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Comparison of Two Versions of SWAT Models in Predicting the Streamflow in the Xuanmiaoguan Reservoir Catchment

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ABSTRACT

Correct streamflow prediction is critical for determining the availability and efficiency of watershed spatial plans and water resource management. In the Xuanmiaoguan (XMG) Reservoir Catchment, two different versions of the Soil and Water Assessment Tool (SWAT) model are compared to discharge predictions. One version is the Topo-SWAT, in which the overland flow is generated by saturation excess (Dunne) runoff mechanism, while the other is driven by infiltration excess runoff mechanism, i.e., the Regular-SWAT. These SWAT models were calibrated and validated with discharge at daily and monthly steps, and then, the annual runoff volume and spatial distribution of runoff generation areas were also discussed. At the monthly scale, the un-calibrated Topo-SWAT model outperformed the un-calibrated Regular-SWAT model throughout the whole time (2010-2016). The Nash-Sutcliffe efficiency coefficients (NSE) using Topo-SWAT and Regular-SWAT were 0.59, 0.58 for calibration and 0.69, 0.72 for validation for daily streamflow, and 0.69, 0.65 for calibration and 0.73, 0.88 for validation for monthly streamflow, respectively, based on the parameter sensitivity analysis results. There was a 5-year understatement for yearly runoff volume using Regular-SWAT, but a 4-year underestimation using Topo-SWAT, which had a different year in 2015. Regular-SWAT and Topo-SWAT have significantly different geographical distributions of runoff generating locations within the watershed for one occurrence (greater rainfall). The findings reveal the most accurate contributing regions for runoff generation in the research catchment, allowing for more effective implementation of best management techniques (BMPs).

INTRODUCTION

The location of frequently-generated overland runoff areas, (i.e., hydrologically sensitive areas), is important to select to implement best management practices (BMPs) to cut down on non-point source (NPS) pollution (Gerard-Marchant et al. 2006). Because streamflow is the primary transporter of nutrients into the water, runoff-producing sites could be considered critical source areas (CSAs) for nutrient loss (where higher potential nutrient loss corresponds to higher runoff loss) (White et al. 2009). Hydrological models are vital and effective instruments for locating HSAs and CSAs, and they are increasingly employed in soil and water management, as well as pollution control. The models may reduce the cost of implementing and evaluating management methods, hence reducing waste and unwanted results (Golmohammadi et al. 2017).

The SWAT model (Arnold et al. 1998), one commonly used semi-distributed model, is utilized to estimate basin hydrological cycle and quantify nutrient movement, transformation, and loads in a huge number of watersheds around the world (Gan et al. 2015). Green-Ampt infiltration mechanism (G&A) and curve number (CN) procedures are two rainfall-runoff methodologies for estimating overland flow. They're also both founded on the infiltration excess principle, which states that overland runoff occurs when precipitation density exceeds soil infiltration capacity. They do not, hows ever, account for runoff source areas or topographic effects. According to a prior study (Dahlke et al. 2012), in many humid and well-vegetated places, overland flows originate in a small part of the basin and then expand as precipitation increases, forming variable source areas (VSAs) (Lyon et al. 2004) driven by saturation excess runoff. Because the genesis of runoff in a region is such a complicated process with spatial and temporal fluctuations, neither saturation excess (Dunne) nor infiltration excess (Horton) runoff could account for hydrological processes. Beven and Kirkby (1979) simulated the runoff variations using a soil topographic index referred to as a saturation excess runoff mechanism. But, in flat watersheds, the topographic index is not appropriate since the runoff directions are undefined. Steenhuis et al. (1995) suggested reinterpreting the CN approach to determine the proportion of runoff generation in a watershed for a rainfall event and (Easton et al. 2008) later incorporated the soil topographic index into SWAT to better account for saturation excess runoff. Then Fuka & Easton (2015) re-conceptualized SWAT (Topo-SWAT) which did not change the SWAT code.

Huangbaihe River, which is a first-order tributary of the Yangtze River, is a primary water source for Yichang city, so the accurate prediction of streamflow is primarily important. The XMG Reservoir, the headwater of the Huangbaihe River Basin, is witnessed a large amount of precipitation and has a humid subtropical monsoon climate. The study area is made up of hillslopes and valleys where overland runoff flows from up to downslope, allowing groundwater and soil saturation to occur, which is compatible with the saturation excess runoff mechanism. The geology and land cover have also been altered as a result of large-scale phosphate mining. Because of the flow routes altered by surface subsidence and fissures produced over goaves, phosphate mining activities may have an impact on hydrological processes (mined-out areas). When the soil water content is exceeded during rainfall, the XMG Reservoir Catchment witnesses variable source areas (VSAs) where overland runoff should be generated (Woodbury et al. 2014, Needelman et al. 2004). To the best of the author's knowledge, the implementation of the Topo-SWAT model in China is rarely recorded, and no similar studies in the XMG Reservoir Catchment have been described previously in the literature.

Therefore, the major objective of this paper is to compare two versions of SWAT models and then to assess each ability for simulating the hydrological processes in the XMG Reservoir Catchment, i.e., Regular-SWAT and Topo-SWAT. The performance was assessed adequately for predicting streamflow at daily and monthly time intervals and identifying the spatial distribution of runoff generation.

MATERIALS AND METHODS

Site Description

The Xuanmiaoguan (XMG) Reservoir Catchment is situated in the headwater of the east branch of Huangbaihe River, which is between 110°08′ and 111°30′ E longitude and 30°42′ and 31°22′ N latitude (Fig. 1). The elevation is from 444 m at the XMG Reservoir dam to 1781 m at the headstream above average sea level. The XMG Reservoir Catchment has an area of 380 km^2. The climate belongs to a humid subtropical monsoon region with a mean annual precipitation of 1101 mm. Meanwhile, in this catchment, the rainy season could extend from May to October, with heavy rainfall in summer. The average annual temperature is approximately 16.9 °C. The land cover types are forest, agriculture field, water, bare land, and urban, in which forest and agriculture field are the main land-use types. The soil types are Haplic Luvisols (LVh1, LVh3, and LVh3) for the Regular-SWAT model, Lithosols and Chromic Cambisols (LCC), and Lithosols and Eutric Cambisols (LEC) for Topo-SWAT model. Over the past 40 years, the study catchment has experienced industrialization and rapid economic growth, resulting in serious soil erosion

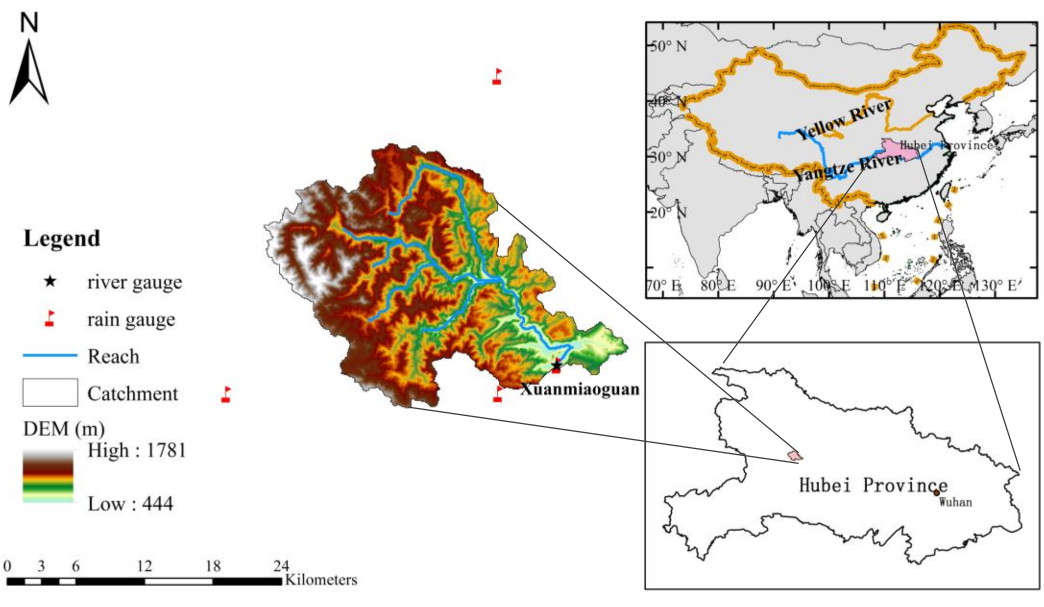


Fig. 1: Map of the Xuanmiaoguan (XMG) reservoir catchment showing the DEM, rivers, and location of observed discharge station.

and nutrient loss. Hence, it is an important region for the research of understanding and predicting the hydrological processes, and identifying the runoff generation areas.

Description of SWAT Model

The SWAT is a watershed-scale, continuous-time, and semi-distributed hydrological model, which incorporates meteorological elements, soil characteristics, land cover/use, and management practices to predict streamflow, sediments, nutrient loading, pesticide transport, and so on (Arnold et al. 1998). It allows the simulation of spatial details according to dividing the whole watershed into a series of sub-watersheds; then each sub-watershed is composed of hydrologic response units (HRUs), which represent homogenous soils properties, land cover, and slopes. Surface runoff, soil water, nutrient cycles, sediment, and crop yields are calculated in each HRU (i.e., the smallest element), and afterward lumped to the sub-catchment using the weighted mean method, last routed into the river systems. There are four water storages including surface runoff, soil water, shallow, and deep aquifer. The SWAT model assumes that shallow groundwater can run into the river channel as base flow or return to the soil by evaporation, but flow in deep aquifer leaves the watershed system. Details about the SWAT model are given in (Neitsch et al. 2011) and http://swatmodel.tamu.edu.

Regular-SWAT

Within regular-SWAT, two methods are applied to calculate the overland flow, such as the curve number procedure (CN) and G&A approach, in which the G&A method is not adopted due to there being any sub-daily input data.

The CN equation was estimated as (USDA-SCS, 1972).

$$Q = Pe^2 / (Pe + S) \quad \text{for } Pe > Ia \qquad \dots(1)$$

where Q is the streamflow depth (mm/d), Pe is effective rainfall (mm.d^{-1}), i.e., rainfall minus initial abstraction (Ia), S is the overall soil water-storage capacity (mm) which is calculated according to the soil type:

$$S = 25.4\left(\frac{1000}{CN} - 10\right) \qquad \dots(2)$$

where CN is the curve number and could be adjusted by the antecedent soil moisture content using daily rainfall series.

Topo-SWAT

In humid regions, overland runoff is mainly produced by the saturation excess runoff mechanism. So, the Topo-SWAT provides the CN-VSA method to estimate overland flow and redefine the HRUs. In Regular-SWAT, HRUs are composed of homogeneous vegetation, soil characteristics, and slope classes, whereas in Topo-SWAT, soil topographic index (TI) was combined to define the HRUs, which has been seamlessly integrated into SWAT representing the VSA hydrology and can be derived from digital elevation model (DEM). TI estimates runoff based on the digital elevation and topography data (Suliman et al. 2015). And the equation can be obtained (Easton et al. 2008):

$$TI = \ln\left(\frac{\alpha}{\tan\beta}\right) \qquad \dots(3)$$

where a is the upslope contributing area of a given point (m), tan β is the slope gradient.

The TI layer, representing VSA hydrology in Topo-SWAT, is calculated applying the DEM and ArcGIS hydrology tools. And then it is reclassified to generate a new class layer, i.e., ten wetness index classes with equal area. They range from one wetness class (10% of the catchment with the lowest potential of runoff generation) to ten classes (10% of the catchment with the highest potential of runoff generation). For this study, we applied the Topo-SWAT toolbox (Fuka & Easton 2015), an automated ESRI ArcMap toolbox, to create a new substitute wetness class layer to cover the Digital Soil Map of the World (FAO 2007). Furthermore, we create as well as its lookup tables (Collick et al. 2014).

Input Data

To derive the SWAT model, a large number of input data would be required, including temporal (hydrometeorology data) and spatial data (soil characteristics, land use, and topographic data).

Temporal data

Hydrological Data: Daily streamflow series data for the XMG Reservoir dam gauge station in the study catchment were collected from the Huangbaihe Catchment Authority.

Weather Data: Daily rainfall series, temperature, wind speed, relative humidity, and solar radiation were all needed. The measured records for daily rainfall data from the outlet station were available for different periods spanning from 2008 to 2016 and could be used directly. Other precipitation datasets were obtained from CMADS 1.1 (The China Meteorological Assimilation Driving Datasets for the SWAT model) (http://westdc.westgis.ac.cn/). The other meteorological elements were generated using SWAT's weather generator (WGEN). Weather stations w3231134 and w3261138 (https://globalweather.tamu.edu/) were included to calculate the statistical parameters of WGEN for the study catchment.

Spatial data

DEM Data: The Digital Elevation Model (DEM) map of the XMG Reservoir Catchment was collected from the Geospatial Data Cloud website (http://srtm.csi.cgiar.org/), with a spatial resolution of 3 arc-second (roughly 90 m).

Soil Data: In this study, two soil maps were used including the Harmonized World Soil Database (HWSD) version 1. 1 (http://westdc.westgis.ac.cn/data/tag/key/HWSD) and FAO-UNESCO Digital Soil Map of the World (DSMW) (http://www.fao.org/geonetwork). HWSD is used for Regular-SWAT setup (Fig. 2(a)), with a 1km resolution and associated lookup table was obtained for the initialization of Regular-SWAT. Three soil groups were identified for the delineation in the XMG Reservoir Catchment. For Topo-SWAT, DSMW combined with soil topographic wetness classes was adopted to generate the soil map.

Land Cover/ Land Use Data: This map was downloaded from 2015 LANDSAT data and then reclassified using supervised image classification. There are five different land use detected with its lookup table to match the land use database of SWAT model, i.e., agricultural field (AGRL for SWAT), forest (FRST), bare land (BARR), urban (URBN), and water (WATR).

Model Setup, Calibration and Validation

The study area was first separated into multiple sub-catchments, which described spatially correlation between one and another. The boundary of the study catchment was delineated applying a threshold area of 1400 ha so that the extracted river networks keep consistent with the topographic map. And 9 sub-catchments were delineated for both two versions of SWAT. All layers were projected in the "WGS_1984_UTM_Zone_49N" coordinate system. And soil types and land use were linked with their lookup tables, space databases, and attribute databases. Through reclassifying the layers of soil types, land cover/use, and slope classes, the sub-catchment layer was overlaid to the HRUs layer. The threshold percentage (0%) was adopted for the whole of the databases. But due to the different types in soils (Fig. 2), the numbers of the HRUs are 250, 173, and 404 for the Regular-SWATH, Regular-SWATD, and Topo-SWAT, respectively (Table 1).

Parameters sensitivity analysis is also a major concern to model calibration and validation (Cibin et al. 2010). Therefore, the calibrated parameters were selected by referring to previous literature, recommendations from the SWAT manuals (Stehr et al. 2010). The method of sequential uncertainty fitting Version 2 (SUFI-2) algorithm (Yang et al. 2008) incorporated into SWAT Calibration Uncertainty Procedure (SWAT-CUP) program (Abbaspour 2015) was adopted for parameter sensitivity analysis, model calibration, and validation procedure.

Table 1: Differences in total HRUs for the three SWAT models.

	Regular-SWATH	Regular-SWATD	Topo-SWAT
Number of soil types	3	2	20
Number of slope classes	4	4	1
Number of HRUs	250	173	404

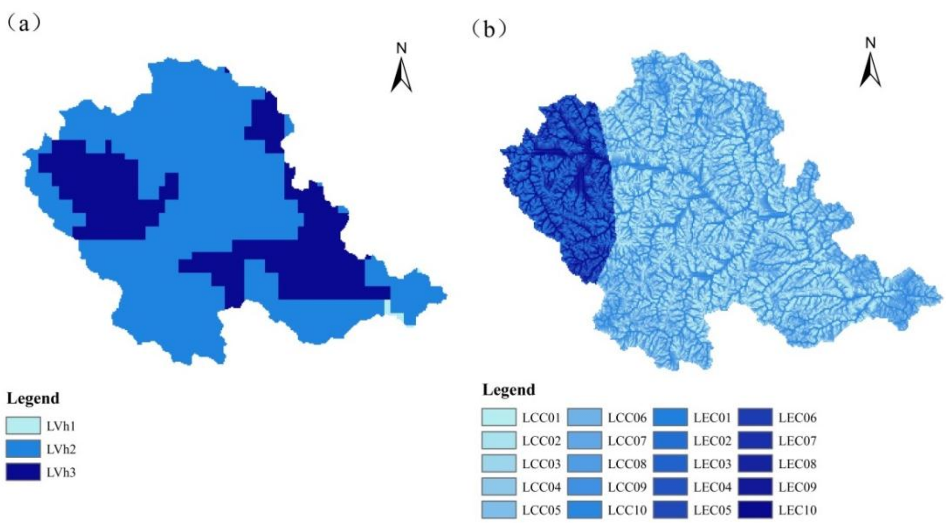


Fig. 2: Soil maps of the XMG Reservoir Catchment (a) Regular-SWAT and (c) Topo-SWAT.

Based on data availability, the two models in this study were calibrated for streamflow at monthly and daily time scales for the period 2010-2013 after two years of warm-up, which is to allow parameters to reach equilibrium. The following three years, from 2014 to 2016, were used to validate models. Nash Sutcliffe coefficient of Efficiency (NSE) was selected as the objective function, due to it can reflect the overall model fit (Nash & Sutcliffe 1970). The following parameters were identified for Regular-SWAT and Topo-SWAT (Table 2).

Performance Evaluation

Both graphical and statistical approaches should be applied to evaluate the model performance (Nyeko 2015). The graphical method, such as streamflow hydrographs, can provide a visual and direct comparison between the observed and simulated datasets, which could detect the trends of variation in magnitude and timing of the flows. Besides the graphical approach, the agreement between simulated and observed data was also evaluated based on statistical indicators, including the NSE coefficient, the RMSE-observations standard deviation ratio (RSR), and percent bias (PBIAS). The performance of the model for flows was divided into four categories at monthly and daily time scales based on the research of (Moriasi et al. 2007).

RESULTS

Simulation Using the Un-Calibrated Models

Two different versions of SWAT models were established and then compared with each other based on the initial parameters. Fig. 3 graphically displays the results for total monthly streamflow using both un-calibrated SWAT models. In dry months like November 2012 to February 2013, and November 2015 to February 2016, both models overestimated base flow. Except for 2016, Topo-SWAT overestimated peak flow rate the most, whilst Regular-SWAT underestimated. The model comparison statistics values with original findings parameter analysis were presented in Table 3. For the calibration period (from 2010 to 2013), the flow output simulated by Topo-SWAT has higher NSE and PBIAS than the Regular-SWAT flow outputs, but for the validation period (2014-2016), the NSE value of Regular-SWAT is higher. In general, the initial parameter result showed that Topo-SWAT (saturation excess) has better output finding than Regular-SWAT (infiltration excess) in the entire study

Table 2: Parameters sensitivities and calibrated parameters of Regular-SWAT and Topo-SWAT using SUFI-2.

Regular-SWAT					Topo-SWAT				
Parameters	Parameter sensitivity			Optimal value	Parameters	Parameter sensitivity			Optimal value
	t-Stat	p-value	Ranking value			t-Stat	p-value	Ranking value	
r_SOL_AWC.sol	-23.4	0	1	-0.16	r_CN2.mgt	11.6	0	1	-0.23
r_CN2.mgt	19.36	0	2	0.31	r_SOL_AWC.sol	-4.8	0	2	-0.34
v_CANMX.hru	-12.69	0	3	3.91	v_ALPHA_BF.gw	3.96	0	3	0.47
v_ALPHA_BF.gw	8.63	0	4	0.94	v_CANMX.hru	-3.63	0	4	5.35
v_ESCO.hru	6.48	0	5	0.32	v_SLSUBBSN.hru	-2.61	0	5	35.85
v_HRU_SLP.hru	5.25	0	6	0.25	v_SMTMP.bsn	-2.33	0.02	6	10.45
v_SLSUBBSN.hru	-4.65	0	7	110.84	v_ESCO.hru	2.26	0.024	7	0.99
r_SOL_Z.sol	-4.38	0	8	-0.83	v_CH_N2.rte	-2.05	0.04	8	0.03
v_RCHRG_DP.gw	3.97	0	9	0.74	r_SOL_Z.sol	-1.61	0.107	9	-0.21
v_CH_K2.rte	-3.88	0	10	64.79	v_CH_K2.rte	-1.57	0.12	10	59.84
v_OV_N.hru	-3.68	0	11	4.11	v_HRU_SLP.hru	1.41	0.15	11	0.33
v_EPCO.hru	-2.46	0.014	12	0.27	v_SMFMX.bsn	1.25	0.21	12	12.46
a_GW_DELAY.gw	2.31	0.0212	13	2.89	v_OV_N.hru	-1.225	0.22	13	19.44
v_CH_N2.rte	-2.3	0.0215	14	0.04	v_EPCO.hru	-1.223	0.221	14	0.42
v_SMFMN.bsn	-1.72	0.08	15	10.68	r_SOL_K.sol	-1.03	0.3	15	0.34
r_SOL_BD.sol	1.64	0.1	16	-0.47	v_RCHRG_DP.gw	0.927	0.35	16	0.76

v: the initial value of the parameter is replaced by an active value; a: an active value is added to the initial value; r: the initial value is changed by multiplying (1+ a given value) (Abbaspour et al. 2007).

period from 2010 to 2016 (NSE: 0.63 vs. 0.54, PBIAS: 7.22 vs. 20.06, and RSR: 0.61 vs. 0.68).

Temporal Simulation Using Calibrated Models

Two different versions of SWAT models were calibrated and validated, which were Regular-SWAT using the HWSD soil data and Topo-SWAT using the DSMW soil data. In the SWAT model, there is a multitude of parameters, in which the sensitivity is different for the specific region. Hence, sensitivity analysis should be first performed to detect a candidate set of parameters most influencing the hydrological processes. Then data from the period 2010-2013 were used

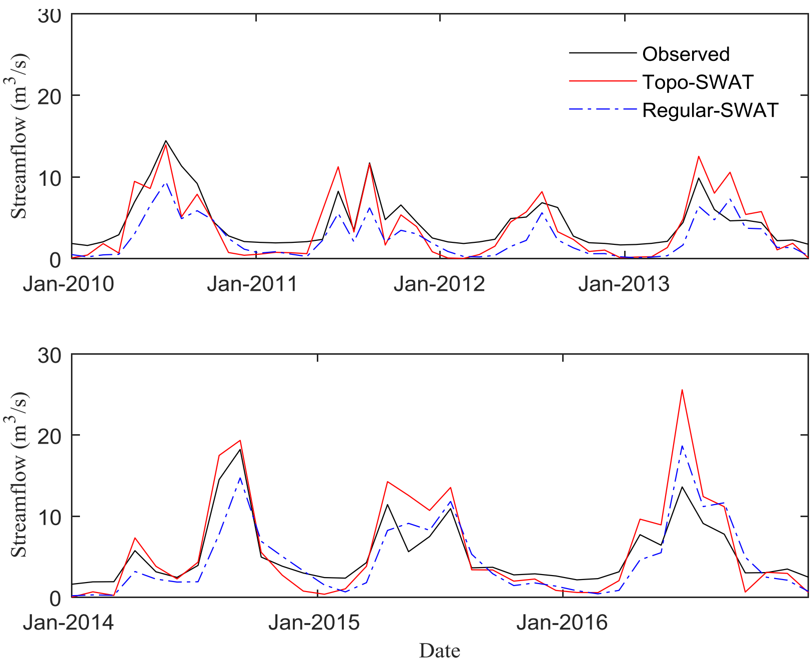


Fig. 3: Monthly observed streamflow and un-calibrated simulations in study catchment for Jan 2010-Dec 2013 period and Jan 2014-Dec 2016 period.

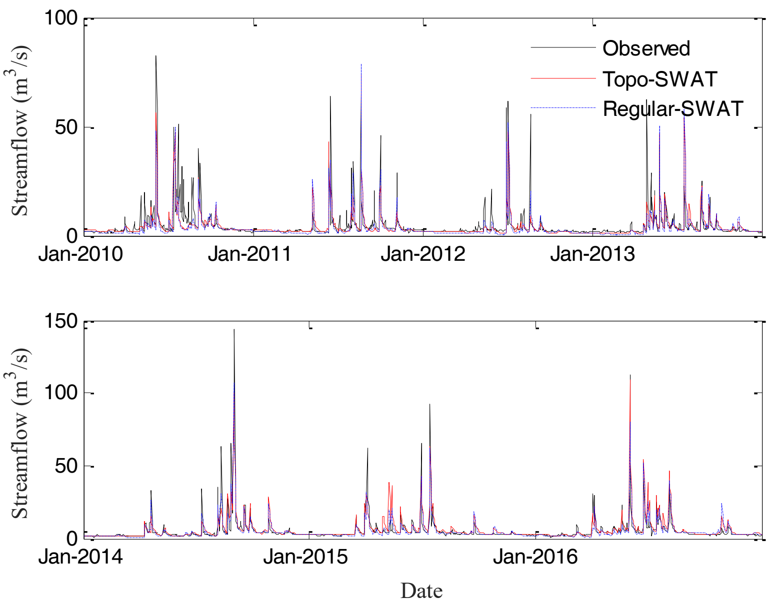


Fig. 4: Daily simulation and observation for a calibration period of 2010-2013 and validation period of 2014-2016.

for calibration, and data from 2014 to 2016 were applied for validation at daily and monthly time scales. Finally, the runoff volume was also evaluated.

Sensitivity Analysis

Sensitivity analysis results for daily flows using Regular-SWAT and Topo-SWAT given by the SUFI-2 algorithm were listed in Table 2. Based on the result, the parameters related to surface runoff, the soil water storage, and groundwater are highly sensitive for two versions of SWAT (Table 2), including soil available water storage capacity (SOL_AWC), runoff curve number for moisture condition II (CN2), baseflow recession factor (ALPHA_BF) and maximum canopy storage (CANMX). Therefore, it is concluded that the most sensitive parameters for the two models are consistent, but the ranking value is different. Based on the results of sensitivity analysis, both calibrated and validated models were performed at the outlet of the study catchment at both daily and monthly scales.

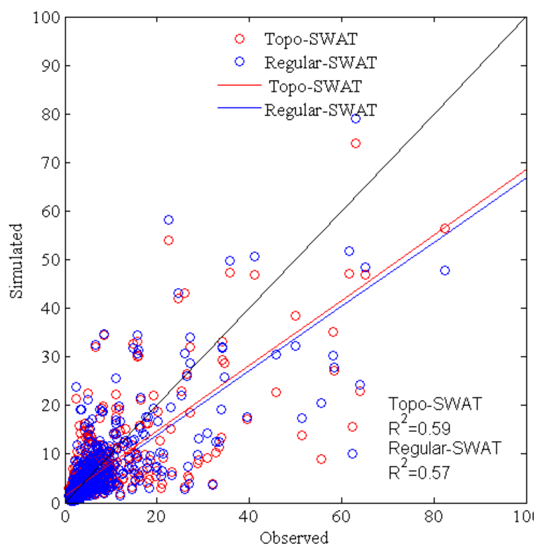
Daily Data Simulation

In this study, the evaluation of model performance included not only visual comparisons between the simulations and measurements but also statistical methods. The final parameter values after the model calibration were listed in Table 2. As shown in Table 2, the most of optimized parameter values were different mainly due to the distinct runoff generation mechanism

Fig. 4 graphically illustrated the observed and simulated discharge values at the daily time scale. It could be seen that the simulation and observation had a similar trend as well as the timing of the peak flows. Whereas, some simulated peaks were underestimated like 7 June 2010, 2 September 2014, and 2 June 2016. The greatest underestimation was located on 2 September 2014, which is more than 51% for both two models and during the 2 June 2016, the underestimation was approximately 29% for Topo-SWAT and 31% for Regular-SWAT. And some peak flows were greatly overestimated during some flood periods, e.g. in 18-21 July 2013. In general, daily peak flows were not matched well.

Standard regression plot (Fig. 5) showed that measured and simulated stream flows at daily time step for both periods of calibration and validation. As shown in these scatter plots, the aggregations of the daily stream flows were from 0 to 20 $m^3.s^{-1}$ for the calibration period and between 0 and 30 $m^3.s^{-1}$ for the validation period. It indicated that the dispersion of Regular-SWAT and Topo-SWAT values were consistent for calibration and validation.

The coefficient of determination (R^2) described the variance portion between the measured and simulated streamflow. The range value of R^2 is between 0 and 1. The higher value, the lower the error variance. The reported performance rating for R^2 is acceptable when its typical values exceed 0.5 (Santhi et al. 2001). In the calibration period, R^2 was obtained as 0.59 and 0.57 for Topo-SWAT and Regular-SWAT, respectively, which indicated an acceptable result. While the values of 0.69 and 0.72 for R^2 for Topo-SWAT and Regular-SWAT models indicated a good fit during validation. In general, the simulation result of the



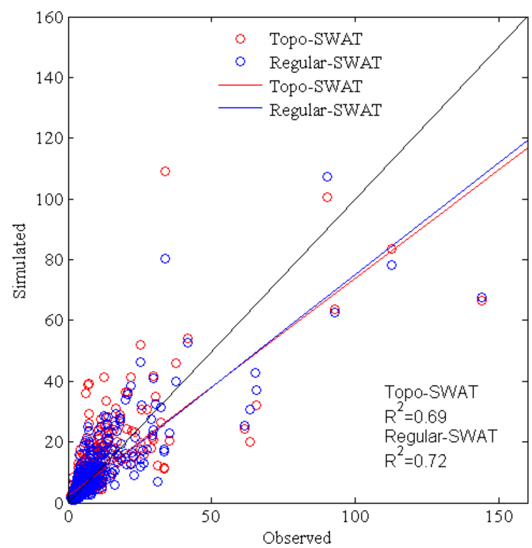


Fig. 5: Regression correlation between simulations and measurements using Regular-SWAT and Topo-SWAT models (a) calibration (2010-2013) and (b) validation (2014-2016).

Table 3: Evaluation indicators of the monthly streamflow based on the initial parameters.

SWAT version	Calibration (2010-2013)			Validation (2014-2016)			Total period (2010-2016)		
	NSE	PBIAS	RSR	NSE	PBIAS	RSR	NSE	PBIAS	RSR
Regular-SWAT	0.39	44.1	0.78	0.65	12.52	0.59	0.54	29.06	0.68
Topo-SWAT	0.65	21.61	0.59	0.61	-8.61	0.63	0.63	7.22	0.61

Topo-SWAT was more accurate in the calibration period, on contrary, the Regular-SWAT exhibited good performance in the validation period.

The statistical indexes of mean, median, standard deviation, maximum and minimum were compared between simulations using Regular-SWAT and Topo-SWAT and measured time series. The results were listed in Table 4. It could be seen that the mean, median, and minimum values obtained for Topo-SWAT were closer to the measured data, while Regular-SWAT underestimated the minimum streamflow, but the maximum was closer for calibration. By comparison, in the validation period, the Regular-SWAT had closer values to the observed data.

Monthly Time Series Simulation

For the calibration (Jan 2010-Dec 2013) and validation (Jan 2014-Dec 2016) periods, Fig. 6 compared graphically observed and simulated monthly data for Regular-SWAT and Topo-SWAT models. The trend of simulated monthly discharge was similar to that of the measurements and peak flow timing was usually also well simulated during most months. Whereas, the streamflow for the peak was overestimated in 2012 for calibration, in 2015 and 2016 during validation, respectively.

The results of model statistics for observations and simulations at a monthly scale using the two models were compared in Table 5. It could be seen that the Topo-SWAT simulated more accurately for calibration with the values of NSE, RSR, and PBIAS for Topo-SWAT were 0.69, 0.55, and 7.92, respectively, compared with the statistical values for Regular-SWAT. Regular-SWAT, on the other hand, performs better statistically during the validation period, with NSE, PBIAS, and RSR values of 0.88, 1.71, and -15.54, respectively. For both models, the values of assessment markers improved significantly at the monthly time step.

A comparison result of monthly annual streamflow for two models was exhibited in Fig. 7. It showed that the peak flow for Topo-SWAT and Regular-SWAT occurred in July, but the observed peak flow was in August. That may be because of the rainfall input for both SWAT models. The majority of peak flows occur during June to September, which just is the wet season. During the months from Jan-

Table 4: Statistical index obtained via two models during the periods of calibration and validation.

Statistics	Measured		Regular-SWAT		Topo-SWAT	
	Calibration	Validation	Calibration	Validation	Calibration	Validation
Mean (m^3/s)	4.36	5.27	3.62	5.18	4.01	6.09
Median (m^3/s)	2.44	3.08	2.02	3.19	2.41	3.65
Standard deviation	6.83	8.82	5.84	7.69	5.6	8.33
Minimum (m^3/s)	0.78	0.79	0.38	0.74	0.79	1.23
Maximum (m^3/s)	82.3	144.15	79.07	107.4	80.88	109
NSE	-	-	0.58	0.72	0.59	0.69
RSR	-	-	0.65	0.53	0.64	0.59
PBIAS	-	-	16.9	1.64	7.91	-15.67

Table 5: Evaluation indicators of Topo-SWAT and Regular-SWAT performance for monthly streamflow predictions after calibration.

SWAT versions	Calibration (2010-2013)			Validation (2014-2016)		
	NSE	RSR	PBIAS	NSE	RSR	PBIAS
Regular-SWAT	0.65	0.59	16.99	0.88	0.35	1.71
Topo-SWAT	0.69	0.55	7.92	0.73	0.52	-15.54

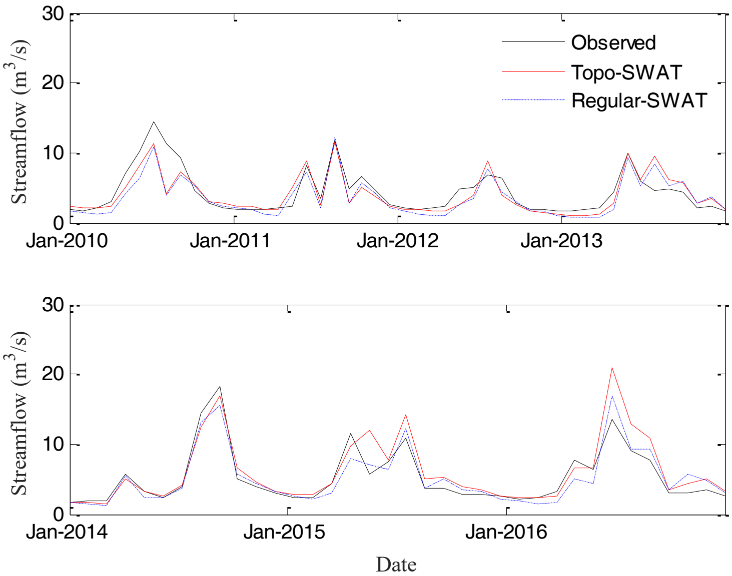


Fig. 6: Observed and simulated flow at monthly scale by two models for a calibration period of 2010-2013 and validation period of 2014-2016.

uary to June, and in August, September, and December, the simulated streamflow of Regular-SWAT was entirely lower than the observed streamflow. While in July, October, and November, the simulated was higher than the observed. For Topo-SWAT, the simulated streamflow in January, February, May to July, and October to December was higher than the observed streamflow. In contrast, in other months (March, April, August, and September), the observed was higher. In general, the result of Topo-SWAT was closer to the observed streamflow.

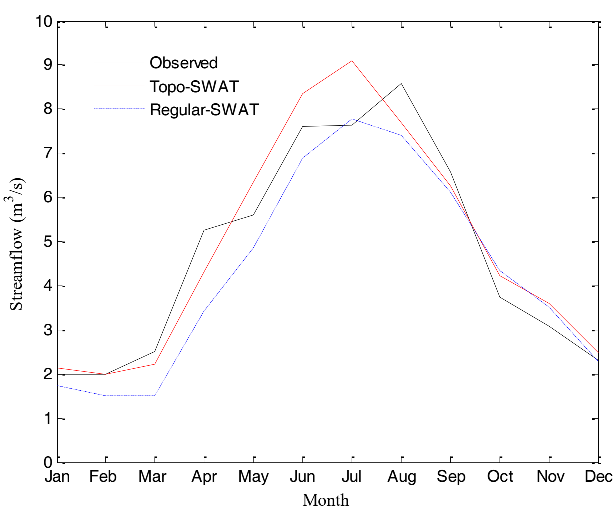


Fig. 7: Observed and simulated hydrograph in mean monthly streamflow for 2010-2016.

Runoff Volume

Fig. 8 illustrated the cumulative daily runoff volume for the study catchment in calibration Fig. 8 (a) and validation Fig. 8 (b) periods. Fig. 8 (a) showed that the simulated daily runoff volumes all have been underestimated over the calibration period for the two models. But, the simulated runoff volume of Topo-SWAT was much closer to observed values than that of Regular-SWAT. For the validation period (Fig. 8 (b)), the performances of the two models were satisfactory in the year 2014. Beyond that, the simulated daily runoff volume had been overestimated using Topo-SWAT. In contrast, the Regular-SWAT underestimated from Sep 2014 through Dec 2016.

A comparison of annual runoff volumes between observed and simulated applying Regular-SWAT and Topo-SWAT was shown in Fig. 9. The result showed that the simulated annual runoff volume using Topo-SWAT and Regular-SWAT had been underestimated for 4 years and 5 years, respectively, which was different in the year 2015. The simulated values applying Topo-SWAT were higher than observed runoff volume, while the result calculated by Regular-SWAT was lower in 2015. Furthermore, two years of annual runoff volumes using Topo-SWAT had been simulated to be profoundly overestimated (2015 and 2016).

Spatial Distribution of Runoff Generation Areas Using Calibrated Models

What is more interesting is the difference in the predicted runoff distribution using the Regular-SWAT and Topo-SWAT

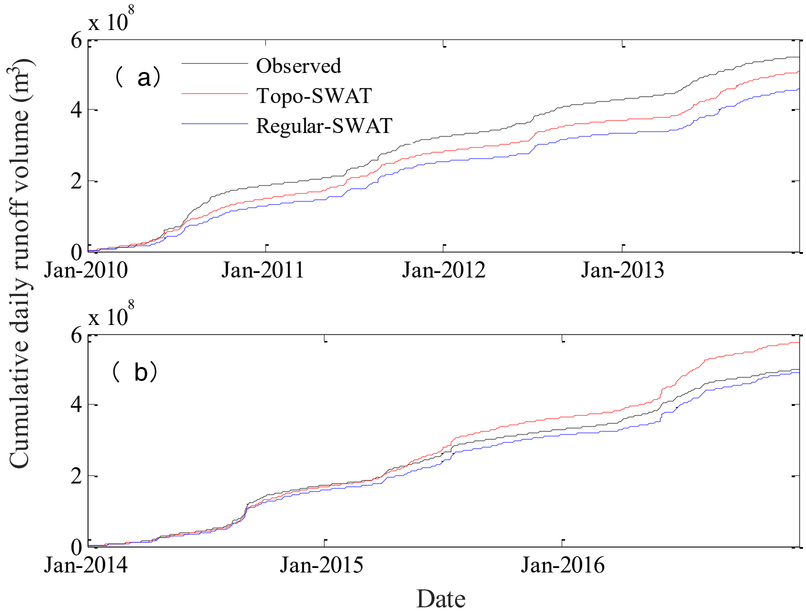


Fig. 8: Cumulative daily runoff volume for periods of calibration (a) and validation (b).

in the study catchment. The information about the spatial distribution and extent of runoff source areas is important for watershed management. For instance, Fig. 10 showed the predicted spatial distribution of runoff generation for one storm event in September 2014 (193 mm). The darker shades in the areas, the higher runoff generation. Regular-SWAT predicted the most proportion of catchment would generate more runoff, and the different locations were significantly affected by differences in soil types and land cover/use. However, for the same rainfall event, Topo-SWAT calculated

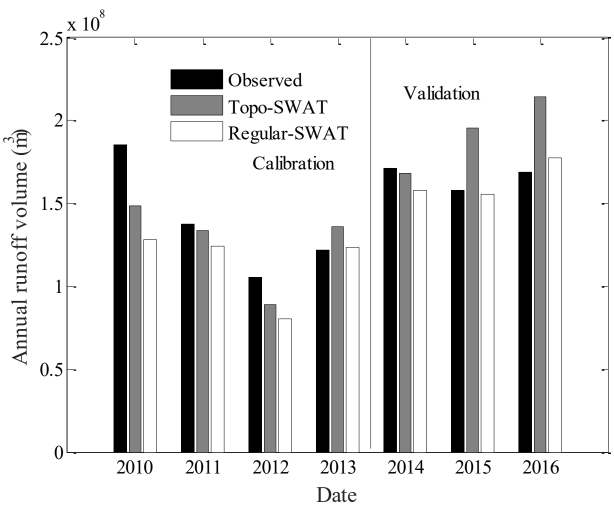


Fig. 9: Annual runoff volume calculated by Topo-SWAT and Regular-SWAT.

a majority of the catchment producing less surface runoff, and the distribution of runoff generation reflected the topographic position, the topography is the main element associated with runoff generation. In general, higher runoff generation was related to HRUs with higher wetness index classes, which were low-lying wet areas and closer to the streams.

DISCUSSION

Sensitivity Analysis

The sensitivity of parameters is always analyzed before calibration, but there is no common guide to identify the sensitivity bound. (Van Griensven et al. 2006) pointed out that parameter sensitivities were different in specific catchments because of the distinct watershed characteristics including soil properties, land use, and slope types. So, the parameters used to calibrate in this catchment may be different. Based on the previous research by (Yang et al. 2012), the main hydrological processes and parametric interactions should firstly be identified, and then the model setup should also be examined to ensure the accuracy of the calibration. In general, the sensitive parameters were those related to physical processes including surface runoff, evapotranspiration, groundwater, and channel routing. In this study, the parameters related to surface runoff generation, soil water movement, and groundwater are highly sensitive for two versions of SWAT (Table 2). In the most sensitive parameters, CANMX is mainly determined by the leaf area index of the vegetation and precipitation can only reach the soil when the canopy storage is filled (Guse et al.

2013), which is significant to affect infiltration, surface runoff, and evapotranspiration in the highly vegetated catchment (Nyeko 2015). Baseflow alpha-factor (ALPHA_BF) is an index reflecting the changes in recharge with groundwater flow. SOL_AWC is used to calculate the field capacity of each soil layer by adding to the wilting point. Curve number (CN) primarily influences the amount of runoff generation, which is a relatively sensitive parameter for most of the catchments (Noori & Kalin 2016). The ranking of other parameters was different due to the rainfall-runoff generation mechanism. Hence, the results suggested the sensitivity analysis was important before the model calibration (Demaria et al. 2007). Consequently, the final parameter values should be checked to be in line with the catchment characteristics and corresponding hydrologic processes.

Simulation Results

From the land use map of XMG Reservoir Catchment, the forest is the mainland cover (88.37%), which can delay the surface flow and generate substantial subsurface flow, due to forest surface soils having high infiltration capacities (Jiang et al. 2012). And there is a great quantity of rainfall (1010 $mm.a^{-1}$). Thus, in this catchment, the saturation excess runoff generation approach may be more appropriate than the infiltration excess runoff mechanism, which could be proved by the statistical indexes of model performance (Table 3). And the simulation result using un-calibrated Topo-SWAT was slightly better than that by un-calibrated Regular-SWAT (Fig. 3), so we conclude that the topography is a major factor in hydrological processes. But, after the much more complex parameter sensitivity and calibration, the simulation by Regular-SWAT is similar to that of Topo-SWAT in the calibration period (Fig. 6 & Fig. 4).

In a few cases (2010, 2014, and 2015), the peak flows were underestimated applying two SWAT models (Fig. 4). This may be due to soils on mountainous forested slopes can absorb a large amount of precipitation in the wet season and later slightly releasing water from the storage to be as base flow. One possible reason may attribute to the uncertainty of input data, such as meteorological data. And only one weather station was in this study catchment, the other three were outside the catchment. Therefore, the spatial distribution of precipitation was not representative which might lead to not so rigorous calibration of the model (Masih et al. 2011). The other possible reason may be the pattern of precipitation had a considerable effect on the simulated peak flows. Furthermore, the physical processes of runoff generation over a watershed in nature are extremely complicated and exhibit considerable temporal and spatial variability.

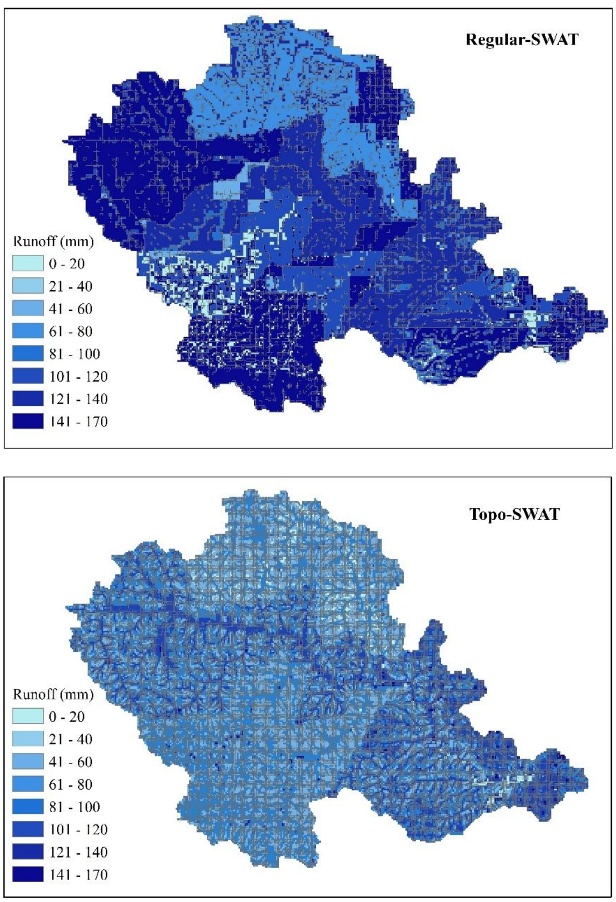


Fig. 10: Spatial distribution of runoff generation areas predicted by Regular-SWAT and Topo-SWAT.

The different spatial distribution of runoff predicted by the two models is exhibited in Fig. 10. For the same large rainfall event, Regular-SWAT predicted the majority of the catchment generating high runoff, whereas Topo-SWAT predicted a majority of the catchment generating less surface runoff and the near-stream regions producing more runoff in line with the other researches. In Topo-SWAT, the soil wetness index and topography are considered to model runoff, in other words, the degree of saturation and VSA hydrological principles are taken into account. And it assumes that HRUs located at the flat, near river would become moist and contribute a large amount of runoff, due either to the hydraulic gradient decreased by shallower slope, or maybe the accumulation of lateral flow from upland regions (Collick et al. 2014). Whereas, Regular-SWAT treats these HRUs the same as any upland region with the same soil and land use.

CONCLUSION

Two versions of the SWAT model, Regular-SWAT and Topo-SWAT, were established for the XMG Reservoir Catchment, to compare their abilities to simulate stream flows and to identify critical runoff generation regions, which could provide important information for temporal and spatial water management. Each performance and applicability were successfully examined by parameter sensitivity analysis, model calibration, and model validation. The main conclusions are obtained as follows:

(1) based on sensitivity analysis results, SOL_AWC, CN2, CANMX, and ALPHA_BF were the most sensitive parameters for both two models.

(2) Both Regular-SWAT and Topo-SWAT models provided reasonable simulations of stream flows. Statistical comparisons revealed good model performance due to values of NSE for monthly and daily streamflow in calibration and validation periods being larger than 0.65, 0.55, respectively. Nevertheless, some discrepancies were evident between the observations and simulations of high stream flows.

(3) By contrast, the highest flow simulated by Topo-SWAT was better than that of Regular-SWAT, while Regular-SWAT had better model performance in the period of validation.

(4) Regular-SWAT mostly underestimated the annual runoff volume, while Topo-SWAT provided a slightly better prediction.

(5) The results of spatial runoff source areas demonstrate that the Topo-SWAT is slightly better due to it reflecting the effect of topography and soil characteristics.

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