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Effects of spatial resolution of soil data on hydrological processes modelling: A case study using the SWAT model

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Abstract: The prediction accuracy of a distributed hydrological model depends on how well the model input spatial data describe the characteristics of the watershed. Especially in a large catchment, could a higher resolution of input data contribute to improving the accuracy of model simulations? In this study, surveyed soil data with two different spatial resolutions were used as input data for a SWAT model simulation in a large catchment of Xinjiang River basin (15535km^2) in China. The purpose of this study is to (1) evaluate the effect of different spatial resolutions of soil type on the simulation of hydrologic components of the SWAT model and (2) examine the adaptability of applying high precision of soil resolution in large catchments.

The first soil data set has a coarse resolution of 1:3,000,000 and five major types of soils are classified. The second one has a finer resolution of 1:1,000,000, in which 36 major soil types were classified.

Evaluation of the distribution of SWAT hydrologic response units (HRUs) is conducted by examining the changed percentages of soil class and land use of the two soil types. Result show that when the threshold of soil area definitions in the watershed is increased, the number of HRUs decreases when the higher resolution soil data was used, but there is little change when the lower resolution soil data was used.

In order to evaluate the differences in model predictions of the two SWAT setups with differing soil data, modelled streamflows were compared before and after calibration. Before calibration, the coarse resolution soil data performed marginally better than the fine resolution soil data. After calibration, streamflow predictions of both SWAT setups improved. In the study watershed, using a higher resolution soil data didn't yield improvements in monthly streamflow modelling with the SWAT model. This lack of difference in streamflow predictions between the two data sets is attributed to theapplication of the SCS curve number method in SWAT.

Monthly soil water storage and evapotranspiration outputs of the SWAT model were also compared. Results show that the finer resolution data produced higher monthly soil water storage estimates than the coarse resolution data across the entire watershed during the simulation period. However, there was little difference in evapotranspiration output. This insensitivity of evapotranspiration to soil properties suggests that perhaps a relatively simplified computation method for the evapotranspiration module in SWAT could be considered.

The implications of this study are that improvement of the resolution of soil data does not necessarily contribute to a more accurate prediction of streamflow in large catchments.

Keywords: *SWAT model; Hydrological processes; spatial resolution of soil data; Xinjiang catchment*

1. INTRODUCTION

The prediction accuracy of a model depends on a number of factors including the spatial resolution of the input data (Waring and Running, 1998). Previous research has shown that the spatial resolution of soil types has a great effect on hydro-ecological processes modeling. A number of existing models such as MIKE SHE, TOPMODEL and SWAT use different methods to cope with soil information. These spatially distributed models allow a multi-objective evaluation of the impact of spatially variable catchment properties on the hydrological responses. Questions are raised about the appropriate resolution of the spatially distributed input data, especially for a large catchment. Is it necessary to use a high resolution of input data which greatly increases preparation work and slows the model's simulation process? Does the use of more precise input data improve modeling accuracy?

Modelling studies have been conducted to evaluate the sensitivity of the SWAT model to the soil and land use data parameterization. Some researchers have shown that different spatial resolutions of soil data can lead to different modelling results (Muttiah and Wurbs, 2002; Geza and McCray, 2008). Others have indicated that the spatial resolution of some input data has no significant effects on the accuracy of model predictions (Chaplot, 2005; Li, 2007). However, the effects of spatial resolution of soil data on hydrological processes are still not studied in large catchments, and the adaptability of applying high precision of soil resolution in large catchments need to be further investigated.

In this paper, a case study was conducted for a 15535 km^2 watershed in the Xinjiang River basin by using two different spatial resolutions of soil type to evaluate their effects on hydrological processes such as stream flow, soil water storage and evapotranspiration simulated by the SWAT model. The purpose of this study is to (1) evaluate the effect of different spatial resolutions of soil type on the simulation of hydrologic components of the SWAT model and (2) examine the adaptability of applying high precision of soil resolution in large catchments.

2. DESCRIPTION OF THE STUDY AREA

Figure 1 shows the geographic location and the elevation of the Xinjiang River basin, which is one of the five river basins of Poyang Lake catchment located in the lower reaches of the Yangtze River. The catchment above Meigang Hydrostation covers about 15535 km^2 with elevation ranging from 45 to 2178m. The basin is in a wet climate zone with an annual mean precipitation of 1878 mm for the period of 1960–2005 and annual mean temperature of 18 ^{o}C. The Xinjiang River flows primarily from the east to the west and enters Poyang Lake. The average streamflow at Meigang station for the 1960 to 2002 period was 578 m^3/s.

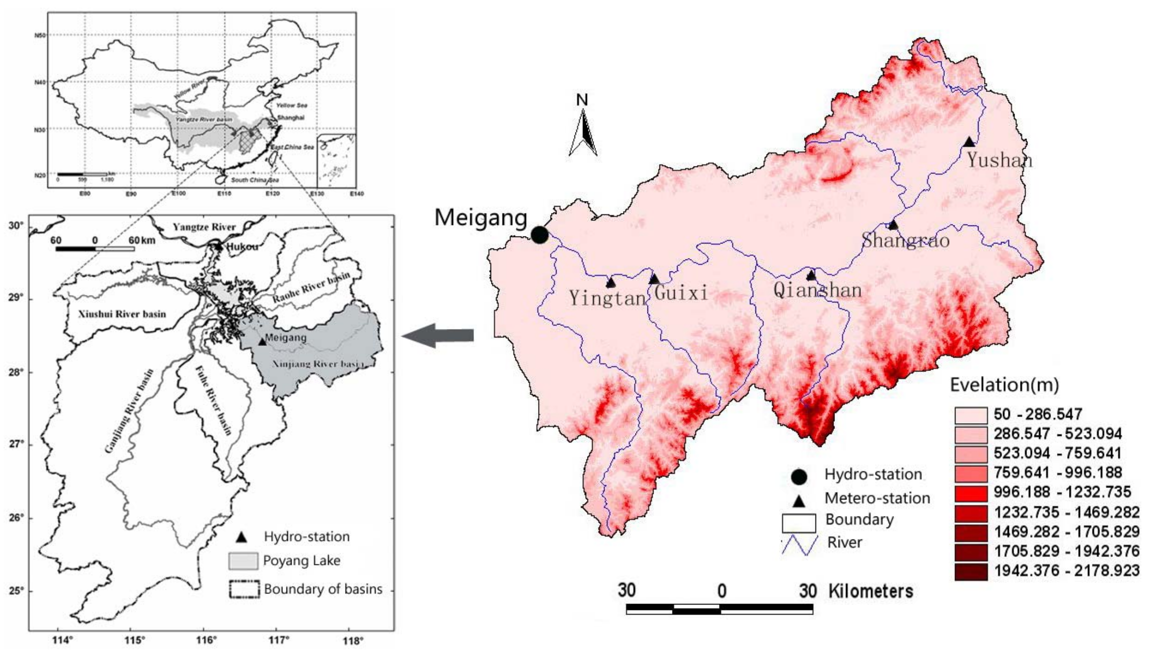

Figure1. Topography and river tributaries of Xinjiang River basin. Hydrological and meteorological gauging stations in the catchment are marked

3. METHODOLOGY

3.1. Model Description

The SWAT model was used in this study to evaluate the effect of spatial resolution of soil types in the Xinjiang River basin. One of the major features of SWAT is its partitioning of the study basin into subbasins (Neitsch et al., 2002b). Each subbasin is further discretized into a series of hydrologic response units (HRUs), which are unique soil–land use combinations. Soil water content, surface runoff, nutrient cycles, sediment yield, crop growth and management practices are simulated for each HRU and then aggregated for the subbasin by a weighted average. In each HRU, hydrological components in the water budget for surface, soil, and groundwater are calculated.

The model computes evaporation from soils and plants separately. In this study, potential ET was estimated using the Penman-Monteith method. Actual soil evaporation is estimated by using exponential functions of soil depth and water content. Plant water evaporation is simulated as a linear function of potential ET, leaf area index, and root depth, and can be limited by soil water content.

3.2. Model Parameterization

The basic data sets required to develop the SWAT model inputs are: topography, soil, land use and climatic data. Climate data were obtained from five national meteostations (Figure1) from which daily precipitation, maximum and minimum temperature, solar radiation and relative humidity are available. The digital elevation model (DEM) of the basin was derived from topographical data at the resolution of 1:250,000. Land cover data comes from the Department of Soil Survey of Jiangxi Province and is categorized into seven types.

In this study, two soil data sets are used. The first soil data set was obtained from a soil survey completed in 1990 by the Land Management Bureau of Jiangxi Province at the resolution of 1:3,000,000. Five major types of soils according to the Genetic Soil Classification of China are listed in Figure 2a. The area percentage of soil types ranges from 1.3% to 55.8%. Here, we call this resolution of soil data OFJX (obtained from Jiangxi Province). The second soil data set was obtained from Nanjing Institute of Soil Science, Chinese Academy of Science. This data was a partial production of the second national soil survey and was completed in 2000 (Shi et al., 2006; Shi et al., 2004). The resolution of the data is 1:1,000,000. A total of 36 major soil types were classified in the study area (Figure 2b). The area percentage of soil types range from 0.02% to 16.4%. This resolution of soil data we call OFNISS (obtained from Nanjing Institute of Soil Science). It must be pointed out that the two spatial resolutions of soil data were completed in two periods by two departments and are different in soil layer definition. In the OFJX soil data, every soil type was classified into 3–4 layers across the profile and every layer has a different thickness ranging from 40mm to 840mm. In the OFNISS soil data, every soil type was classified into 1–3 layers, and each layer has a common thickness from 0–300mm, 300–700mm and 700–1200mm.

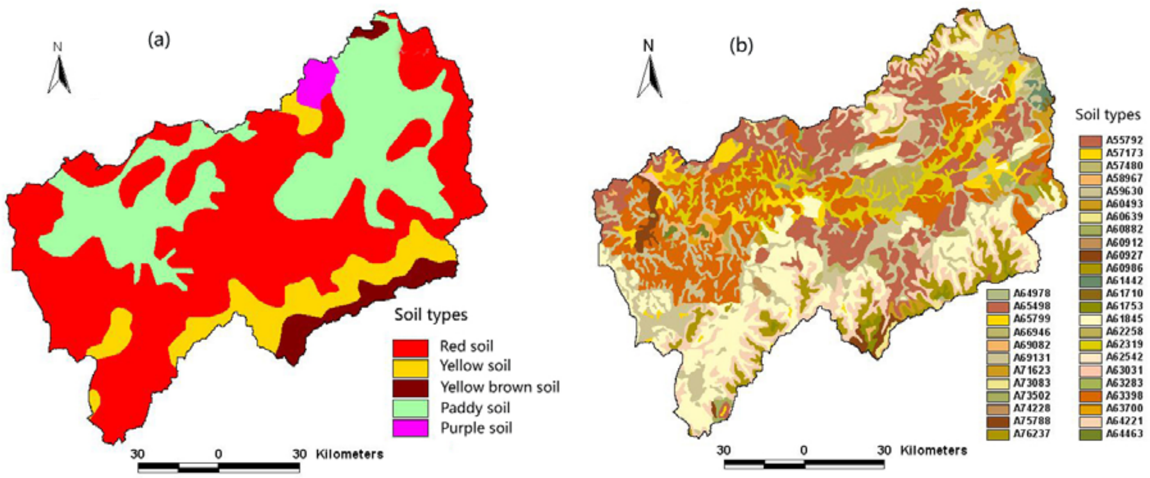

Figure 2. Different soil map of Xinjiang River catchment (a: OFJX soil data; b: OFNISS soil data). The soil definitions are unimportant; these figures are intended to illustrate the differences in data resolution.

3.3. Sub- basin delineation

In order to incorporate more complexity into a data set, it is recommended in the SWAT user manual (Neitsch et al., 2002b) that the user defines a greater number of subbasins in the watershed rather than many HRUs within a few sub-basins. Consequently, we here set the threshold of sub-basin area to 8000 ha, and accordingly the number of sub-basins becomes 79.

4. RESULTS AND DISCUSSION

4.1. Evaluation of hydrologic response units distribution

Since the HRU is the basic calculation unit, definition of HRUs is very important in the model. To avoid having HRUs that represent only a very small proportion of the basin, it is necessary to place minimum limits on the percentage of the basin that any soil class or land use class can occupy. Figure 3 shows the HRU distributions under different percentages of soil class for the two soil data sets. As the soil class threshold increases, there is an obvious decrease in the number of HRUs when OFNISS data was used, but there is little change when OFJX data was used.

There is no doubt that the number of HRUs is more sensitive to the more detailed OFNISS data. Since it is known that using small HRUs may reduce the error of modeling results, we chose 4% as the threshold percentage for land use over the basin and 2% as the threshold percentage for soil classes over the basin. Using these thresholds, the total number of HRUs was 438 when OFJX data was used and 1103 when OFNISS data was used. The following simulations were based on these HRU distributions.

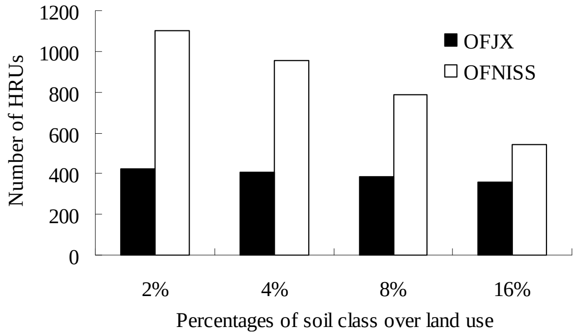

Figure 3. Number of HRUs under different threshold percentages of soil class of the two soil types

4.2. Evaluation of stream flow modeling

Evaluation of stream flow modeling was performed by using stream flow data from the gauging station located at Meigang at the outlet of the catchment to compare the predicted stream flows under the two soil data sets. The time series of 1998–2003 were used here, with 1997 being used for model warm up.

The goodness-of-fit measures used were the coefficient of determination (R^2) and the Nash-Sutcliffe efficiency (E_{NS}) (Nash and Sutcliffe, 1970). Relative error (R_E) was used to assess systematic over- or under-prediction.

4.2.1 Comparison before model calibration

After all the data pre-processing works are finished, the SWAT model can automatically calculate default parameters from the input data. Model outputs were compared for the two data sets before calibration. Comparison using uncalibrated models is useful to evaluate the differences in model predictions because calibration masks the differences that may occur as a result of the soil data sets.

Result before model calibration show that both of the simulated stream flows fluctuate substantially in response to monthly rainfall. Both SWAT setups underpredict the average monthly stream flow compared to the measured data with R_E values of –6.1% and –8.0% respectively. However, both setups have a good performance in predicting the stream flow variation, and the E_{NS} and R^2 are 0.90 and 0.96, for OFJX, and 0.88 and 0.95 for OFNISS, respectively. With regard to these figures, while we may say that the coarse resolution of OFJX data performs marginally better than the fine resolution of OFNISS data on modelled stream flow, in fact the difference is negligible between the two soil data.

4.2. 2 Comparison after model calibration

Before calibration, measured streamflow was separated into base flow and surface flow by using the SWAT base flow filter program (Arnold and Allen, 1999). Results show that about 38% of the flow was baseflow, and the alpha factor of the base flow is 0.032. Calibration parameters were adjusted until the relative error (R_E) of surface and base flow value is less than 5%. In this section, we first compare the calibration results of the two data sets, and then look at the cross-simulations (OFNISS data with OFJX parameters and OFJX data with OFNISS parameters).

During the first step, flow calibration with OFJX data were performed by adjusting the curve number across the whole basin. The curve number values were uniformly increased by 4.8% to adjust predicted mean monthly stream flow. In addition, minor adjustments were made on other SWAT parameters such as soil evaporation compensation factor (ESCO), which has an average value of 1.0 across the basin. For base flow, we changed the default ALPHA_BF to 0.032 according to the SWAT base flow filter program and set REVAPMN to 50mm. To calibrate the model with OFNISS data, we keep the curve number, ESCO and ALPHA_BF the same values as for the OFJX data, but the parameter REVAPMN was increased to 100mm, and SOIL_AWC was decreased by 0.01 from default values on all HRUs.

SWAT predicted values were compared after calibration and time series of monthly average measured and predicted streamflow is shown in Figure.4. The results of stream flow calibration are shown in Table 1. Compared to the result of the uncalibrated model, relative error (R_E) between predicted and observed flow has decreased after calibration, while E_{NS} and R^2 have increased a little for both OFJX and OFNISS data. By calibrating the model separately in the first step, we can see that the relative errors of both surface flow and base flow reach the acceptable range, and both soil data can predict streamflow fairly well.

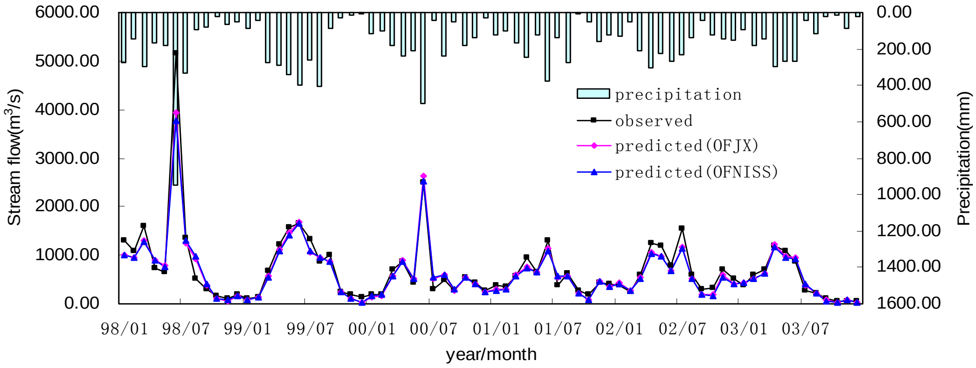

Figure 4. Calibrated model streamflow simulations and observed streamflows at the Meigang gauging station

In the second step, cross-simulations of the two soil data were applied. Visual comparison of modelled and observed stream discharges for the two resolutions of soil data are not shown here, but the statistical results appear in Table 1. When the OFJX parameters are applied with the OFNISS data, the evaluation index E_{NS} is 0.904 which is smaller than for the calibrated OFJX data. The predicted stream flows are generally lower than the observed data, while relative error (R_E) of predicted base flow is –5.45%, which indicates that the model doesn't reach the acceptable criterion. When the OFNISS parameters are applied with the OFJX data, we find that E_{NS} increased to 0.908, relative error (R_E) of total flow is 1.94%, which is slightly higher than for the OFNISS calibration. Under this calibration, both soil data can reach the acceptable range of relative error with a relatively high E_{NS} and R^2 of more than 0.9.

Table 1. Calibration results for Xinjiang basin

Calibration processes	Soil data	Item	Surface flow(m^3/s)	Base flow(m^3/s)	Total stream flow(m^3/s)	E_{NS} for Total stream flow	R^2 for Total stream flow
No calibration		Measured	409.53	250.98	660.51		
First step: calibration separately	OFJX soil	Predicted	414.04	244.21	658.25	0.913	0.964
		Relative error	1.10%	-2.7%	-0.34%		
	OFNISS soil	Predicted	410.80	244.37	655.15	0.902	0.961
		Relative error	0.3%	-2.63%	-0.81%		
Second step: cross-simulation	OFJX soil	Predicted	416.77	256.53	673.30	0.908	0.959
		Relative error	1.77%	2.21%	1.94%		
	OFNISS soil	Predicted	412.83	237.29	650.12	0.904	0.958
		Relative error	0.8%	-5.45%	-1.57%		

From the above analyses, in the first step, we can see that using a higher resolution of soil data doesn't show any advantage in hydrologic modeling with the SWAT model. During the second step, when using the calibrated OFNISS parameters with the OFJX soil data in the model, the result still can reach a satisfactory result, which it gives us an indication of parameter uncertainty issues during the model calibration. While we used the calibrated OFJX parameters with the OFNISS soil data, the lower resolution OFJX data did a little better in average monthly stream flow simulation, the relative error of the base flow simulated by OFNISS soil data is -5.45% which is not meet the calibration criterion. Interestingly, predictions using both parameter sets tend to be slightly better when applied with the lower resolution OFJX soil data than when applied with the OFNISS data.

4.2.3 Discussion of stream flow modeling results

The analysis in the previous section shows that the total number of HRUs is significantly different between the two soil data, but the differences between the simulated stream flows are slight. This indicates that in application to SWAT, the differences in soil information between the two soil data sets were masked or weakened during the simulation.

The SWAT model calculates surface runoff using the SCS runoff equation, which is an empirical model that came into common use in the 1950s. Changes of curve number (*CN*) could contribute to the variety of surface runoff. According to the SWAT theory, the threshold of *CN* was determined by soil hydrologic groups which were summarized into four categories ranked by descending soil permeability. The use of just four hydrological groups means that different soil types, which may actually have notable differences in physical properties, are given the same hydrologic characteristics

Here, we did a statistical analysis on the weighted average area of some soil attributes of the two data sets. Results show that the relative differences between the soil properties which were not affected by soil hydrological groups such as SOL_AWC, SOL_BD, CLAY, SILT and SAND are 16%, 14%, 19%, 19% and 7% respectively, but the relative difference between the average *CN* values, which are greatly affected by soil hydrological groups, are small: the average *CN* is 73. 7 for OFJX, and 71.7 for OFNISS, and the relative error is just 3%. This investigation suggests that the SCS-CN method may weaken the discrepancy between the different resolutions of soil information and contributes to the similarity of the simulation results.

4.3. Evaluation of soil water storage and evapotranspiration

Figure 5 shows the comparison of simulated monthly average soil water storage from the two SWAT setups. The main difference between the two data sets is that the calculated water storage by the OFNISS data is always higher than that for the OFJX data. The average difference is about 13.8mm for each month. As discussed in the previous paragraphs, soil properties such as SOL_AWC, SOL_BD, CLAY, STLT and SAND show great differences, as do the thicknesses of soil layers, and therefore contribute to different porosity and water capacity of the soil. When considering the variation of precipitation in a year, we find that when the monthly precipitation is continuously increasing, soil water storage also increases. However there is an upper limit when the soil becomes saturated. The Xinjiang river basin is in a wet climate zone. From January to June precipitation continuously increases and the soil approaches saturation. When precipitation decreases sharply from July to September, so does the soil water storage. The properties of soil information and precipitation condition explain the variance of soil water storage through the year.

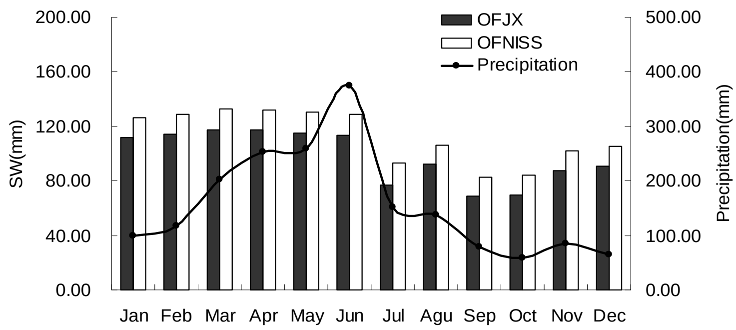

Figure 5. Comparison of monthly average soil water storage of the two soil types

Comparison of simulated evapotranspiration (ET) trends of the two soil data is shown in Figure 6. Results indicate a good agreement between the two soil data for long-term average monthly ET estimation. The annual variation in ET is closely related to the variation in air temperature. Calculated ET by the OFNISS soil is just slightly higher than the OFJX soil in each month (average monthly discrepancy is 1.5 mm) which indicates that ET calculation is insensitive to soil properties. This suggests that perhaps a relatively simplified computation method for the evapotranspiration module in SWAT model could be considered, possibly some correlation with the local climate.

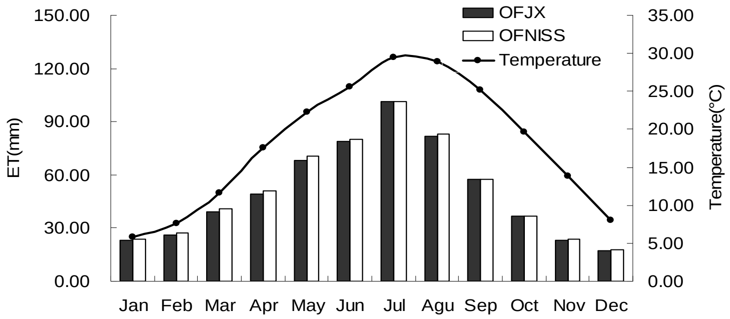

Figure 6. Comparison of monthly average ET of the two soil types

5. CONCLUSION

In this study, the effect of spatial resolution of soil types on hydrological process modeling in the SWAT model was studied by applying surveyed soil data with two different spatial resolutions in a large catchment in the Xinjiang River basin. Results indicate that the different resolutions of soil data have great impact on the distribution of HRUs in the SWAT model, but show no obvious discrepancies in stream flow simulation and ET. In addition, the evapotranspiration calculation method in the SWAT model is insensitive to the difference between the soil maps with different resolutions.

Improvements in the resolution of the soil data will not necessarily contribute to a more accurate prediction of stream flow in a large scale catchment because soil variability information was highly aggregated by using the Curve Number method. In addition, the evapotranspiration calculation method in the SWAT model is relatively simplified, which makes evapotranspiration computation within SWAT insensitive to soil properties. Modellers need to weigh the benefits before selecting the type of data resolution they are going to use depending on the watershed size and level of accuracy required. Furthermore, for some practical applications it is necessary to have a definite concept of model mechanisms and the physical meanings of some key parameters in order to make a reasonable explanation of modeling results and to avoid the resolution of input data being summarized or weakened in the model.

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