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Effects of Spatial Information of Soil Physical Properties on Hydrological Modeling Based on a Distributed Hydrological Model

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Abstract: The spatial distribution of soil physical properties is essential for modeling and understanding hydrological processes. In this study, the different spatial information (the conventional soil types map-based spatial information (STMB) versus refined spatial information map (RSIM)) of soil physical properties, including field capacity, soil porosity and saturated hydraulic conductivity are used respectively as input data for Water Flow Model for Lake Catchment (WATLAC) to determine their effectiveness in simulating hydrological processes and to expound the effects on model performance in terms of estimating groundwater recharge, soil evaporation, runoff generation as well as partitioning of surface and subsurface water flow. The results show that: 1) the simulated stream flow hydrographs based on the STMB and RSIM soil data reproduce the observed hydrographs well. There is no significant increase in model accuracy as more precise soil physical properties information being used, but WATLAC model using the RSIM soil data could predict more runoff volume and reduce the relative runoff depth errors; 2) the groundwater recharges have a consistent trend for both cases, while the STMB soil data tend to produce higher groundwater recharges than the RSIM soil data. In addition, the spatial distribution of annual groundwater recharge is significantly affected by the spatial distribution of soil physical properties; 3) the soil evaporation simulated using the STMB and RSIM soil data are similar to each other, and the spatial distribution patterns are also insensitive to the spatial information of soil physical properties; and 4) although the different spatial information of soil physical properties does not cause apparent difference in overall stream flow, the partitioning of surface and subsurface water flow is distinct. The implications of this study are that the refined spatial information of soil physical properties does not necessarily contribute to a more accurate prediction of stream flow, and the selection of appropriate soil physical property data needs to consider the scale of watersheds and the level of accuracy required.
Keywords: soil physical property; hydrological modeling; groundwater recharge; soil evaporation; runoff component; Water Flow Model for Lake Catchment (WATLAC)

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1 Introduction

Distributed hydrological models have been widely used to help understand the hydrological processes and tackle water-related problems (Abbott and Refsgaard, 1996), and these models require the spatially distributed data as inputs to reflect the heterogeneity of watersheds. The spatial arrangements of watershed characteristics (e.g., topography, soil, vegetation type, surface roughness, *etc*.) vary significantly in space (Grayson and Blöschl, 2001),

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and they directly determine the proportion of precipitation retained in subsurface storage and water transmission rates to stream networks (Zimmermann *et al*., 2006; Tetzlaff *et al*., 2007; Price *et al*., 2010). Therefore, the spatial distribution of soil physical properties is essential for modeling and understanding hydrological processes, such as runoff generation, infiltration, evapotranspiration, groundwater recharge, and erosion. Compared with the topography and the spatial variation of vegetation which could be derived easily from remote sensed imagery at high resolution (Quinn *et al*., 2005), the spatial information of soil physical properties require numerous soil observations and laboratory analyses and costly and not easy to obtain (Ye *et al*., 2009; 2011b). Moreover, the standard soil surveys are not designed to provide the detailed (high resolution) soil information due to the cartographic model and manual delineation process used in producing conventional soil maps (Zhu and Mackay, 2001). Actually, the considerable uncertainties might stem from the spatial detail of soil data rather than other watershed characteristics data. Therefore, numerous studies have been conducted to evaluate the effects of the spatial detail of soil data on hydrological modeling and corresponding responses.

Previous studies mainly were focused on the following three aspects. The first aspect is about the effects of the resolution of soil type data on hydrological processes. Based on the Soil and Water Assessment Tool (SWAT) model, Muttiah and Wurbs (2002) found that the watershed water balance and average soil water storage had a large variation in some semi-arid regions when the scale of soil map was changed from 1∶250000 to 1∶24000, but evapotranspiration (ET) remained about the same. Peschel *et al*. (2006) assessed the runoff modeling with two different spatial resolution soil data (US State Soil Geographic (STATSGO) and US Soil Survey Geographic database (SSURGO)), and they found that the total flow modeled using SSURGO soil data (high resolution) was higher than that modeled using STATSGO soil data (low resolution), because the transmission losses were lower when SSURGO soil data were used. Levick *et al*. (2004) gained the opposite conclusions when he compared the runoff modeling using Food and Agricultural Organization (FAO), STATSGO and SSURGO soil data respectively, and the results indicated that FAO soil data produced more runoff than SSURGO soil data but less runoff than STATSGO soil data. However, another opinion is also universal. Chaplot (2005) found that the scale of soil map greatly affected nitrogen as well as sediment loads, but not on runoff fluxes in a small central Iowa creek. Ye *et al*. (2009; 2011b) found that the resolution of soil data did not cause significant difference in the predicted overall stream flow using SWAT model, but might affect the partitioning of surface and subsurface water flow. Similarly, Mukundan *et al*. (2010) found that models using different spatial resolution of soil data had comparable model efficiency in simulating stream flow and sediment loading process. In addition, Li *et al*. (2007) and Wen *et al*. (2010) found that there was low sensitivity of runoff simulation for both SWAT model (Arnold *et al*., 1998) and the block-wise use of topographic model (TOPMODEL) with Muskingum-Cunge routing model (BTOPMC) (Takeuchi *et al*., 1999; Ao, 2001) when using different spatial resolution of soil data.

The second aspect is about the effects of spatial variability of soil hydraulic properties. Sciuto and Diekkrüger (2010) investigated the impacts of spatial variability of soil hydraulic properties on the water balance and spatial patterns of soil moisture in a headwater catchment using a fully coupled flow simulation model. Cho and Olivera (2009) found that although spatially distributed data could help to understand the characteristics of the watershed and provide valuable information for distributed hydrological models, application of the spatially distributed data might not necessarily improve model performance when the watershed was small. Unlike studies by Grayson *et al*. (1995) and Merz and Barbossy (1998) that investigated the effects of the spatially heterogeneous distribution of soil physical characteristics on short-term runoff of hillsides and catchments, Maeda *et al*. (2006) studied the long-term spatio-temporal influence and noted that heterogeneous distributions of soil thickness and soil physical characteristics greatly affected the fluctuations of soil moisture and runoff in a suburban forest catchment. In addition, Loague and Kyriakidis (1997) found a high relevance of the spatial variability of saturated hydraulic conductivity for the description of infiltration processes. Similarly, Woolhiser *et al*. (1996) studied the effects on hortonian runoff production, and Zhu and Mackay (2001) investigated the effects of detailed and spatial soil thickness and saturated hydraulic conductivity on hydro-ecological modeling over a mesoscale watershed.

The last aspect is about the effects of spatial variability of antecedent soil moisture on hydrologic responses. The soil moisture conditions prior to a rainfall event play a central role in affecting the generation of surface runoff by controlling the local infiltration capacity (Bronstert and Bárdossy, 1999). Two early studies showed that considering spatial variability of antecedent soil moisture could yield a greater runoff compared to conditions when soil moisture was assumed uniform (Merz and Plate, 1997; Bronstert and Bárdossy, 1999). Later studies have also begun to pay more attention to the effects of spatial variability of antecedent soil moisture (Castillo *et al*., 2003; Famiglietti *et al*., 2008; Noto *et al*., 2008; Minet *et al*., 2011).

Currently, different methods have been used to include spatial information into existing distributed hydrological models (Ye *et al*., 2011b). The spatial information of soil physical properties is typically derived from conventional polygon-based soil type maps, with a scale likely to be substantially lower than that of other data used, to feed distributed hydrological models (Quinn *et al*., 2005). This treatment is based on an assumption that soil physical properties are spatial homogeneous for one specific type of soil, and this assumption leads to following questions: whether this assumption of soil spatial homogeneity is acceptable in hydrological processes modeling and would it further affect estimation accuracy of runoff generation, infiltration, soil water content and evaporation? However, few previous studies focused on the influences of spatial distribution of soil physical properties, such as field capacity, porosity and saturated hydraulic conductivity. In addition, most studies were performed by using Institute of Hydrology Distributed Model (IHDM) (Calver, 1988), SWAT model or BTOPMC model, *etc*. These models did not directly use the spatial distribution information of soil physical properties. Instead, they used polygon-based data, and the data were then converted into soil physical properties through several parameters, which might not properly reflect the influence of soil physical properties. By contrast, the Water Flow Model for Lake Catchment (WATLAC) (Zhang, 2007) is a grid- based spatially distributed hydrological model that includes spatial information of soil physical properties directly. The model has been successfully applied for water balance analysis of Fuxian Lake catchment (Zhang and Werner, 2009), surface-groundwater flow interactions modeling of Xitiaoxi catchment (Zhang and Li, 2009) and assessment of the effects of future climate change on catchment discharges and lake water levels of Poyang Lake (Ye *et al*., 2011a) and Xinjiang catchment (Li *et al*., 2012b). More important, the parameters of WATLAC model are automatically optimized by the Parameter ESTimation (PEST) optimization tool (Doherty, 2004), and a preliminary assessment of sensitivity to soil hydraulic conductivity has been accomplished (Zhang, 2011; Li *et al*., 2012a).

Therefore, the objectives of this study are: 1) to evaluate and compare the effectiveness of using different spatial information of soil physical properties, including field capacity, soil porosity and saturated hydraulic conductivity in hydrological processes simulation; and 2) to expound the effects using spatial information of soil physical properties on model performance in terms of estimating groundwater recharge, soil evaporation, runoff generation as well as partitioning of surface and subsurface water flow.

2 Materials and Methods

2.1 Study area

The Xitiaoxi catchment, one of the most important tributaries in the upstream of Taihu Lake in the lower reaches of the Changjiang (Yangtze) River Basin is selected as the study area (Fig. 1), which covers an area of 2200 km^2. The elevation in the catchment varies significantly from 1 m to 1575 m, with high elevation at the mountains and hilly lands in the southwest and low elevation at the alluvial plains in the northeast. The Xitiaoxi catchment has a subtropical monsoon climate with a mean annual precipitation of 1465 mm and a mean annual temperature of 15.5℃. The Xitiaoxi River is one of the most important water sources of Taihu Lake, and the main channel is about 143 km originating from the Tianmu Mountains, and it supplies 28% of water volume of the Taihu Lake. And 67.30% of the land in the catchment is covered by forest, and 26.80% is used as arable land, which lies in the low alluvial plains. Other land types in the catchment include urban area (2.35%), grassland (0.66%) and water bodies (1.98%).

2.2 Data sources

The digital elevation data (DEM) was derived from the National Aeronautics and Space Administration (NASA)

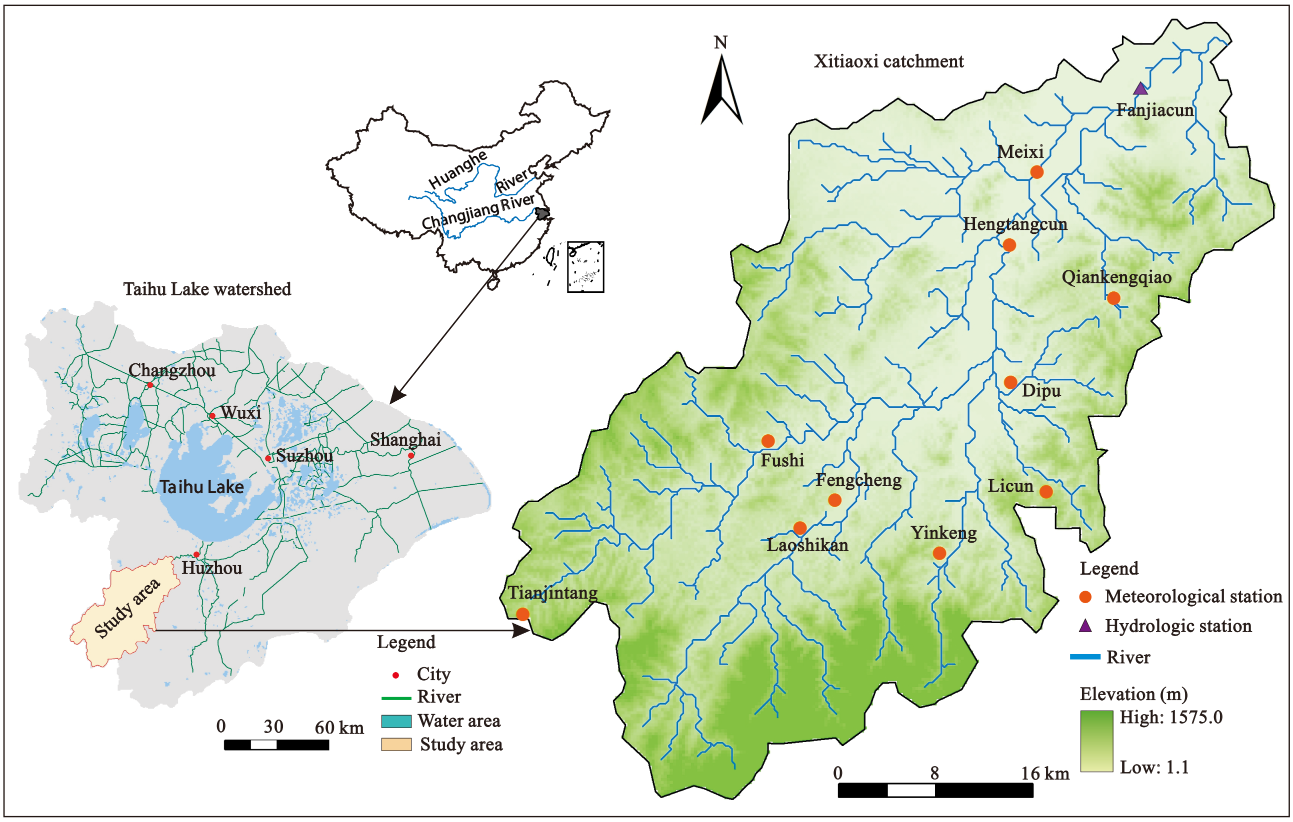

Fig. 1 Location, topography and stream system of Xitiaoxi catchment

Shuttle Radar Topographic Mission (SRTM) at a spatial resolution of 90 m (http://srtm.csi.cgiar.org), which were used to delineate the physical boundary and river network of the catchment. The soil types in the catchment were classified according to the Genetic Soil Classification of China, and the distribution of soil types was obtained from a soil survey completed by the Institute of Soil Science, Chinese Academy of Sciences (Fig. 2). The catchment is dominated by yellow-red soil (47.6%) and paddy soil (28.7%); other soil types include yellow soil (5.7%), acid regosol (5.6%), brown rendzina (5.4%), brown-red soil (2.8%), acid purple soil (2.6%) and latosol (1.6%).

Two different spatial distribution of soil physical properties, including field capacity, soil porosity and saturated hydraulic conductivity, was used in this study to depict the heterogeneity of soil physical property. One is the spatial information derived from conventional soil type map (denoted by STMB) (Fig. 2) and determine the physical property values according to the literature, soil survey database and previous studies, with the assumption that soil physical properties are spatial homogeneous for one specific soil type. Table 1

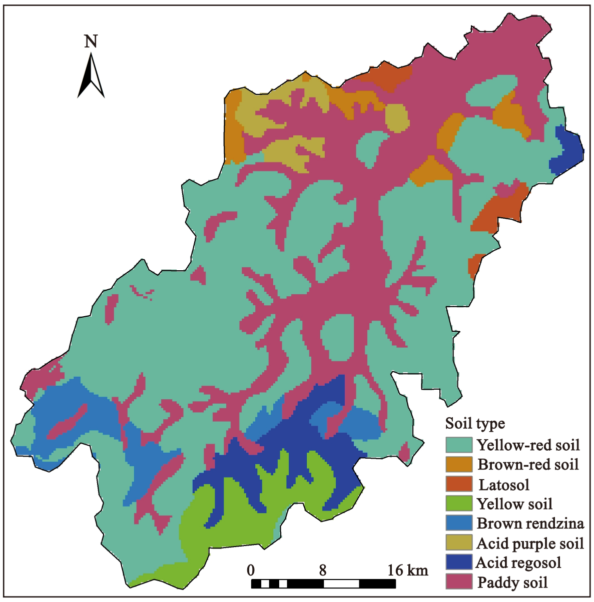

Fig. 2 Spatial distribution of soil types in study area

shows the physical property values of each soil type, with field capacity ranging from 16.3% to 31.1%, soil porosity ranging from 52.1% to 68.8%, saturated hydraulic conductivity varying from 0.31 m/d to 5.78 m/d, and all the spatial distribution are shown in Fig. 3 (a–c). The other one is a recently refined spatial information map of soil physical properties (denoted by RSIM) with a resolution of 250 m × 250 m as shown in Fig. 3 (d–f). The refined spatial information is obtained through an extensive field sampling with further numerical interpolation completed by the Institute of Soil Science, Chinese Academy of Sciences, and more reliable information could be derived from the latter one.

Table 1 Physical property values based on conventional soil types map

Soil type	Field capacity (%)	Soil porosity (%)	Saturated hydraulic conductivity (m/d)
Yellow-red soil	25.5	59.7	2.95
Brown-red soil	30.2	56.0	0.35
Latosol	25.1	57.7	0.51
Yellow soil	16.3	68.8	1.88
Brown rendzina	24.6	62.1	5.78
Acid purple soil	31.1	52.1	0.31
Acid regosol	22.8	58.8	2.21
Paddy soil	29.2	55.8	1.17

The rain gauge data collected from ten meteorological stations (Fig. 1) were also used to drive the hydrological model. Moreover, other meteorological data including daily maximum temperature, daily minimum temperature, solar radiation, wind speed, and relative humidity were also used in this study to calculate the evapotranspiration and related processes. These data have been widely used for many other studies, and they are proved to be good qualities. The relation between elevation and rainfall was also examined to reflect the difference between mountainous and lowland regions, although there was no clear evidence that the rainfall changed with elevation in the study area. Therefore, the spatial distribution of daily rainfall were directly interpolated to grid (250 m × 250 m) for the whole catchment by the inverse distance weighted (IDW) technique with a power of 2 to satisfy the requirement of the distributed hydrological model. In addition, the observed daily stream flows from the Fanjiacun hydrologic station were available to calibrate model parameters and validate the simulation results.

2.3 Distributed hydrological model

The WATLAC model is a grid-based spatially distributed hydrological model with unique and effective computational techniques to simulate complex spatial variability of surface and subsurface flows. The model can simulate hydrological processes, including canopy interception, overland flow, stream flow routing, soil lateral flow, soil water percolation to groundwater and saturated groundwater flow driven by rainfall and evaporation. The land surface (including river networks), unsaturated soil layer and saturated groundwater aquifer are coupled in the model and can reflect the interactions between the groundwater and the surface water. The WATLAC model has been successfully applied in many catchments and the details of model structure could be found in Zhang and Li (2009) and Zhang and Werner (2009). The WATLAC model first calculated the throughfall (P_n) taking into account canopy interception which would be evaporated back into the atmosphere. The water that infiltrated into the soil subsequently percolated downwards under gravity to the groundwater table, or flowed laterally close to the surface as soil lateral flow, or else it might be evaporated. The groundwater recharge rate (R_G) was computed as a function of the drainable soil water, saturated soil hydraulic conductivity and shallow aquifer conductivity (Neitsch *et al.*, 2002). The soil lateral flow (R_L) was calculated as a function of soil drainable water, soil hydraulic conductivity, soil slope length and slope gradient (Neitsch *et al.*, 2002). The calculation of actual evapotranspiration followed the same approach as that in USACE (2000), i.e., the total evapotranspiration was a sum of various components from canopy storage, soil storage and shallow groundwater. The potential evapotranspiration was calculated by using the Penman-Monteith method (Xu *et al.*, 2006). Overland flow routes were generated from DEM by the D-8 method considering time lag effects when the overland flow was transferred from overland to known waterways. Stream flow routing was simulated by using the Muskingum method. The saturated groundwater flow was simulated through MODFLOW-2005 (Harbaugh, 2005), which was integrated in WATLAC and could achieve the interactions with the surface water flow, i.e., on one hand, the groundwater recharge calculated from the surface water model was passed to the MODFLOW for groundwater flow modeling; on the other hand, groundwater table simulated from MODFLOW was used in surface water model to update the thickness of the soil column (Zhang and Li, 2009).

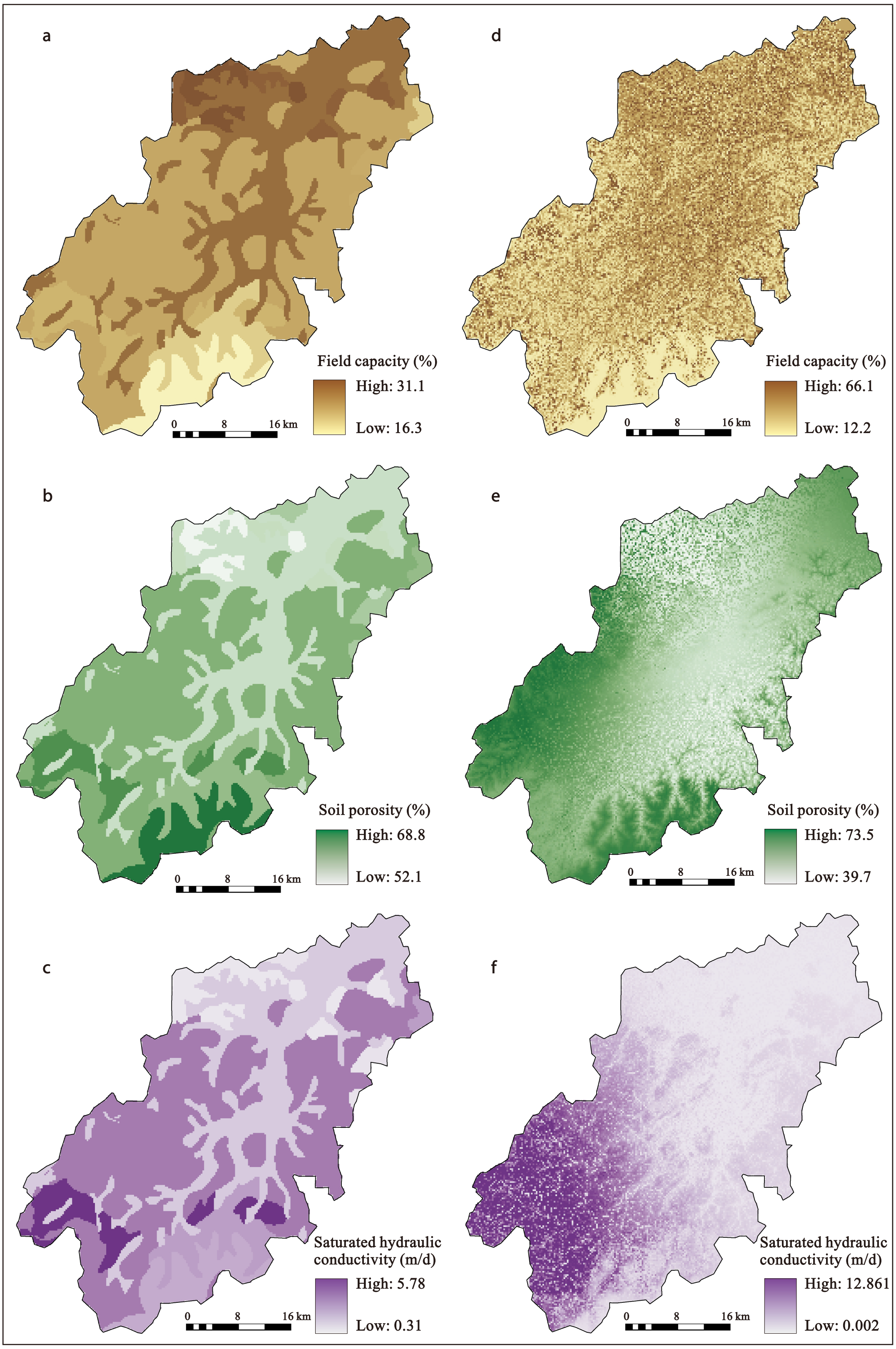

Fig. 3 Spatial distribution of field capacity (a, d), soil porosity (b, e) and saturated hydraulic conductivity (c, f) in conventional soil types map-based spatial information (STMB) soil data (Left) and refined spatial information map (RSIM) soil data (Right)

The model parameters were automatically optimized by the PEST optimization tool (Doherty, 2004). In this study, the physical parameters of WATLAC included parameters that described the properties of landuse, river, *etc*., and these properties were derived from the surveyed database and related literature. Several empirical parameters, such as C_{lag} for overland flow lag effect, β_1 and β_2 for groundwater recharge estimation and soil lateral flow calculation, e and k for parameters in the Muskingum method, were automatically optimized by the PEST. The model performance was evaluated by using statistical analyses of model outputs. Evaluation criteria, e.g., Nash-Sutcliffe efficiency (E_{ns}), relative runoff depth error (DE) and determination coefficient (R^2) were used to measure the capability and reliability of the model in describing the observed processes. The values of E_{ns} and DE were calculated as the followings:

$$E_{ns} = 1 - \sum_{i=1}^{n}(Qobs_i - Qsim_i)^2 \Big/ \sum_{i=1}^{n}(Qobs_i - \bar{Q}obs)^2 \quad (1)$$

$$DE = \sum_{i=1}^{n}(Qsim_i - Qobs_i) \Big/ \sum_{i=1}^{n} Qobs_i \times 100\% \quad (2)$$

where $Qobs_i$ is the observed stream flow at the ith step; $Qsim_i$ is the simulated stream flow at the ith step; $\bar{Q}obs$ is the mean observed stream flow over all time steps; and n is the total time step.

3 Results and Analyses

3.1 Effects on stream flow simulation

The study area was discretized into a number of square grids (250 m × 250 m) to consider the heterogeneity of the topography of the basin, and the stream flow simulation was carried out using the WATLAC model from 1 January 2007 to 31 December 2010. Moreover, in order to avoid the influence of different model parameter values, PEST was designed to preferentially estimate identical values for the same parameters in the different model domains (STMB and RSIM). Therefore, the final optimal values of model parameters might not be the best for WATLAC model, but were moderate and acceptable for each model scenes. Figure 4 shows the comparison of observed and simulated daily stream flow hydrographs produced by the STMB-based model and RSIM-based model respectively at Fanjiacun station. It is found that the simulated stream flow hydrographs with STMB soil data and RSIM soil data reproduced the observed hydrographs, although there is a tendency for the model to underestimate the discharges in low water periods and to miss the extreme peak flows.

The summary values of model performance using different spatial information of soil physical properties are shown in Table 2. The results reveal that the model using STMB soil data produces an overall good fit. The E_{ns} ranges between 0.86 and 0.91, with an average of 0.89. Additionally, the relatively high values of R^2 (between 0.87 and 0.93) indicate that the model describes the variation of the observed stream flow well, with an exception that the DE is more than 10% in 2009 and 2010. Therefore, WATLAC model is robust and sound, which could provide a reasonable basis for testing the effects of different spatial information of soil physical properties. However, the model using RSIM soil data also produces satisfactory results, with E_{ns} ranging between 0.85 and 0.92, the DE between –12.01% and 8.93%, and the R^2 between 0.88 and 0.93. There might be no significant increase in model accuracy as more

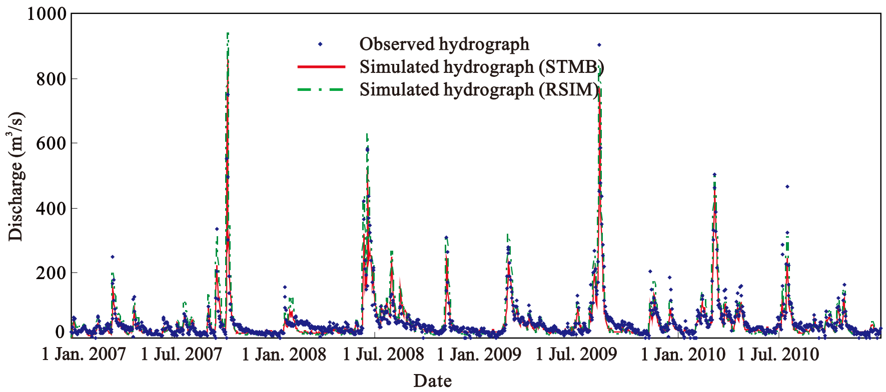

Fig. 4 Comparison of observed and simulated daily hydrographs at Fanjiacun station

Table 2 Comparison of model performance by using STMB and RSIM soil data

Year	STMB soil data			RSIM soil data		
	E_{ns}	*DE* (%)	R^2	E_{ns}	*DE* (%)	R^2
2007	0.908	–2.64	0.918	0.846	8.93	0.918
2008	0.865	–4.10	0.868	0.845	1.94	0.881
2009	0.911	–15.22	0.930	0.916	–10.78	0.927
2010	0.856	–14.89	0.891	0.894	–12.01	0.906
All periods	0.889	–9.98	0.896	0.881	–4.45	0.899

Notes: STMB, conventional soil types map-based spatial information; RSIM, refined spatial information map

precise information of soil physical properties has been used in the analysis, but WATLAC model using the RSIM soil data could predict more runoff volume and reduce the relative runoff depth errors.

3.2 Effects on groundwater recharge and soil evaporation

The soil physical properties play an important role in determining soil moisture, which is involved in the processes of groundwater recharge, unsaturated soil evaporation, and so on. Given this, the influences on groundwater recharge and unsaturated soil evaporation are also analyzed. Figures 5 and 6 show the comparison of simulated monthly groundwater recharges and soil evaporation using different spatial information of soil physical properties at forest and arable land. It is clear from Fig. 5 that the monthly groundwater recharges simulated using both spatial distribution data of soil physical properties have a consistent trend, while the STMB soil data tend to produce higher groundwater recharges than RSIM soil data, irrespective of the land type. The results in Fig. 6 show that monthly soil evapo-

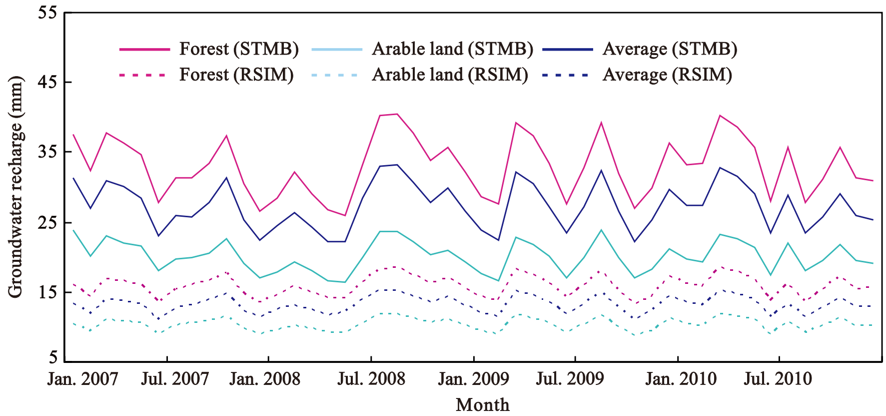

Fig. 5 Comparison of simulated monthly groundwater recharge by using STMB and RSIM soil data

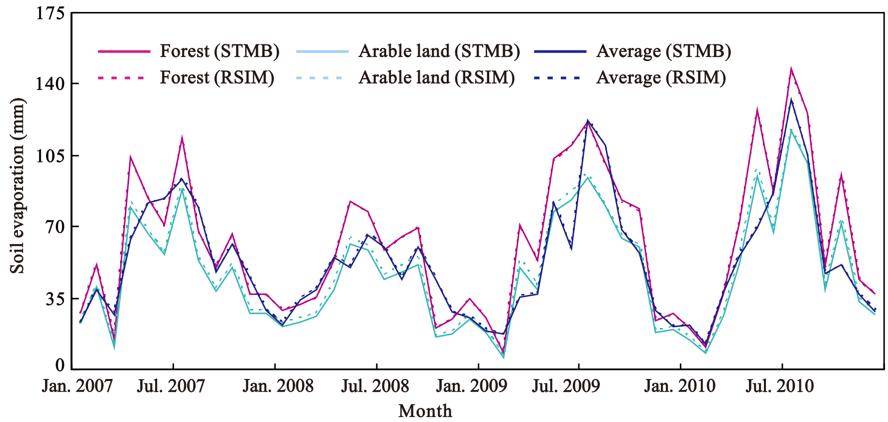

Fig. 6 Comparison of simulated monthly soil evaporation by using STMB and RSIM soil data

ration based on STMB soil data is equivalent to the one based on RSIM soil data, although monthly soil evaporation varies between forest and arable land. Therefore, the refined spatial information of soil physical properties induces a reduction of the groundwater recharges, but has a negligible effect on soil evaporation.

Table 3 and Table 4 show the simulated annual groundwater recharges and soil evaporation, respectively, and the simulation is based on STMB and RSIM soil data with different land use types. The annual groundwater recharges estimated using STMB soil data range between 323 mm and 330 mm, with an average of 328 mm, whereas for RSIM soil data, the estimated values range between 156 mm and 161 mm, with an average of 158 mm. The annual soil evaporation are 527–684 mm (with an average of 636 mm) and 532–683 mm (with an average of 637 mm), respectively, and this trivial difference indicates that the estimated results are independent of dataset type or land use type.

The spatial distribution of annual groundwater recharges simulated using the STMB and RSIM soil data is shown in Fig. 7. It is obvious that the spatial distribution of annual groundwater recharges is quite different in two cases, although the annual groundwater recharges are low in alluvial plains and high in mountains and hilly lands. The annual groundwater recharges are also high in the middle zones except for the river valley area (they actually have low values based on the STMB soil data). In addition, although the highest annual groundwater recharge in the STMB case (982 mm) is 200 mm lower than that in the RSIM case (1178 mm), the former with larger groundwater recharges has larger area than the latter. The results of Fig. 7 indicate that the spatial information of soil physical properties affects the spatial distribution patterns of the groundwater recharges. However, it is interesting that the annual soil evaporation simulated using the STMB and RSIM soil data is similar to each other (Figures are omitted due to their semblable spatial distribution.). Therefore, the effects of different spatial information of soil physical properties on the estimation of groundwater recharge are significant, but become negligible when dealing with the estimation of unsaturated soil evaporation.

3.3 Effects on runoff components

Subsequently, the runoff volume and components estimated using different spatial information of soil physical properties are also examined (Table 5). It is found that the base flows simulated using the STMB soil data ranged between 146 mm and 258 mm, with an average of 218 mm during 2007–2010, which accounted for 29.1% of the total runoff. By contrast, the surface flows (ranged between 446 mm and 612 mm) were the main runoff components that accounted for 70.8% of the total runoff. When the RSIM soil data was applied, the base flows decreased markedly and ranged between 82 mm

Table 3 Comparison of simulated annual groundwater recharges by using STMB and RSIM soil data (mm)

Year	STMB soil data			RSIM soil data		
	Forest	Arable land	Basin average	Forest	Arable land	Basin average
2007	397	248	330	187	123	156
2008	395	238	329	192	125	161
2009	390	236	323	188	122	157
2010	402	244	330	192	125	159
Average	396	242	328	190	124	158

Table 4 Comparison of simulated annual soil evaporation by using STMB and RSIM soil data (mm)

Year	STMB soil data			RSIM soil data		
	Forest	Arable land	Basin average	Forest	Arable land	Basin average
2007	725	561	674	717	578	675
2008	580	429	527	575	455	532
2009	801	605	657	793	629	658
2010	849	647	684	840	666	683
Average	739	561	636	731	582	637

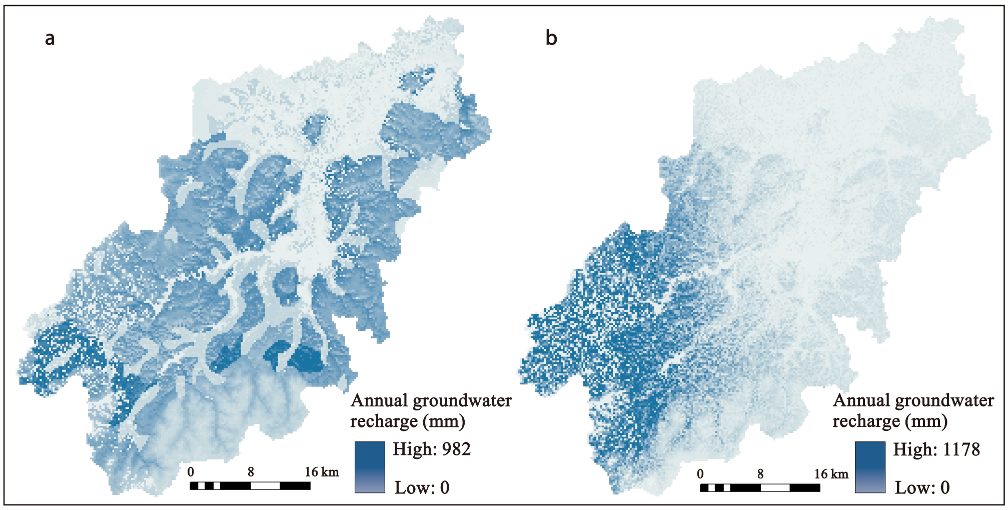

Fig. 7 Spatial distribution of simulated annual groundwater recharges by using STMB soil data (a) and RSIM soil data (b)

Table 5 Comparison of simulated runoff components by using STMB and RSIM soil data

Year	STMB soil data					RSIM soil data				
	Base flow		Surface flow		Total runoff (mm)	Base flow		Surface flow		Total runoff (mm)
	V (mm)	P (%)	V (mm)	P (%)		V (mm)	P (%)	V (mm)	P (%)	
2007	146	24.6	446	75.3	592	82	12.2	588	87.8	670
2008	221	26.5	612	73.5	833	109	12.2	783	87.8	892
2009	245	30.6	555	69.4	800	119	14.1	730	85.9	849
2010	258	33.7	506	66.2	764	126	16.1	661	83.9	787
Average	218	29.1	530	70.8	748	109	13.6	690	86.4	799

Notes: V, volume; P, percentage of total runoff

and 126 mm (with an average of 109 mm), but the surface flows were higher than estimated values based on the STMB soil data.

Correspondingly, the proportions of base flows and surface flows to the total runoff were quite different in the two cases (Fig. 8). The STMB soil data estimated a larger proportion of base flows, due to the larger groundwater recharges as discussed in Fig. 5 and Table 3. In addition, the annual total runoff values estimated using both the STMB and RSIM soil data are quite close and there are no significant difference (average values are 748 mm and 799 mm, respectively (Table 5). Therefore, different spatial information of soil physical properties mainly influenced the partitioning of surface and subsurface water flow, but does not cause a significant difference in overall stream flow.

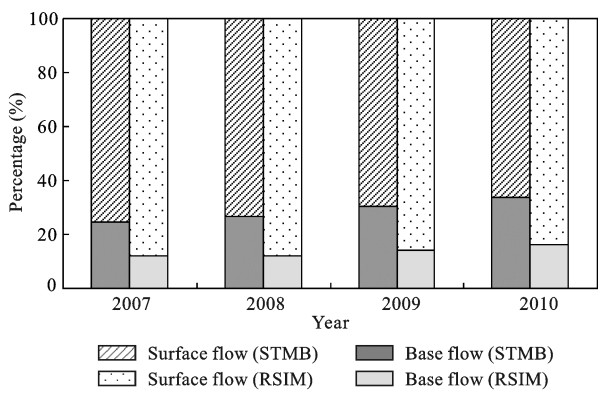

Fig. 8 Comparison of partition proportion of base flow and surface flow to total runoff

4 Conclusions

In this study, the spatial information of soil physical properties (e.g., field capacity, soil porosity and saturated hydraulic conductivity) derived from the conventional soil-type maps and the refined spatial information are both used as input data for WATLAC model to determine their effectiveness in hydrological process modeling. The influences of different spatial information of soil physical properties on groundwater recharge, unsaturated soil evaporation and runoff components are also further evaluated. The results show that the simulated stream flow hydrographs with different spatial information of soil physical properties reproduce the observed hydrographs well. There might be no significant increase in model accuracy as more precise information of soil physical properties information being used. The monthly and annual groundwater recharges simulated using the refined spatial information of soil physical properties are lower than the ones using the conventional soil type data. The two soil data cases show similar soil evaporation values, and the spatial distribution patterns are also insensitive to the spatial information of soil physical properties. And, the partitioning of surface and subsurface water flow has a close relationship with the spatial information of soil physical properties. In sum, it can be concluded that the refined spatial information of soil physical properties does not necessarily contribute to a more accurate prediction of stream flow, and the selection of appropriate soil physical property data needs to consider the scale of watersheds and the level of accuracy required.

In addition, it should be pointed out that the results of this study may vary when the physiographic regions and the model parameters change. The influences of spatial information of soil physical properties may be more pronounced in smaller watersheds where the effects of soil variability are not lumped, whereas the computational efficiency is lower in larger watersheds because more time and effort are required to set up and calibrate a model with more detailed spatial information of soil physical properties. Also, the influences of different climatic zones need to be considered explicitly in the future study, because that the mechanisms of rainfall-runoff processes and the principle of the model could be quite different.

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