and NSE is reduced by

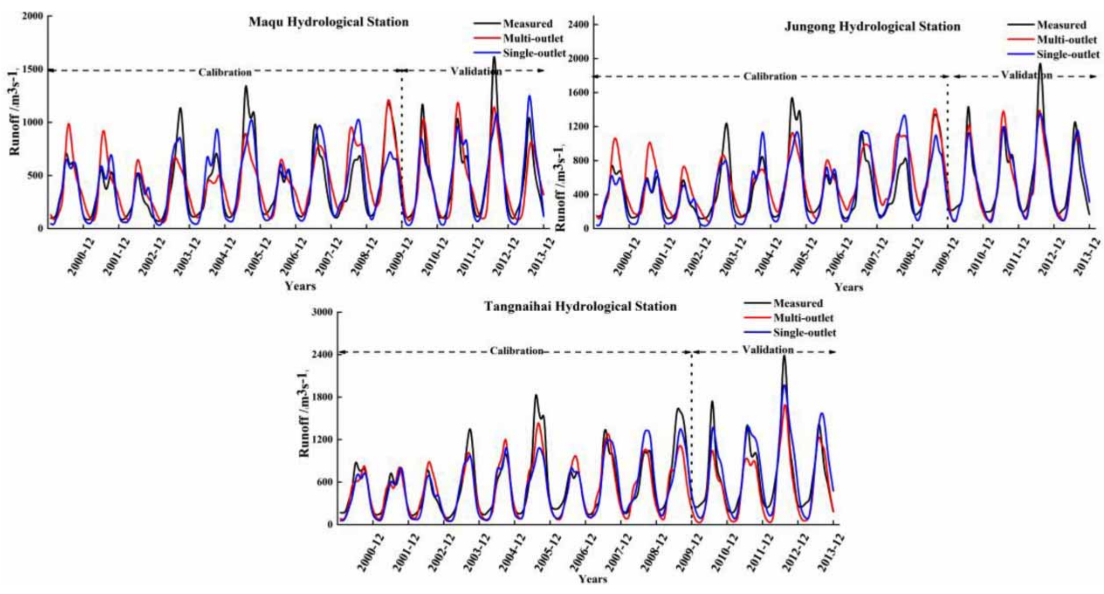

Figure 3 | Comparison of single-outlet and multi-outlet of three hydrological stations.

Table 5 | Evaluation results of single-outlet and multi-outlet simulation effect

		Single-outlet			Multi-outlet		
Period	Station	R^2	NSE	PBIAS %	R^2	NSE	PBIAS %
Calibration period (2000–2009)	Jimai/Maqu	0.72	0.71	−0.9	0.59	0.56	−8.1
	Jimai/Maqu/Jungong	0.73	0.71	2.7	0.66	0.61	−16.9
	Jimai/maqu/Jungong/Tangnaihai	0.79	0.77	10.4	0.78	0.76	9
Validation period (2010–2013)	Jimai/Maqu	0.75	0.75	1.5	0.77	0.77	5.7
	Jimai/Maqu/Jungong	0.81	0.8	4.7	0.8	0.79	6.2
	Jimai/Maqu/Jungong/Tangnaihai	0.77	0.75	−6.4	0.83	0.74	23.5

21%. During the verification period, the R^2 and NSE indicators were slightly improved through the multi-outlet calibration method: under the multi-outlet calibration at Maqu Station, R^2 and NSE increased by 1% and the R^2 at Tangnaihai Station increased by 5%. In general, the multi-outlet simulation does not reduce the simulation accuracy of the basin total outlet, and it also enables the spatial differences of each sub-basin hydrological characteristics to improve the simulation accuracy of the sub-basin simulation.

As shown in Table 6, after multi-outlet calibration, the model parameters have changed significantly. Most of the parameter values are different to those under single-outlet calibration. For example, when the parameter GWQMN is in single-outlet calibration mode, the value of this parameter is proportional to the simulation effect, the larger the value, the better the simulation effect. In the multi-outlet calibration mode, the parameter value is inversely proportional to the stimulation effect, and the change of each parameter is more in line with the underlying surface characteristics of the sub-basin.

CONCLUSION

This article evaluates the applicability of the CFSR data set in the source region of the Yellow River from both statistical and hydrological aspects. In the hydrological evaluation, in order to reasonably evaluate the data and reduce the impact of the SWAT model calibration method on the simulation results, single-outlet simulations and multi-outlet simulations were carried out.

Table 6 | The parameter fitted value of single-outlet and multi-outlet simulation effect

	Maqu		Jungong		Tangnaihai	
Parameter name	Single-outlet	Multi-outlet	Single-outlet	Multi-outlet	Single-outlet	Multi-outlet
CN2	59.68	51.78	25.78	51.75	48.18	61.27
ALPHA_BF	0.27	0.07	0.47	1.00	0.43	0.07
GWQMN	3,703.59	4,463.84	3,855.93	3,328.98	5,000.00	0.00
GW_REVAP	0.20	0.20	0.13	0.12	0.12	0.12
EPCO	0.20	0.10	0.11	0.97	0.96	1.00
SLSUBBSN	87.63	128.38	91.58	75.22	38.92	113.65
SFTMP	−20.00	−1.34	−15.69	−9.05	−25.76	4.20
SURLAG	0.00	23.96	6.99	24.00	23.00	5.69
SOL_ALB	0.04	0.06	0.07	0.23	−0.03	0.13
CH_N2	0.30	0.19	0.30	0.23	0.19	−0.01
CH_K2	405.32	268.96	402.13	311.82	500.00	30.91

According to the data statistical evaluation, it is found that the CFSR temperature data at the source of the Yellow River is basically consistent with the measured temperature data, but the temperature is overestimated. CFSR precipitation data has a general linear relationship with GMS precipitation data, but the precipitation is also overestimated.

This paper used CFSR data and GMS data to drive the SWAT model, and compared model runoff simulation results at Jimai, Maqu, Jungong, and Tangnaihai Hydrological Stations. It found that both data set-driven models can achieve satisfactory simulation results. In general, the simulation effect of GMS is better than that of CFSR data.

The simulation result of the CFSR data set under the multi-outlet calibration was not as good as the single-outlet calibration method. However, during the verification period, the simulation result of the multi-outlet calibration method was worse than the single-outlet calibration method. In addition, the multi-outlet calibration method did not reduce the simulation accuracy of the total outlet of the basin, but it can consider the spatial differences of the hydrological characteristics of each sub-basin to improve the simulation accuracy of the sub-basin simulation.

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DATA AVAILABILITY STATEMENT

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

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