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ORIGINAL ARTICLE

Runoff simulation using a modified SWAT model with spatially continuous HRUs

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Abstract The Soil and Water Assessment Tool (SWAT) model is a well-established eco-hydrologic model that employs the hydrological response unit (HRU) as the basic unit. Land surface patches within one HRU have identical hydrological properties (e.g., land use, soil, slope and management) and thus have similar hydrological responses. The non-spatial aspects of HRUs, however, are considered a key weakness of the SWAT model because it is difficult to determine the spatial locations and describe the interactions between different HRUs. Here, a new method to produce continuous HRUs with a clear spatial position for SWAT using Geographic Information System tools is proposed and then tested in a small catchment of the Taihu Basin, China. The SWAT model was then modified based on spatial continuous discretized HRUs accounting for the surface runoff lag difference of HRUs in one sub-basin. The results showed that the modified model was more sensitive to the lag in runoff processes and thus had better simulation accuracy.

Keywords Hydrological model · Hydological response unit · Spatial discretization · Runoff lag · Taihu basin

Introduction

The distributed hydrological model (DHM) has become an important technique for exploring the effects of climate change and human activities on hydrological cycles and water resources. Through a mathematical description of the hydrological process, DHM can account for spatial variation in watershed parameters using horizontally discretized hydrological response units (HRUs). Accordingly, the Digital Terrain Model (DEM)-based DHM has been used increasingly in hydrological modeling (Wise 2000; Di Luzio et al. 2004). In theory, the physical DHM builds on the exact mathematical description of each individual process and the overall hydrological processes (Beven 1989; Refsgaard 1997). However, most DHMs are actually based on empirical relationships between spatially variable characteristics and hydrological responses. Indeed, none of the currently available DHMs can absolutely describe strict hydrological processes, and most are based on several hypotheses. The spatial heterogeneities of watershed hydrology underscore the ever-increasing importance of the role of the DHM (Neitsch et al. 2002, 2005).

As a semi-distributed hydrological model, the Soil and Water Assessment Tool (SWAT) is widely used to simulate runoff, sediment and water quality of agricultural watersheds (Gassman et al. 2007). SWAT is also based on physical parameters in continuous time and has been used to assess the impact of land management and climate patterns on water supply and non-point source pollution in large, complex watersheds over long periods (Arnold et al. 1998, 2005). Owing to its user-friendly interface, open source code and extensive regional adaptation, the SWAT model is becoming increasingly popular worldwide (Srinivasan et al. 2010; Yang et al. 2010; Ouyang et al. 2010; Kingston and Taylor 2010; Smith and Dragovich 2008; Schuol et al. 2008; Salvetti et al. 2008; Arnold et al. 2000; Tobin and Bennett 2009). Additional uses of the calibrated and validated SWAT model include analysis of the effects of climate and land use changes on catchment-wide hydrologic processes (Saha et al. 2014) as well as

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turbidity control and groundwater nitrate vulnerability assessment (Noh et al. 2014; Uhan et al. 2011).

Study of heterogeneous river systems requires subdivision into regions with a similar geoenvironment and hydrological characteristics (Migiros et al. 2011). In the SWAT model, a watershed is spatially divided into smaller sub-basins using digital elevation data according to the resolution specified by the user. Sub-basins are further discretized into non-spatial HRUs with similar landscape characteristics including slope, soil, land-cover and management conditions over long periods (Douglas-Mankin et al. 2010). HRUs serve as the modeling unit and can simplify the modeling process and improve computational efficiency. However, owing to the absence of spatial interconnectivity among HRUs in the SWAT model, its surface runoff routing module does not account for potential through flow entering the HRU from neighboring upslope HRUs (Bryant et al. 2006). The non-spatial aspect of the HRU has been suggested as a key weakness of the SWAT model. The current SWAT model structure computes runoff and pollutant loading from different landscape positions with equal weights within a sub-basin (Gassman et al. 2007). As a result, spatial analysis is traditionally conducted at the sub-basin scale instead of the finer spatial scale of HRUs. A more accurate and detailed description of hydrological processes should consider the concentration time of surface runoff at different locations inside a sub-basin and explicitly simulate the transport of water across landscape positions.

GIS tools have been widely used in hydrological modeling to allow for spatial data processing. For example, Bathrellos et al. (2008) used GIS to show that the concentration of different ions in groundwater varied with land use and cover. GIS techniques can also be applied to geomorphological analysis, including the spatial distribution of soil physico–chemical properties (Papadopoulou-Vrynioti et al. 2014) and the geogenic and anthropogenic factors controlling the distribution of elements in sediments (Papadopoulou-Vrynioti et al. 2013).

With the aid of the spatial functionality of GIS, this study further developed the spatial discretization of HRUs by incorporating information describing their spatial connectivity. Using this HRU discretization method, the SWAT model can explicitly calculate the concentration time of surface runoff for various HRUs in the same sub-basin. The aim of this study was to improve the simulation accuracy of the SWAT model. Performance of the modified SWAT model was examined using the Xitiaoxi catchment in the Taihu Basin, China.

Data

The Xitiaoxi catchment of Taihu Basin in Zhejiang Province, China was used as a test case to validate the proposed spatial discretization of HRUs. The Xitiaoxi River originates from Yonghe, Anji County and flows southwest into Taihu Lake. The annual surface runoff of the Xitiaoxi River is about 2.68×10^9 m^3, accounting for 27.7 % of the total annual inflow to Taihu Lake. Two large upstream reservoirs influence natural runoff processes. This catchment has a subtropical monsoon climate, with an annual mean air temperature of 15.5 °C, and 1465.8 mm annual precipitation. Seasonal trends in runoff follow those of precipitation, peaking in May–June and also in September. Runoff during May–June accounts for 45–54 % of annual runoff. The surface runoff of the upper and middle catchment (1885.36 km^2, upper to Gangkou Station) was simulated using the modified SWAT model.

Spatial data used in the study included a digital elevation model (DEM), as well as land use, soil type and climate data (Fig. 1) The 30-m-resolution DEM product from the ASTER GDEM were provided by the International Scientific and Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences (e). Spatial soil data with a scale of 1:1,000,000 were obtained from the Data Sharing Infrastructure of Earth System Science, IGSNRR, CAS. Land use maps were created by combining the China land use and land cover collection from IGSNRR, CAS with the interpreted results of ALOS (Advanced Land Observing Satellite) images in 2009, which had a maximum resolution of 2.5 m. Daily stream flow and reservoir outflow records for the gauging stations were obtained from the Yangtze River Hydrological Yearbook from 2000 to 2009. Climate data for 2000–2009 were obtained from the China Meteorological Data Sharing Service System. To more accurately describe the spatial distribution of precipitation and avoid bias resulting from data collected from a single station in the research area, precipitation input data were prepared by interpolating ground climate records using the Kriging method (Fig. 2). The precipitation data of each sub-basin were then extracted for SWAT input. All input grid data were resampled to 100 m with the projection of UTM, WGS84.

Methods

Spatial discretization of HRUs

To obtain the spatial location of each HRU, land use, soil type and DEM data were analyzed using ArcGIS with the ARCSWAT module. First, the catchment was divided into 61 sub-basins according to DEM and embedded digital rivers. The combined polygons were acquired by overlying sub-basin, land cover and soil layers. Small polygons below the 20 ha threshold were eliminated using GIS

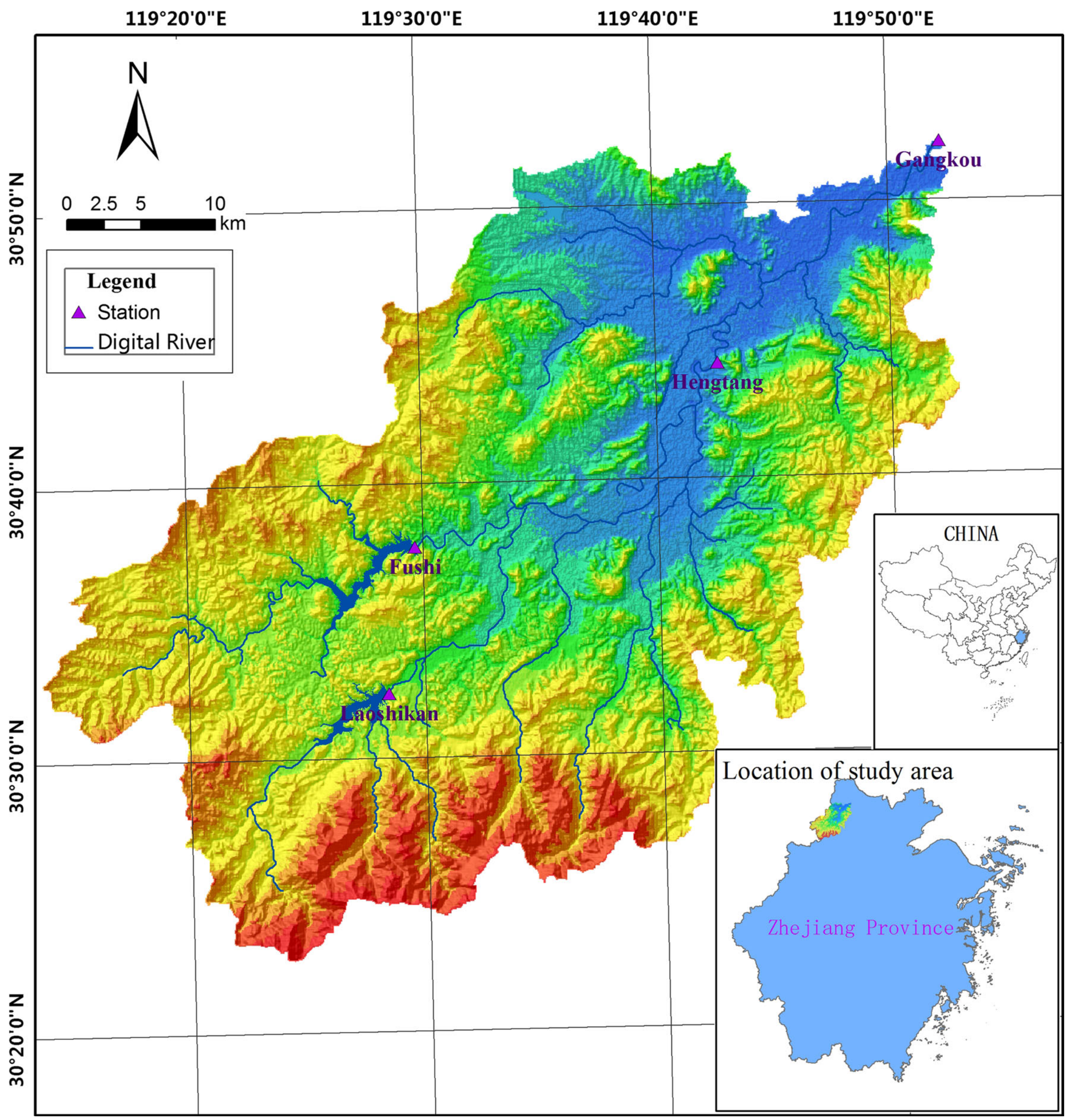


Fig. 1 Altitude map of the study area

analysis tools. To prevent the small patches of different sub-basins from being merged, each sub-basin was operated separately. The realized polygons of the virtual HRUs were uniquely identified and contained both surface properties (land cover, soil type and slope) and geometric attributes (shape, area and barycenters) (Table 1).

The property tables of each polygon (i.e., HRU) were constructed according to surface attributes (land cover, soil type, slope and sub-basin number) and used to update the original SWAT input files. In the modified ESRI shape file of soil type, each patch had a unique soil-type code. To implement modifications of the soil input file, the soil type database for SWAT should be updated with a new field corresponding to the polygon soil codes. The land use input data only has one type of the LUSE (Table 1).

The modified land cover and soil type data were then used to produce HRUs with identical thresholds as those used in the spatial generalization step (20 ha). The definitive soil types and specific spaces spatially discretize the HRUs, which are then automatically updated into the SWAT model input files. A comparison of our spatially discretized HRUs with those produced by the original SWAT model (Fig. 3) shows that the modified HRUs create a continuous patch with explicit hydrological properties (land cover, soil type and slope) and a specific location.

Soil type is coded differently for spatial discretized HRUs; thus, the original attributes (land use and soil type) should be

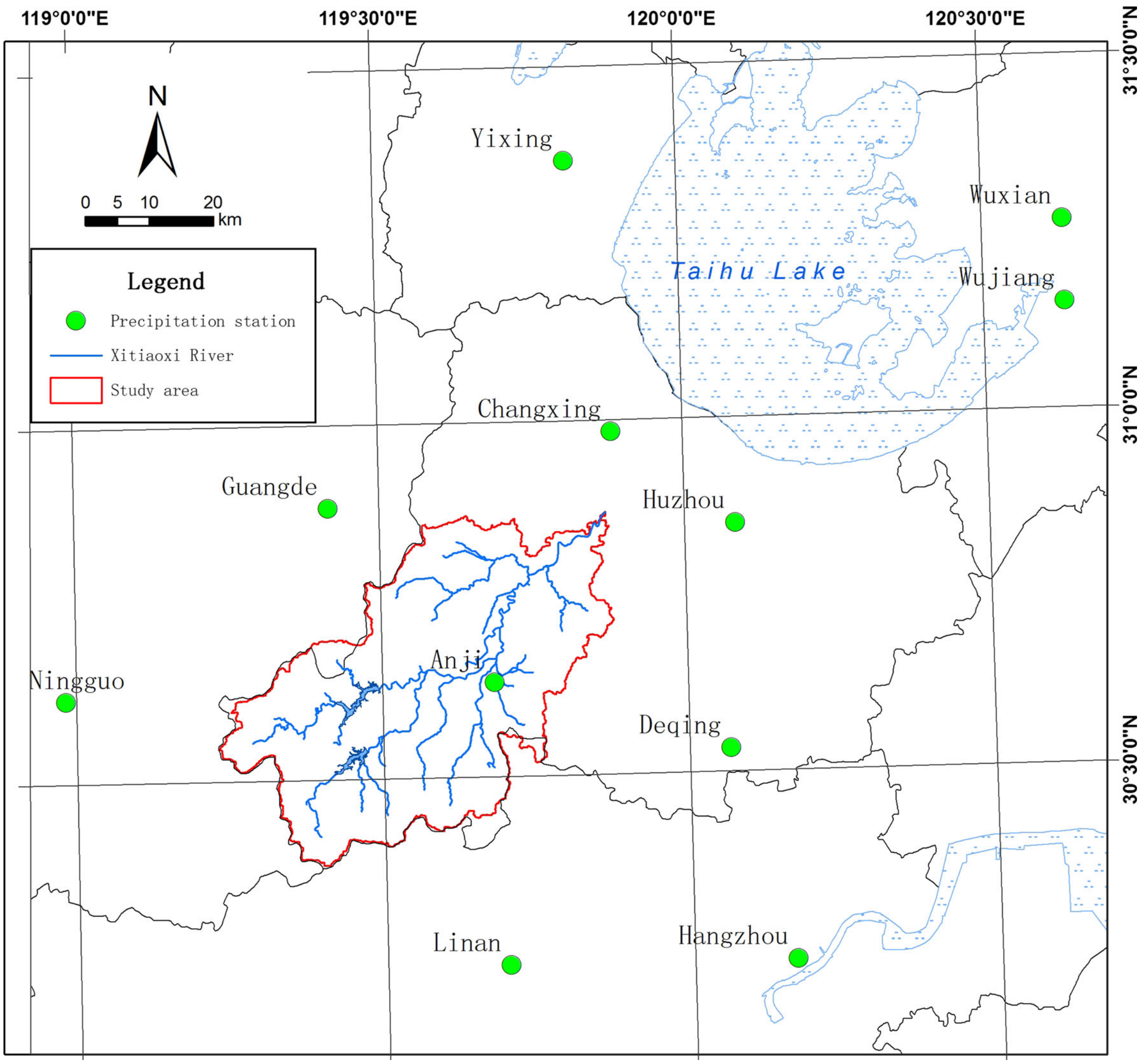


Fig. 2 Map of precipitation stations

Table 1 Attributes comparison of original polygons and modified HRUs

Polygon_Id	Original land use	Original soil type	Area	Slope	HRU_Id	HRU_GIS	Modified land use	Modified soil type
1	TEAG	HRZA	34.94	6.69	1	000010001	LUSE	C001
2	RICE	HRZA	49.41	5.94	2	000010002	LUSE	C002
3	FRSE	ZSTZ	58.90	4.12	3	000010003	LUSE	C003
4	TEAG	ZSTZ	82.35	2.66	4	000010004	LUSE	C004
5	URMD	ZSTZ	20.46	4.14	5	000010005	LUSE	C005

added to the SWAT input file according to the corresponding polygon and HRU IDs (Table 1) to link the surface patch code with a unique soil type. This modification would facilitate the input of land surface properties into the SWAT model, and the produced HRUs make it impossible for spatial analyses of runoff, sediment and pollution.

The spatial discretization of HRUs enables the creation of one continuous HRU (Fig. 3 right), as well as smaller-scale spatial analyses of hydrological processes. This approach also allows the estimation of runoff lags of different HRUs according to the distances between each barycenter and the corresponding sub-watershed outlet.

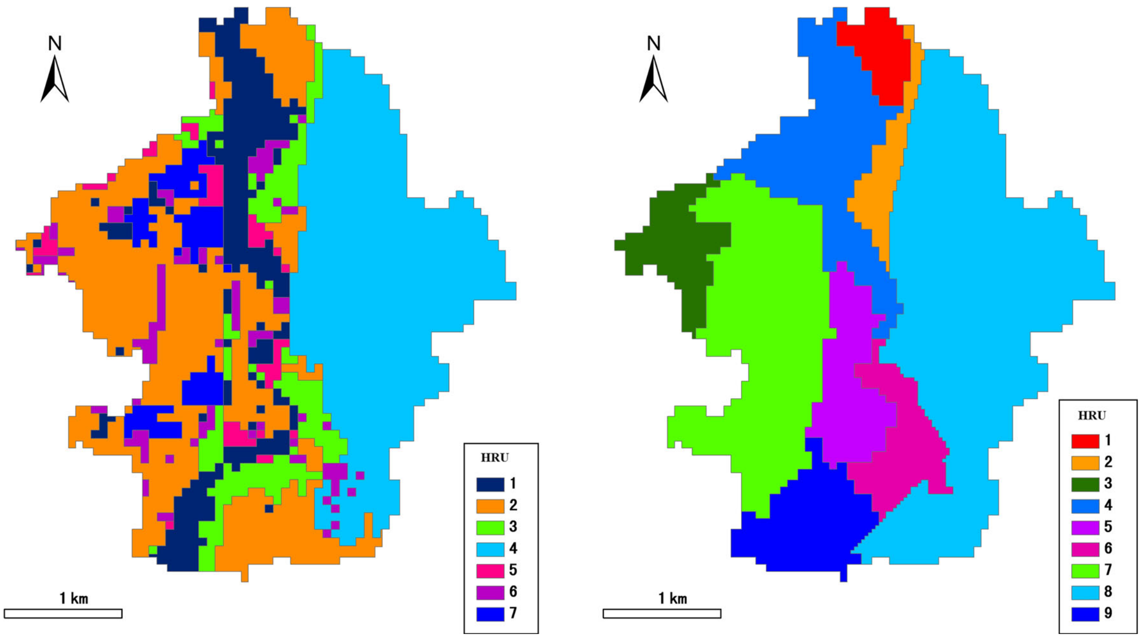


Fig. 3 Spatial distribution of HRUs within sub-watershed using traditional (*left*) and modified (*right*) approaches

Simulation of surface runoff lag with non-spatial HRUs

The SWAT model includes a surface runoff lag feature to express the time difference between surface runoff production and stream conflux, temporarily postponing a proportion of the inflow of the runoff into the stream in each HRU. SWAT models this surface runoff lag using the concept of surface runoff storage. The fraction of land surface runoff reaching the main channel can be estimated as:

$$Q_{\mathrm{surf}} = \left(Q'_{\mathrm{surf}} + Q_{\mathrm{stor},i-1}\right) \times \left[1 - \exp\left(-\mathrm{surlag}/_{t_{\mathrm{conc}}}\right)\right] \quad (1)$$

where Q_{surf} is the runoff fraction of the stream inflow on a given day, Q'_{surf} is the total runoff produced by the land surface of a whole HRU on a given day, $Q_{\mathrm{stor},i-1}$ is the runoff fraction from the previous day that has not yet flowed into the stream, surlag is the runoff lag coefficient and t_{conc} is the concentration time in sub-watersheds. Figure 4 shows the influences of surlag and t_{conc} on runoff. For a certain t_{conc}, an increase in surlag causes a larger fraction of runoff to be temporarily retained.

The concentration time for a sub-watershed is the duration from precipitation to when the total runoff volume has reached its outlet. This time can be estimated by adding the periods of surface runoff production and stream transmission. Similarly, the sand, organic matter and pesticides carried by runoff are subject to transmission lag. However, SWAT assigns identical runoff lag to all HRUs within a sub-basin, which does not accurately account for differences among sub-basins. As sub-basin size increases, so do the differences in runoff lags between HRUs within the sub-basin. The method described in this study accounts for differences in runoff lag time among HRUs, enabling sensitive estimation of the distance between HRUs and the corresponding sub-basin stream outlet.

Although the HRU is the primary modeling unit of the SWAT model, surface patches of HRUs may be spatially disordered. The smoothing of spatially heterogeneous patches during construction of the HRUs may impair the model accuracy. Furthermore, without spatially explicit HRU patches, SWAT cannot support HRU-based spatial analyses. However, the complicated spatial distributions of patches of land cover and soil type impede the development of accurate descriptions of each HRU. Modification of the original HRU definition to include specific location, continuous distribution and essential surface properties are necessary to achieve more accurate hydrological modeling with SWAT.

Simulation of surface runoff lag with modified spatial HRUs

The specific locations assigned to spatially discretized HRUs allow the calculation of runoff lag using the distance between barycenters and corresponding sub-watershed outlets. To describe differences in the surface runoff lag among HRUs, an adjusted coefficient was introduced. Estimated HRU runoff was modified as follows:

$$\begin{aligned} Q_{\mathrm{surf}} &= d_{\mathrm{i}} \times \left(Q'_{\mathrm{surf}} + Q_{\mathrm{stor},i-1}\right) \\ &\quad \times \left[1 - \exp\left(-\mathrm{surflag}/_{t_{\mathrm{conc}}}\right)\right] \end{aligned} \quad (2)$$

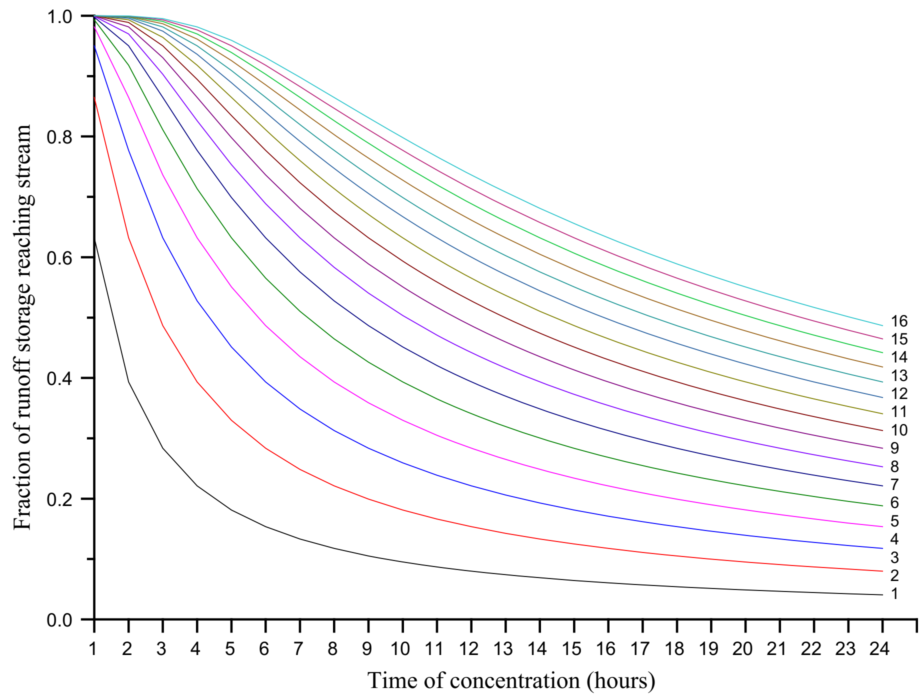


Fig. 4 Influence of surlag and t_{conc} on fraction of surface runoff released

where d_i is the adjusted coefficient of runoff lag in HRU i and d_i is defined as:

$$d_i = \frac{1}{n} \times \frac{n \times \text{MaxDis} - (n-1) \times \text{dis\_stream}_i - \text{MinDis}}{\text{MaxDis} - \text{MinDis}} \tag{3}$$

where dis_stream_i is the distance from the barycenter of HRU i to its sub-watershed outlet, MaxDis and MinDis are the maximum and minimum barycenter distances of all HRUs within the sub-watershed being considered, respectively, and n is the named distance constant (>0) that regulates runoff to the sub-watershed outlet from the HRU with the longest barycenter distance. The parameter dis_stream_i decreases to $1/n$ as d_i increases. The parameter d_i equals 1 if $\text{dis\_stream}_i = \text{MinDis}$, while d_i is $1/n$ if $\text{dis\_stream}_i = \text{MaxDis}$. These equations account for the fact that runoff lag is negatively proportional to the barycenter distance. The coefficient n should be manually modified during SWAT simulation according to the specific characteristics of the watershed surface. Similar improvements in the organic mass, pesticide content and transmission lag over sand were also made in SWAT.

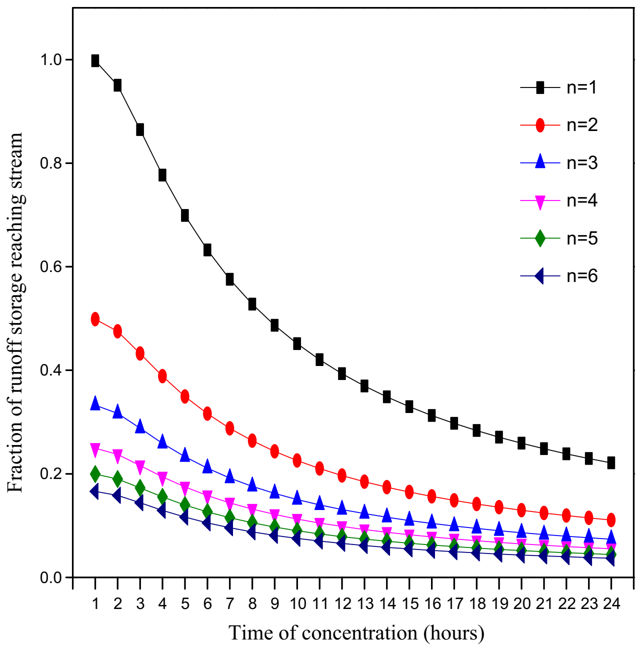
Sensitivity analysis of new parameters in the modified SWAT model

The modified SWAT model can be used to simulate differences in surface runoff lag time for different HRUs with different distances to sub-basin outlets. To illustrate the influence of the distance constant n on runoff lag, the relationship between runoff fraction (Q_{surf}) and concentration time were considered with $n < 6$. When $n = 1$, the modified SWAT model is identical to the original model. The adjusted coefficient (d_i) of the nearest HRU is equal to 1, so Q_{surf} of this HRU does not change, regardless of the value of n. Q_{surf} of the farthest HRU, however, is significantly decreased in the modified model, where $Q_{surf} < 0.2$ when $n = 6$ and the concentration time is 1 (Fig. 5 left). The mean distance of all HRUs in the basin was 5777.19 m (Fig. 5, right). When the concentration time equals 1, Q_{surf} is always above 0.8, regardless of n. The influence of n on Q_{surf} decreases with increasing concentration time.

Figure 6 shows how d_i changes with distance. For all HRUs in the research area, the minimum and maximum distances were 320 and 23,182 m, respectively. The HRU with the minimum distance always has $d_i = 1$, regardless of n. Q_{surf} of this HRU is the same as that of the original SWAT model. As distance increases, Q_{surf} decreases in an accelerating pattern. For a given HRU, larger n results in smaller Q_{surf}. The maximum distance HRU has $d_i = 0.5$ when $n = 2$. Overall, the modified SWAT model described the physical processes of runoff lag in greater detail.

Results

An appropriate calibration strategy is necessary to reduce model uncertainty (Pluntke et al. 2014). In this study, the SWAT model was calibrated using the Generalized



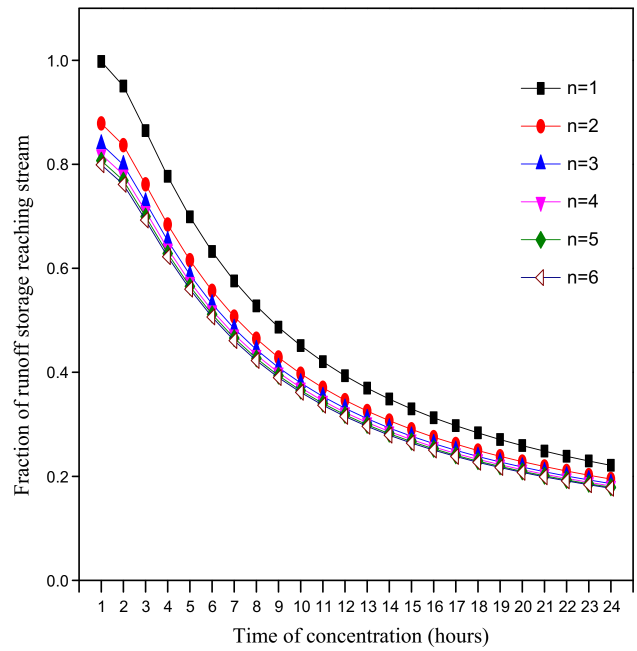


Fig. 5 Runoff fraction for HRU with the farthest (*left*) and the mean distance (*right*)

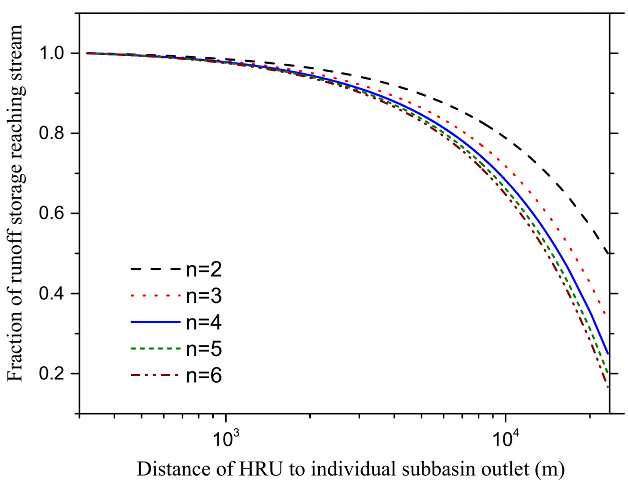


Fig. 6 HRU runoff fraction of mean distance

Likelihood Uncertainty Estimation (GLUE) method (Beven and Binley 1992) along with tests of model sensitivity. The model was calibrated using runoff observations at Gangkou Station and Hengtang Station on the Xitiaoxi River (Fig. 1). The runoff simulated by the modified SWAT was compared with the original model. The sensitivities of 17 parameters were explored during calibration to determine parameter maxima and adjust parameter ranges accordingly. This step was iterated to attain satisfactory calibration results. The parameters from model calibration of the original SWAT were also used for calibration of the modified model.

Calibration period

In the Xitiaoxi catchment, base flow accounts for a large fraction of the total runoff and should be accounted for during calibration. Historical runoff records show a base flow coefficient of 0.112. The calibrated simulated runoff was consistent with the observed daily runoff at Gangkou Station (Fig. 7). The Nash–Sutcliffe Efficiency (NSE) was 0.67 ($R^2 = 0.67$) at Gangkou Station. During the calibration period (2001–2005), the NSE of monthly runoff was even higher at 0.79 ($R^2 = 0.81$). The calibration results at Hengtang were better during this period, with the NSE of daily and monthly runoff being 0.71 ($R^2 = 0.72$) and 0.83 ($R^2 = 0.84$), respectively.

The simulation results demonstrated that both the original and modified SWAT model described the study area well. In general, comparison indicated that the modified model attained more accurate results with a higher NSE (Table 2). The same results were observed during model validation (Table 3).

The incorporation of spatially discretized HRUs into the SWAT model also produced results more consistent with observations at Gangkou and Hengtang Stations, improving the accuracy of runoff lag simulations.

Validation period

Runoff during 2006–2008 was modeled with SWAT to validate the model modifications. The results showed NSE values of 0.76 ($R^2 = 0.77$) and 0.81 ($R^2 = 0.83$) at

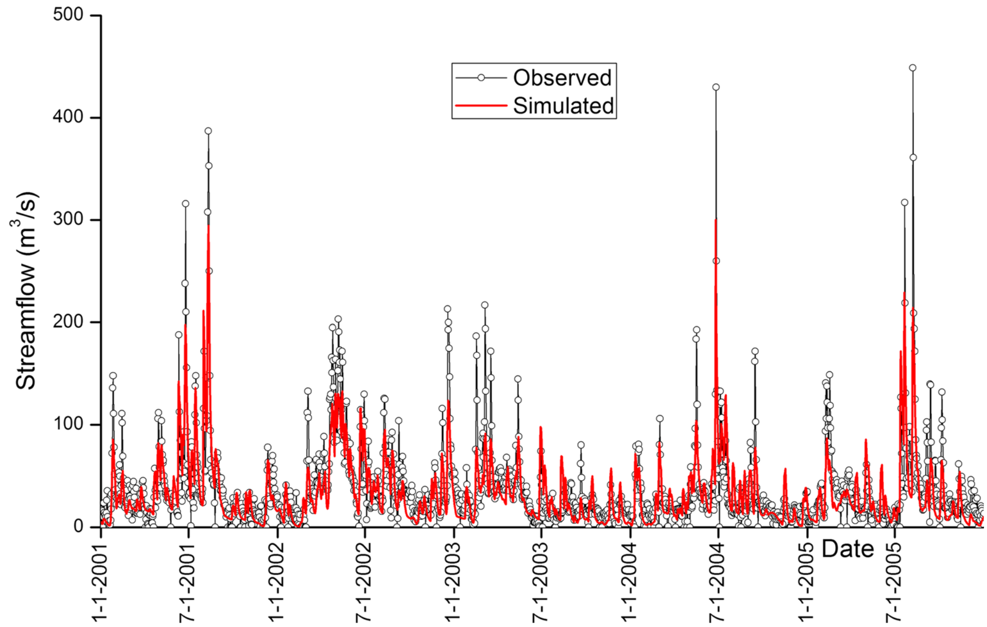


Fig. 7 Daily flow hydrograph of Gangkou Station during calibration period

Table 2 Simulation results comparison of unmodified to modified model in calibration period

Station	Model	NSE	R^2
Gangkou	Original	0.64	0.64
	Modified	0.67	0.67
Hengtang	Original	0.7	0.7
	Modified	0.71	0.72

Table 3 Simulation results comparison of unmodified to modified model in validation period

Station	Model	NSE	R^2
Gangkou	Original	0.7	0.71
	Modified	0.76	0.77
Hengtang	Original	0.805	0.827
	Modified	0.809	0.834

Gangkou Station and Hengtang Station, respectively (Figs. 8, 9).

Runoff simulation accuracy was better during model validation than during calibration, suggesting that the calibrated parameters enhanced the ability of SWAT to model surface hydrological processes.

Discussion

The modified SWAT model with spatially discretized HRUs simulated hydrological processes in the Taihu Basin more accurately than the original SWAT model, both during calibration and validation. The two reservoirs near the upper Hengtang Station are likely to have weakened the capability of the modified model to simulate differences in runoff lag. The NSE values were always higher at Gangkou Station than at Hengtang Station (Tables 2 and 3), resulting in more obviously improved model results at Gangkou Station. These findings suggest that the modified SWAT model may not improve simulation accuracy in large areas of the reservoirs. The difference in simulation between stations can likely be attributed to differences in surface complexity. Gangkou Station is located in the plains region, where canals and ditches strongly alter natural hydrological processes of the land surface and main stream.

In this study, variation in spatial and temporal resolution and provider of the SWAT inputs may have decreased the SWAT simulation accuracy. The reclassification of soil type during the preparation of the soil input data may also have introduced error. The soil profile data were identified by standard samples; however, the properties of the same soil type may vary across regions, allowing uncertainty in soil type to affect the simulation of surface runoff. Additionally, possible changes in land cover were not considered during simulation of SWAT, which may introduce error to runoff simulations.

To evaluate factors that may have caused the higher NSE value in model validation than in calibration, the amount and temporal distribution of precipitation was examined (Table 4).

Simulation accuracy was greater during years with high precipitation. The NSE values were 0.78, 0.73 and 0.80 during rainy years (2001, 2002 and 2008, respectively). In 2003, when there was less rainfall, the NSW was only 0.49. However, the low runoff in 2004 (28.63 m^3/s) did not

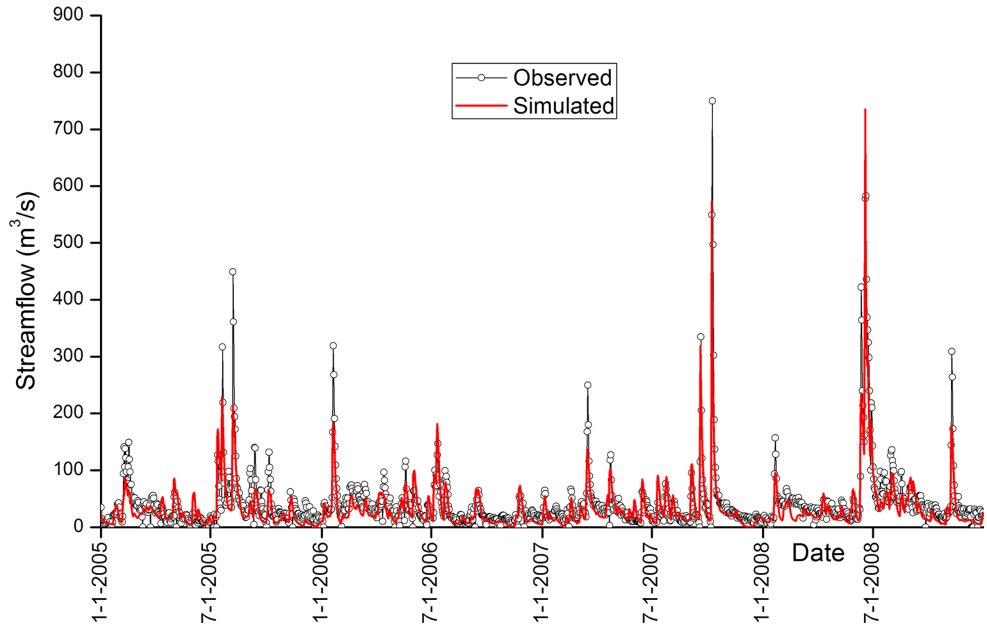


Fig. 8 Daily flow hydrograph of Gangkou Station during validation period

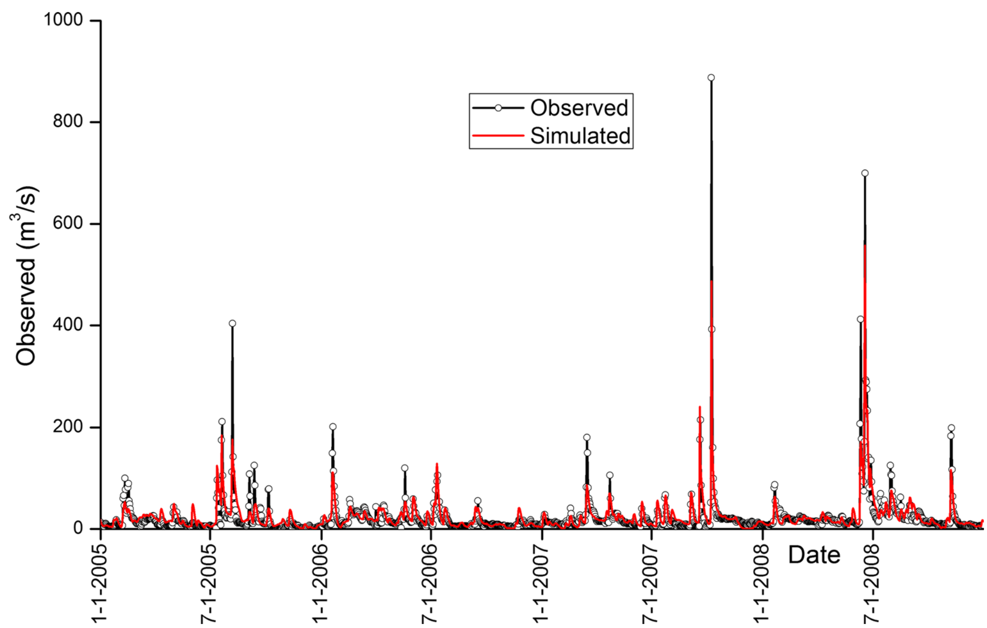


Fig. 9 Daily flow hydrograph of Hengtang Station during validation period

Table 4 Validation of simulation results using modified model at Gangkou station

Year	Precipitation (mm)	Observed daily runoff (m^3/s)	Simulated daily runoff (m^3/s)	NSE
2001	1377.2	39.84	39.89	0.78
2002	1462.8	47.85	40.94	0.73
2003	1106	30.17	25.94	0.49
2004	1344.1	28.63	31.19	0.57
2005	1240	36.83	30.89	0.58
2006	1178.9	33.88	29.84	0.63
2007	1288.6	37.79	34.34	0.72
2008	1434.3	53.38	42.62	0.8

appear to correspond to the high precipitation during this year (1344.1 mm), which may have been caused by river inversions. The modified model described runoff more accurately during periods of reduced peak runoff (non-peak periods). Therefore, it is suggested that future studies use a non-linear adjusted coefficient when runoff exceeds a certain limit.

In general, the results of model validation suggest that the incorporation of spatially discretized HRUs into the SWAT model can improve simulation of surface runoff lag time and thus advance the accuracy of simulation of watershed hydrological processes.

Conclusions

This study proposed a method of HRU spatial discretization based on spatial data analyses. Polygons that were assigned the appropriate surface properties including land use, soil type and terrain slope were used as HRUs. Thus, the adjusted HRUs contained both spatial and non-spatial attributes, improving SWAT model simulation under conditions of runoff lags in HRUs. The use of spatially discretized HRU was validated using data from the upper Xitiaoxi catchment of Taihu Basin, China. Runoff simulation with the modified SWAT model resulted in improved NSEs at both Gangkou Station (0.70–0.76) and Hengtang Station (0.70–0.71). These findings suggest that the location of the HRU is important to accurate modeling of runoff lags in patches with different surface types. Moreover, they indicate that related modifications may improve the accuracy of the SWAT model simulation of watershed hydrological processes. The introduction of spatially continuous HRU will provide a useful database for conducting smaller-scale spatial analyses.

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