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Original Research

Daily-Scale Runoff Simulation of Shanxi Drinking Water Based on SWAT Model, Using Separation Dry and Wet Season Calibration Method

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Abstract

In this study, by establishing a daily scale SWAT model with dry and wet seasons separated in the study area, the sensitivity and uncertainty of parameters in the typhoon-affected area are discussed. At the same time quantitative analysis of the temporal and spatial characteristics of water resources. The results show that 1) the sensitivity parameters in the dry and wet seasons are very different. The most sensitive parameters are ALPHA_BF.gw and CN_2.mgt, but the least sensitive parameters are SURLAG.bsn and GWQMN.gw, respectively. This is obviously related to the meteorological conditions of the two periods. 2) Uncertainty analysis shows that the uncertainty of model parameters is mainly caused by extreme daily runoff parameters. 3) Except that the *NSE* and R^2 of the wet season model are slightly lower than 0.7, the *NSE* and R^2 of the dry season are higher than 0.73, and the PBIAS in both periods is within 10%. This shows that the application of separate calibration methods improves the accuracy of the model. 4) The correlation between wet season precipitation and runoff is higher than 0.98. The average wet season runoff for many years accounts for 81.44% of the annual runoff, which is the main period of runoff generation. The key source area of runoff is 51.04% of the total area of the river basin, and the runoff flow accounts for 54.21% of the total runoff of the land. It should be protected.

Keywords: SWAT model, drinking water, daily scale, parameter sensitivity, key source area

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Introduction

For drinking water, studying its hydrological process and clarifying the spatial and temporal distribution of water resources is of considerable significance today. As an essential tool for quantitative assessment of underlying surface changes and hydrological response, it is convenient and intuitive in hydrological research. At the same time, the model can well study the spatial and temporal distribution of water resources in the basin. At present, the Xin'anjiang model, SWAT, HSPF, and other models have been widely explored and applied worldwide [1-3]. With the convenience of model, researchers have carried out a lot of research on the rainfall-runoff process and achieved a series of results. Marhaento et al. [4] applied the SWAT model to quantify the extent of land use influence on runoff and the close relationship between runoff and the area of forest and built-up land in the watershed. The SWAT model was applied to quantitatively analyze the extent of land use influence on runoff and the close relationship between runoff and forest and built-up land area in the watershed. Wenting Yang et al. [5] SWAT model was used as a basis to integrate the effects of land use and climate change on the runoff of the Luan River in China, and to predict the response of future runoff to land use and climate change. Although the model provides convenience for the hydrological and water resources issues in our study area, the model also has problems such as numerous parameters and difficult calibration.

SWAT model, as a distributed mechanism hydrological model, can well simulate the hydrological regularity and the spatial-temporal changes of water resources in the river basin. Chen et al. [6] applied the HSPF and SWAT models to compare the uncertainty of land-use change simulations on the impact of river basin runoff on multiple time scales. Mou et al [7] constructed a SWAT model of the Kelantan River basin in Malaysia with 58 rainfall station absence scenarios and showed that rainfall data from at least four rainfall stations are required to achieve accurate simulation of monthly average runoff in the basin. Golmohammadi et al. [8] applied SWAT models in the Gully Creek Basin in Ontario to assess the temporal change of the predicted flow contribution area and provide the best management practices for basin water resources assessment and planning. However, the problem of difficult parameter calibration and uncertainty also limits the application of the model [9]. Aiming at the issue of calibration and uncertainty of SWAT model parameters, many researchers have proposed many targeted methods based on different characteristics of the watershed, such as monomorphic method [10], genetic algorithm [11], and so on. However, the above methods only consider the evaluation of the numerical results of the model. Although the calibration results are ideal, it does not take into account the natural conditions of the region. The parameters after the calibration cannot reflect the actual situation of the study area. For different spatial and temporal conditions in the same area, the parameters will change with climatic conditions and land-use changes, especially in areas affected by extreme weather [12]. Lin et al. [13] proposed a method for separate determination of dry and wet seasons, which takes into account the significant differences in annual precipitation distribution in the study area, improves the accuracy of the simulation, and has good reference value for the SWAT model calibration. It is difficult to obtain limited meteorological and hydrological data. Most SWAT models are studied on a monthly scale, which makes the model unable to reflect the hydrological process of the basin, especially the daily runoff changes, and cannot accurately show the source of uncertainty of the model.

In this study, we take the Shanxi drinking water, significant drinking water in eastern Zhejiang Province, China, as the research object. Firstly, the SWAT runoff model on a daily scale is established, and the dry and wet season calibration method is used to calibrate the model parameters. Secondly, the SUIF-2 algorithm by SWAT-CUP was used to analyze the parameter sensitivity and uncertainty of the two daily scale SWAT models, and the model parameters were calibrated. Finally, the quantitative analysis of the runoff distribution of the water source area is analyzed, and its spatial and temporal distribution characteristics are analyzed to provide support for watershed management agencies to make water resources management decisions.

Material and Methods

Study Area

The study area is located in the southeastern part of Zhejiang Province, China, at the Shanxi Reservoir basin in the middle reaches of the Feiyun River, which is a drinking water (Fig. 1). Most of the rivers in the basin are mountain rivers, the river slopes are large, and the convergence velocity is fast. The area of the control basin above the dam site is 1,529 km^2, accounting for 47% of the total area of 3252 km^2. The annual average runoff of the river basin is 1.8 billion m^3. The total storage capacity is 804 million m^3, and the annual water supply is 1.34 billion m^3. The water supply range is the Wenrui Plain and the area south of the Feiyun River. The water supply zone benefits 5 million people. There are three counties in Taishun, Wencheng, and Jingning, covering the two cities of Wenzhou and Lishui. The economic characteristics of the townships in the basin are still mainly agricultural. The land-use types in the river basin are mostly forest land, farmland, construction land, grassland, and waters, of which the main is forest land, with a proportion of 78% [14].

The watershed is located in low latitudes. Because it is close to the East China Sea and has sufficient precipitation, it belongs to the subtropical monsoon climate zone. At the end of winter and early spring, due to the influence of the northward subtropical high, the rainfall was mainly light rain. In late spring and early summer, due to the warm Pacific high pressure gradually advancing to the mainland, it moved in the basin to form continuous precipitation, commonly known as "Meiyu." From July to September, affected by the subtropical high pressure, typhoon activities were frequent, and thunderstorms and typhoon rains caused massive floods. In the autumn, the subtropical high moves eastward, and precipitation decreases. Winter weather is mainly sunny and cold with little rain or snow.

Data Source

The data in this study mainly include DEM (Digital Elevation Model), land use, soil data, meteorological data, and hydrological data. The scale of DEM data used in this study is 1:50000, the spatial resolution is 30m, and the data source is ASTER Version 2 data. The land use data were based on Landsat TM 30 m remote sensing images in September 2010, and based on the national land use classification method, combined with the LUCC classification system established by Liu. [15]. The land-use types are classified into 6 first-class and 25 second-class types. Reclassify the original data to obtain 13 types of land use (Fig. 1b). The soil data are HWSD data from the Cold and Arid Region Scientific Data Center, with a scale of 1:1 million and a spatial resolution of 1 km. The data is in the FAO-90 soil data format. A total of 16 soil types were obtained by reclassifying them (Fig. 1c). The meteorological data use daily observation data from 4 stations deployed by the local meteorological department in the study area. The time series is from 1956 to 2012, including data such as precipitation. Hydrological data are daily runoff data for a total of 6 years from 2007 to 2012 and are derived from the local water resources department. The hydrological station is located at the outlet of the basin, as shown in Fig. 1a). According to the characteristics of precipitation during the year in the study area, from April 1st to September 30th is designated as the wet season and from October 1st to March 31st as the dry season.

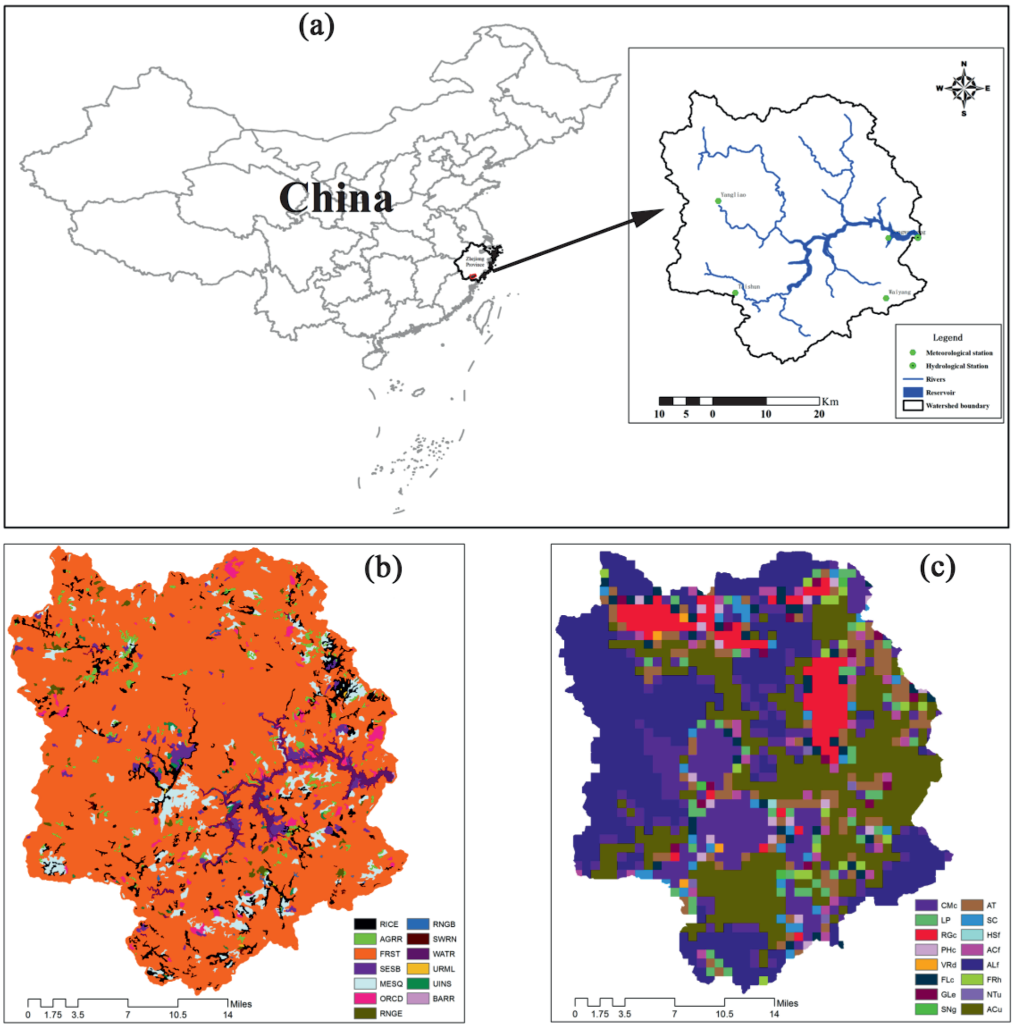

Fig. 1. Location of the study area.

Application of SWAT Model

SWAT Model

The SWAT (Soil and Water Assessment Tool) model was developed by the United States Department of Agriculture (USDA). Continuous calculations can be performed in units of time per day to achieve simulation of hydrological runoff, sediment, nutrients, pesticides, etc. [16]. The hydrological process of the SWAT model is divided into the land phase and the confluence phase of the hydrological cycle. The former controls the input of water, sand, nutrients, and chemicals in the main channel in each sub-basin; the latter determines the movement of water, sand, and other substances from the river network to the exit of the river basin. The entire water circulation system follows the law of water balance [17].

In this study, the ArcGIS 10.2 was used to establish the SWAT model space and attribute database of the Shanxi drinking water based on DEM, soil data, land use, and meteorological data in the study area. Using ArcSWAT 2012 tools and DEM to extract watershed topographic features, including rivers, slope, and river parameters, etc. The entire study area was divided into 37 sub-basins. According to the soil, land use, and slope data, it is further divided into 412 hydrological response units (HRUs). According to the precipitation, the study developed two SWAT models, dry season and wet season.

Calibration and Validation of Models

The calibration of the model was performed using SWAT-CUP software [18]. SUFI-2 method is used for parameter calibration and sensitivity analysis. This method considers all sources of uncertainty, such as driving variables, conceptual models, parameters, and monitoring data, which is widely used in the study of SWAT models [19].

At the same time, 95% prediction uncertainty (represented by 95PPU in SWAT-CUP) was used to quantify the uncertainty of the output result. Two factors, P-factor and R-factor, are given to quantify the uncertainty of the model parameters. Among them, the range of the P-factor value is 0~1, which represents the proportion of measured data in 95PPU. The larger the value, the higher the consistency between the measured data and the simulated data. R-factor represents the ratio of the average thickness of 95PPU to the standard deviation of the measured data. The smaller the value, the better the simulation result [20].

In this study, three statistical parameters: Nash-Sutcliffe efficiency coefficient (*NSE*), coefficient of determination (R^2), and percentage bias (PBIAS) were used to characterize the applicability of the model. The calculation of the three parameters is as follows:

$$\mathrm{NSE} = 1 - \frac{\sum_i (Q_m - Q_s)_i^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2} \quad (1)$$

$$R^2 = \frac{\left[\sum_i (Q_{m,i} - \bar{Q}_m)(Q_{s,i} - \bar{Q}_s)\right]^2}{\sum_i (Q_{m,i} - \bar{Q}_m)^2 \sum_i (Q_{s,i} - \bar{Q}_s)^2} \quad (2)$$

$$\mathrm{PBIAS} = \frac{Q_m - Q_s}{Q_m} \times 100\% \quad (3)$$

Where, Q_m represents the measured runoff data, and Q_s represents the simulated runoff data. Generally, the closer the *NSE* and R^2 are to 1, the higher the model efficiency and the better the applicability. For PBIAS, a value of less than ±10% indicates that the model is very applicable, and it is acceptable in the range of ±15% ≤PBIAS≤±25%. The broader range of applicability parameters for daily runoff models [21].

Results and Discussion

Parameter Sensitivity and Uncertainty Analysis

In terms of parameter selection, based on the existing SWAT research, 11 parameters, such as CN_2, ALPHA_BF, GW_DELAY, which are sensitive to the impact of runoff, were selected and calibrated [13, 22, 23]. SWAT-CUP software was used to carry out sensitivity and uncertainty analysis. The sensitivity ranking of different hydrological season parameters is shown in Table 1.

As can be seen from Table 1, the most sensitive parameters in the dry season SWAT model are CN2.mgt and ALPHA_BF.gw. These two parameters are also the most sensitive in the wet season model, but

Table 1. Data used for SWAT model development in Shanxi drinking water.

Data type	Data	Source
GIS	30 m DEM	ASTER Version 2 data (http://www.gscloud.cn/)
	Land use	National Land Use Data Products Based on Landsat TM 30 m Remote Sensing Image
	Soil data	HWSD data from the Cold and Arid Region Scientific Data Center
Climate	Rainfall and temperature (1956~2012)	Local Meteorological Department
Hydrology	Streamflow (2007~2012)	Local Water Conservancy Bureau

the sensitivity rankings are interchanged. The least sensitive parameters in the dry season are GW_DELAY.gw and SURLAG.bsn. Among them, the sensitivity order of the parameters GW_DELAY.gw in the dry season and the wet season is the same, which are all less sensitive parameters. The most sensitive parameter in the wet season is GWQMN.gw.

It can be seen from Fig. 2 that, except for the individual peak values in the wet season during the typhoon, are not falling under the 95PPU band, the rest are within it. The P-factor and R-factor of the dry season calibration period were 0.66 and 0.63, and through the validation, they were obtained as 0.88 and 0.75, respectively. The P-factor and R-factor in the wet season calibration period were 0.83 and 0.77, and the parameter values in the validation period were 0.75 and 0.61, respectively.

The parameters in the SWAT model have corresponding practical meanings. Sensitivity analysis of parameters revealed that the first two sensitivities in the dry season model are ALPHA_BF.gw and CN2.mgt, which are parameters representing groundwater and surface water, respectively. Among them, CN2.mgt represents the number of net flow curves under the average soil humidity state, which directly affects the size of surface runoff [24]. The soil moisture at the beginning of different hydrological seasons in the Shanxi drinking water varies greatly, and the difference in CN2 values is relatively large. ALPHA_BF.gw is the α factor of the base flow, which is a parameter reflecting the length of the base flow subsiding time. The larger the value, the greater the underground runoff and the more stable the base flow subsiding process [25]. The Shanxi drinking water is located upstream of the Feiyun River basin. This area is a hilly area, where surface runoff has a more significant impact on groundwater recharge [26]. The most insensitive parameter in the dry season is SURLAG.bsn. This parameter is the surface runoff lag index, which represents the percentage of water that can sink into the river on any given day as a percentage of the total available water [27]. Studies show that a time of concentration higher than one day means that the whole amount of surface runoff does not reach the river on a given day [27, 28]. Less rainfall during the

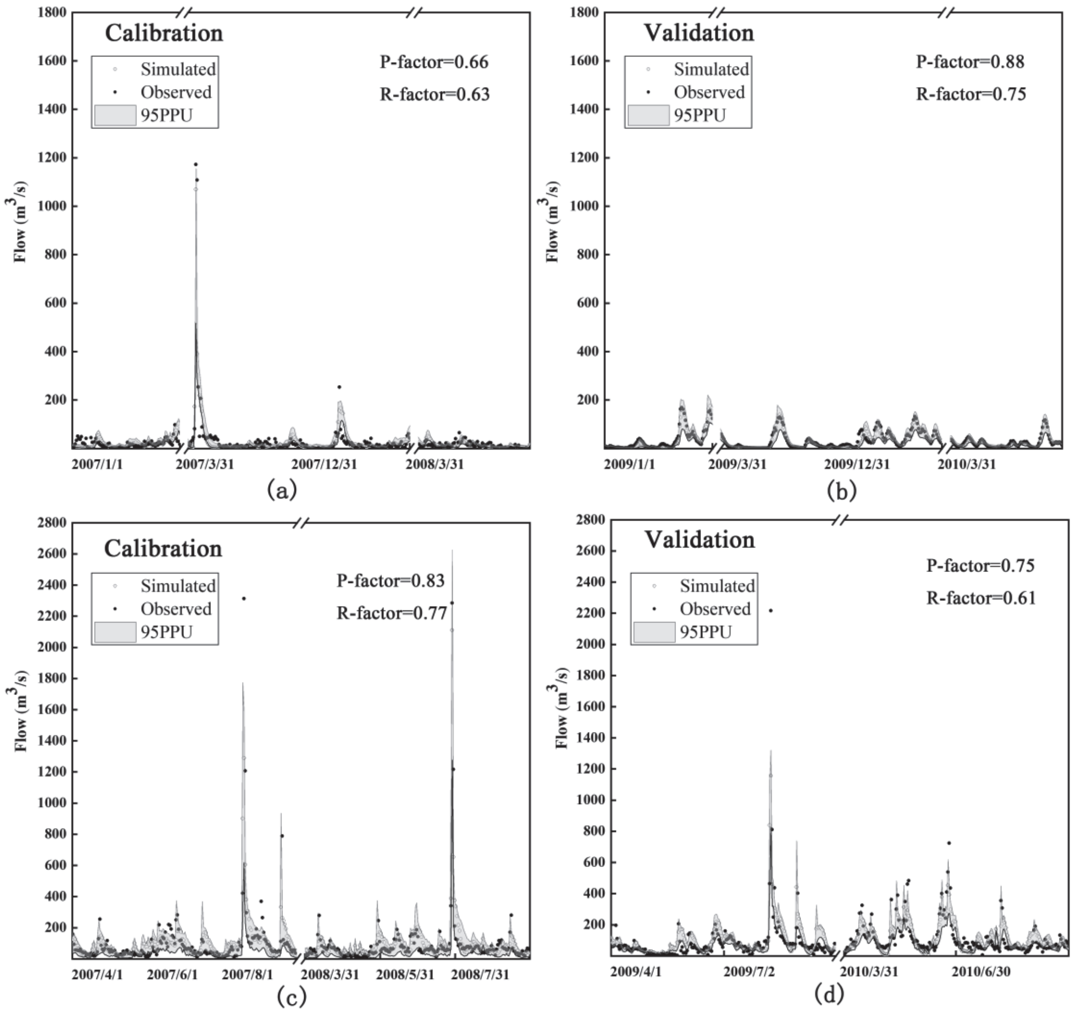

Fig. 2. 95% probability uncertainty plot, simulated and observed streamflow during the dry and wet seasons. (a) and c) are the calibration periods of the dry and wet seasons (2007~2008), and b) and d) are the validation periods of the dry and wet seasons (2009~2010)).

dry season and longer confluence times may be the main reason for this parameter's insensitivity. The most insensitive parameter in the wet season is GWQMN.gw. This parameter indicates that the initial water depth of shallow water storage is required when the return flow is generated. Only when the water depth of the shallow water storage layer is equal to or higher than GWAMN. gw that groundwater enters the river. Groundwater in the wet season is generally shallow, so it is not sensitive to this parameter.

The parameter uncertainty study revealed that the overall simulation effect is better, which is related to the SWAT model is not an ideal simulation of extreme runoff [29, 30]. The P-factor from the dry season calibration period to the verification period increased from 0.66 to 0.88. It can be seen from Fig. 2a) that the dry season calibration period produced a runoff with a mean runoff of three times the verification period in March 2007. At the same time, the study of historical transit typhoons found that the research area during this period was affected by typhoon KONG-REY (China Typhoon 200701). This uncertainty is caused by runoff observations [20]. This may also be the main reason why the wet season calibration period P-factor is greater than the verification period value. The parameter uncertainty analysis of the dry season and wet season models found that when the two-parameter ranges of P-factor and R-factor reached the optimal state, the uncertainty of the parameters was acceptable.

Calibration and Validation of Daily Runoff

The Shanxi drinking water is located on the eastern coast of Zhejiang Province, China, and the region is greatly affected by extreme weather such as typhoons [31]. The vast differences in meteorological conditions will inevitably lead to different model parameters, which was revealed in much other research [31, 32]. Hence, this study used the calibration method of separating dry season and wet season to calibrate the daily runoff model parameters of the Shanxi drinking water. Table 2 shows the applicability parameter values for different hydrological season calibration and validation periods, and the fitted conditions of the daily runoff observation and simulation values, as well as the distribution in the 95PPU interval, are shown in Fig. 2.

As can be seen from Table 2, except that the *NSE* and R^2 in the wet season are lower than 0.7, the *NSE* and R^2 in the dry and wet seasons are all above 0.73, and the *NSE* and R^2 in the dry season are greater than 0.91. Regardless of the dry and wet seasons, the PBIAS is within ± 10%. All these show that the model is highly efficient, and the model built can well implement the daily runoff simulation of the Shanxi drinking water.

The applicability analysis of the model shows that the applicability of the dry season model is better than the applicability of the wet season model. Because the source of Shanxi water is in the area affected by the typhoon, there is more extreme precipitation, and it mostly occurs in the wet season. These extreme

Table 2. The sensitivity ranking of dry and wet season parameters

Dry season			Wet season		
parameter	t-Stat	P-Value	parameter	t-Stat	P-Value
V__ALPHA_BF.gw	19.51847	0	R__CN2.mgt	2.39196	0.01777
R__CN2.mgt	4.42256	0.00002	V__ALPHA_BF.gw	2.31935	0.02147
V__REVAPMN.gw	1.93606	0.05439	V__CANMX.hru	2.05624	0.04117
R__SOL_AWC(..).sol	-1.4589	0.1463	V__GW_REVAP.gw	-1.31576	0.18989
V__CANMX.hru	-1.38872	0.1666	R__SOL_AWC(..).sol	1.19702	0.23284
V__RCHRG_DP.gw	1.29163	0.1981	V__REVAPMN.gw	0.70404	0.4823
R__SOL_K(..).sol	0.98518	0.32583	V__SURLAG.bsn	-0.57098	0.56871
V__GW_REVAP.gw	-0.94117	0.34785	R__SOL_K(..).sol	0.38487	0.70078
V__GWQMN.gw	-0.8189	0.4139	V__RCHRG_DP.gw	0.37087	0.71116
V__GW_DELAY.gw	-0.70721	0.48033	V__GW_DELAY.gw	-0.36435	0.71601
V__SURLAG.bsn	0.60333	0.54703	V__GWQMN.gw	-0.32737	0.74376

[1]Note: .gw indicates the groundwater file, .rte indicates the main channel file, .mgt indicates the HRU management file, .sol indicates the soil input file, and .bsn indicates the general properties file of the river basin. V_ means that the given value replaces the original value of the parameter, and R_ implies that the original value of the parameter is multiplied by (1 + the given value). t-stat and P-value are two values obtained by SWAT-CUP using t-test and statistical significance tests, respectively. The t-star value indicates the degree of parameter sensitivity. The greater the absolute value, the higher the parameter sensitivity, the P-value indicates the significance of sensitivity, the closer the value is to 0, the more significant. The parameters in the table are arranged in ascending order of sensitivity.

meteorological factors make the simulation accuracy of wet season runoff lower than the dry season. Studies by Lin et al. [13] also show that the more stable meteorological conditions in the dry season make it easier for SWAT to simulate hydrological processes.

Distribution of Water Resources

Characteristics of Annual Variation of Water Resources

Based on the rainfall data simulation and statistical analysis of the Shanxi drinking water area from 1993 to 2012, it was found that most of the rainfall in the Shanxi drinking water was concentrated in the wet season (April to September). According to the simulation output results of the SWAT model in the dry and wet seasons on a daily scale, the runoff output in the dry and wet seasons was statistically analyzed to obtain the percentage of the wet season runoff in the whole year (Fig. 3). At the same time, statistics and analysis of the changes in monthly runoff over the years (Table 3). From Fig. 3, it can be seen that the annual runoff ($19.54x10^8$ m^3) in the extreme water year (2005) is about 2.1 times that in the arid year (2003, $8.48x10^8$ m^3). The surface runoff in the wet season as a percentage of the whole year is 68.23% to 90.37%, with a multi-year average of 81.44%. It can be seen from Table 3 that the maximum monthly rainfall is 332.66 mm in August, and the minimum monthly rainfall is 64.33 mm in December. The peak monthly surface runoff for many years was 25.445x107 m^3, which occurred in August, and the minimum value was 3.402x107 m^3, which occurred in January. The flow in August was about 7.5 times that of JanuaryAnalysis of the temporal distribution of runoff in the study area shows that the surface runoff in the wet season exceeds 4/5 of the year, which indicates that the surface runoff in the Shanxi drinking water is mainly caused by the wet season rainfall [33]. The correlation coefficient between the monthly rainfall and surface runoff in the wet season is 0.98, and 0.95 in other periods, which reveals the close relationship between the wet season rainfall and surface runoff, and also reflects that the wet season is compared with different periods, the correlation between rainfall and runoff is more severe. Besides, the multi-year monthly surface runoff peaked in August and was the lowest in January, and the runoff in August was about 7.5 times that of January, which indicates that the surface runoff of the Shanxi water source is exceptionally uneven throughout the year.

Spatial Distribution of Water Resources and Identification of Key Source Areas

Based on the SWAT output results at the sub-basin level, using the geostatistical analysis function of ArcGIS, the runoff modulus of the Shanxi drinking

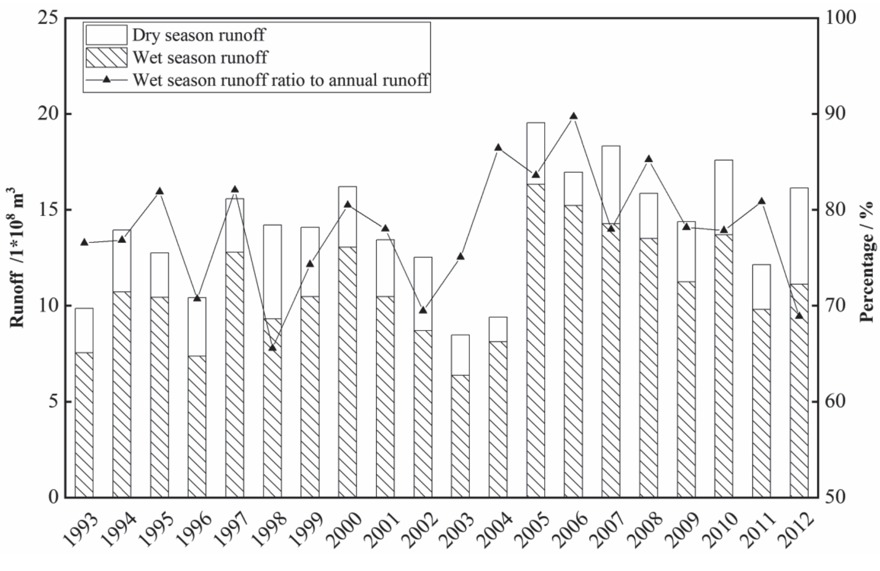

Fig. 3. The percentage of the wet season runoff in the study area.

Table 3. Model suitability parameters for dry and wet seasons.

Time range	Calibration			Validation		
	NSE	R^2	PBIAS(%)	NSE	R^2	PBIAS(%)
Dry season	0.76	0.74	9.3	0.91	0.92	-6.8
Wet season	0.73	0.73	4.4	0.67	0.68	-7.0

Table 4. The average monthly rainfall and surface runoff from 1993 to 2012.

Month	Precipitation/mm	Monthly runoff/10^7m^3
1	71.56	3.402
2	93.28	4.495
3	165.56	9.537
4	176.92	10.994
5	242.86	16.335
6	329.76	24.281
7	270.02	19.625
8	332.66	25.445
9	182.09	13.666
10	79.80	5.185
11	82.55	4.373
12	64.30	3.630

water is divided into five intensity levels at equal intervals. The higher the level, the more the runoff and the levels are expressed in order. For: minor, moderate, moderate, severe, and very Severe, the spatial distribution is shown in Fig. 6. The sub-basin with the highest runoff modulus was identified as the key source area, and the classification results are shown in Fig. 4. It can be seen from the figure that the regions with more water in the Shanxi drinking water real estate are sub-basins No. 15 and No. 18, and the two sub-basins have average annual water production They are 12894.04 mm and 12183.43 mm, respectively. The larger water production areas are the catchment areas above the No. 23 and No. 26 sub-basins. The areas with the smallest water production were No. 4 and No. 6 sub-basins, 8181.33 mm and 8114.62 mm, respectively. The maximum water production area is 1.6 times the minimum area. The smaller production flows are the sub-basins No. 4 and 6, and the catchment area above the No. 32 sub-basin.

It can be seen from the spatial distribution of runoff at the Shanxi drinking water that the overall output flow shows a decreasing trend from a tributary to the main. The areas with large output flows are the catchment areas above the No. 23 and No. 26 sub-basins. As can be seen from Fig. 1b), the land use types in the above regions are mainly forest land, and the area covers 51.04% of the total area of the watershed. The output flow accounts for 54.21% of the total output of the basin, which is the key area for water conservation [34]. The water intake of the Shanxi

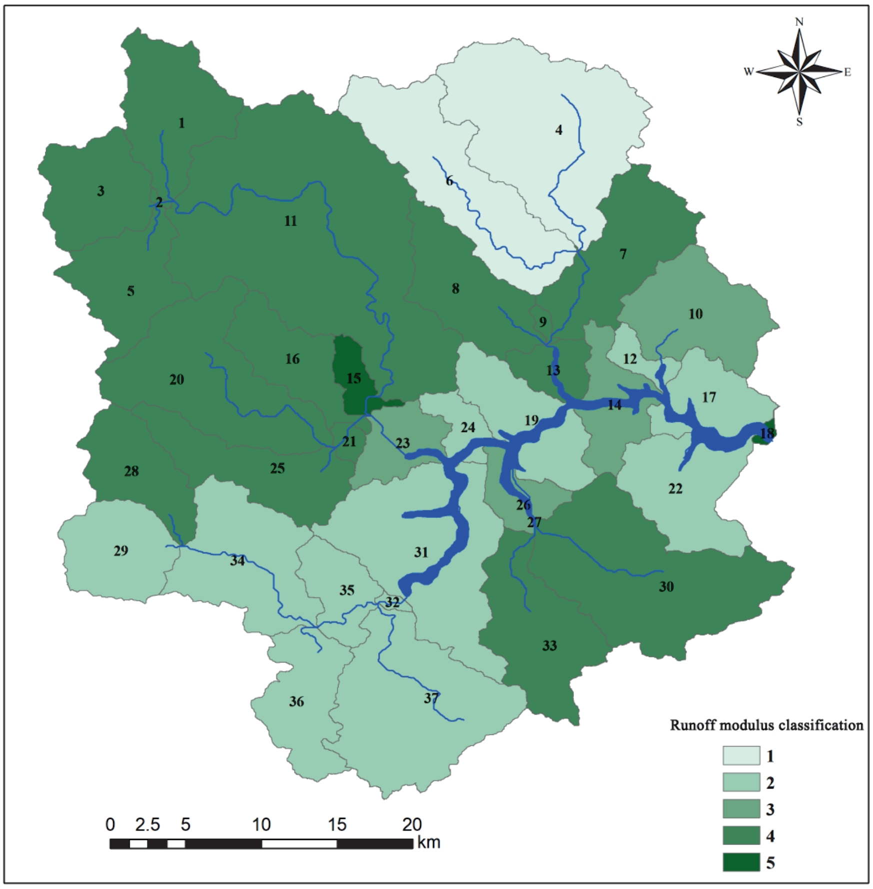

Fig. 4. Spatial distribution of runoff modulus classification.

drinking water is located in the No. 18 sub-basin, and the sub-basin has a large output, which is a crucial source area for regional water resources protection. Sub-basin No. 4, sub-basin No. 6, and catchment area above sub-basin No. 32 are urban construction areas in the watershed, which are greatly affected by human activities. This is the main reason for the small water production in the above areas. Therefore, improving the behavior of social activities and adopting low-impact development measures such as returning farmland to forests, increasing urban greening, and artificial wetlands can significantly reduce surface runoff loss.

Conclusion

In this study, we take the "big water tank" Shanxi drinking water in Wenzhou, Zhejiang, China, as the research object, and establish a SWAT model on a daily scale. Considering the impact of extreme weather such as typhoons on the area, the whole series is divided into dry seasons (January - March, October - November) and wet season (April-September). Establish two daily runoff models in dry and wet seasons. The SUIF-2 algorithm of SWAT-CUP software was used. The measured runoff from 2007 to 2010 was used to calibrate and validate the model parameters. The study also analyzed the sensitivity and uncertainty of the parameters. With the sub-basin as the output unit, the temporal and spatial distribution of water resources in the basin is analyzed. The conclusion are as below:

1) Analysis of parameter sensitivity shows that there is a massive difference in parameter sensitivity between dry and wet seasons. ALPHA_BF.gw and CN_2.mgt are the most sensitive parameters in both seasons. These two parameters represent the surface and underground runoff processes, respectively. The most insensitive parameters of the dry and wet season models differ significantly, one is SURLAG.bsn, and the other is GWQMN.gw. Relatively less precipitation during the dry season and the converging time is longer. The higher groundwater level in the wet season is the main reason for the insensitivity of the above two parameters.

2) Uncertainty analysis of the parameters revealed that when the P-factor and R-factor reach the desired limits, the uncertainty of the parameters was acceptable. The few data that did not fall on the 95PPU belt were mostly extreme precipitation from typhoons, indicating that the uncertainty of the observation data mostly caused the uncertainty of the parameters in this study.

3) Except for the *NSE* and R^2 in the wet season validation period are 0.67 and 0.68, the *NSE* and R^2 in the different periods are above 0.73, PBIAS is within ±10%, the model efficiency is high, and the daily runoff simulation of the water source can be well realized. The dry and wet season separation calibration methods are very suitable for the study area.

4) The annual variation of runoff from the Shanxi drinking water is enormous. The annual runoff mainly comes from the wet season. The correlation between wet season precipitation and runoff is as high as 0.98. The maximum and minimum runoff months are August and January, respectively. The percentage of surface runoff during the wet season ranges from 68.23% to 90.37%, and the average for many years is 81.44%. The key source areas of the distribution are sub-basins No. 15 and No. 18, and the areas with more abundant water production are watersheds above No. 23 and No. 26 sub-basins, respectively. The region accounts for 51.04% of the total area of the watershed. The land-use type is mainly forest. Regional water production accounts for 54.21% of the water production in the basin and is the key area for water conservation. Areas with less water production are mainly places with more human activities. Therefore, reducing human activities, such as returning farmland to forests, is an effective way to protect water resources.

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Conflict of Interest

The authors declare no conflict of interest.

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