Comparison of Daily and Sub-Daily SWAT Models for Daily Streamflow Simulation in the Upper Huai River Basin of China

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Abstract

Despite the significant role of precipitation in the hydrological cycle, few studies have been conducted to evaluate the impacts of the temporal resolution of rainfall inputs on the performance of SWAT (soil and water assessment tool) models in large-sized river basins. In this study, both daily and hourly rainfall observations at 28 rainfall stations were used as inputs to SWAT for daily streamflow simulation in the Upper Huai River Basin. Study results have demonstrated that the SWAT model with hourly rainfall inputs performed better than the model with daily rainfall inputs in daily streamflow simulation, primarily due to its better capability of simulating peak flows during the flood season. The sub-daily SWAT model estimated that 58% of streamflow was contributed by baseflow compared to 34 % estimated by the daily model. Using the future daily and three-hour precipitation projections under the RCP (Representative Concentration Pathways) 4.5 scenario as inputs, the sub-daily SWAT model predicted a larger amount of monthly maximum daily flow during the wet years than the daily model. The differences between the daily and sub-daily SWAT model simulation results indicated that temporal rainfall resolution could have much impact on the simulation of hydrological process, streamflow, and consequently pollutant transport by SWAT models. There is an imperative need for more studies to examine the effects of temporal rainfall resolution on the simulation of hydrological and water pollutant transport processes by SWAT in river basins of different environmental conditions.

1 Introduction

Precipitation is one critical factor affecting the hydrological processes of river basins. One important research question in hydrology is how the spatial and temporal structure of precipitation affects the surface and groundwater movement in river basins (Paschalis et al. 2014). There have been a number of studies evaluating the impacts of rainfall variability on runoff mostly through numerical experiments. Most of these previous studies are focused on examining the impacts of the spatial resolution of rainfall inputs (e.g. Moriasi and Starks 2010; Masih et al. 2011; Wagner et al. 2012; Yoon et al. 2014; Wang et al. 2015) , while few examine the impacts of the temporal resolution of rainfall observations especially in the context of large-sized river basins.

The Soil and Water Assessment Tool (SWAT) model is a basin-scale, physically-based, continuous simulation model that has proven to be a useful tool for studying the water quantity and water quality issues of the basins of a wide range of scales and environmental conditions around the world (Arnold et al. 2014). Regardless of their ultimate objectives, adequate simulation of the targeted watershed's hydrologic balance is foundational for all SWAT applications. Gassman et al. (2007) gave an extensive review of 115 SWAT hydrologic studies, and concluded that their daily prediction results were generally poorer than monthly and annual predictions except in a few cases. They attributed the weaker results of some studies to inadequate spatial rainfall representation, inaccuracy in stream flow measurements, lack of model calibration, and relatively short calibration and validation periods. In the past few years, there has been much increase in using SWAT for daily hydrological simulations. Although the strongest results are still mostly reported by studies of annual and monthly time steps, there has been a trend of increase in the number of successful SWAT applications at the daily time step (Gassman et al. 2014).

Many statistics are available to evaluate the SWAT simulation results. Nevertheless, the most widely used statistics have been the regression correlation coefficient (R^2) and the Nash-Sutcliffe model efficiency (NSE) coefficient. The R^2 value ranges from 0 to 1 and indicates the percentage of variance in measured data accounted for by the variance in the simulated results. The NSE value ranges from $-\infty$ to 1, and measures how well the simulated versus observed data match the 1:1 line. To date, absolute criteria for judging model performance have yet to be established. Generally, NSE values greater than 0.75 indicate very good performance, while values lower than 0.36 indicate unsatisfactory performance, and the values in between indicate satisfactory performance (Krause et al. 2005).

Table 1 summarized a number of recent SWAT simulations of daily streamflow and their R^2 and/or NSE statistics. The results of most of the applications could be considered as satisfactory except a few with very good or unsatisfactory results. For example, Fohrer et al. (2014) used SWAT to assess the environmental fate of the commonly used herbicides flufenacet and metazachlor in the 50 km^2 Kielstau watershed in Northern Germany. They obtained very good simulation results for daily stream flow with an NSE value of 0.83 and 0.76 for the calibration and validation period, respectively. Some SWAT applications have attributed their unsatisfactory performance in daily simulation to SWAT's algorithms, and proposed modifications accordingly. For example, Lv et al. (2014) modified the algorithm for calculating the peak flow rate and peak time in SWAT and got better simulation results for the Pengjiahe Irrigation District in Hubei province of China.

Despite SWAT's capability to incorporate rainfall inputs of higher temporal resolution such as sub-daily and sub-hourly rainfalls, the majority of previous SWAT studies have been utilizing daily rainfall inputs. Few studies have been conducted to evaluate the impacts of the temporal resolution of rainfall inputs on the SWAT model's daily streamflow simulation performance. The limited SWAT studies with rainfall inputs of higher temporal resolution have been mostly conducted in small-sized watersheds (Jeong et al. 2011), and their results have been contradictory. Maharjan et al. (2013) compared the performance of the SWAT models in simulating the amount of runoff from a 0.8 ha field-sized agricultural watershed with 15-min, 2-h, 6-h, and 12-h precipitation data, and concluded that the models generally yielded a better performance with the increase in the temporal resolution of precipitation. Kannan et al. (2007), on the other hand, found that their SWAT models' simulation results of daily runoff using daily precipitation data were consistently better than those using 30-min precipitation data at a small 141.5 ha watershed in England.

Located about the mid-way between the Yellow River and Yangtze River, the Huai River is one of the major rivers in China. Originated from the Tongbai Mountains of Henan province, the Huai River flows 1000 km through four provinces and drains an area of 174,000 km^2. Located in the transition zone between the northern and southern climates in

China and subjected to the great influence of monsoon, the Huai River Basin is prone to the extreme events of both drought and flood. It is estimated that there have been 63 extreme floods and 46 extreme droughts in the Huai River Basin between 1470 and 2010. Establishing adequate hydrological models to understand the hydrological processes and evaluate the potential impacts of future climate change are of great importance to the sustainable management of the water resources and developing programs for climate change adaptation and mitigation in the basin.

There have been some SWAT applications to simulate the monthly streamflow in the Huai River Basin as well as its sub-basins. For example, Zhang et al. (2013) developed a SWAT model to simulate the monthly stream flow at 45 stations from 1961 to 2000 in the Upper and Middle Huai River Basin. For 19 hydrological stations unregulated by reservoirs, their SWAT models' NSE values ranged from 0.40 to 0.89 for calibration and from 0.19 to 0.80 for validation. For 8 stations moderately regulated by reservoirs, NSE values ranged from 0.40 to 0.88 for calibration and from 0.46 to 0.78 for validation. For 12 stations highly regulated by reservoirs, NSE values ranged from 0.15 to 0.78 for calibration and -0.73 to 0.63 for validation. Shi et al. (2013) used SWAT to simulate the monthly river flow at the Xixian sub-basin with a drainage area of 10191 km^2 from 1984 to 2005, and obtained an NSE value of 0.90 and 0.91 for the calibration and validation period, respectively.

In this study, SWAT was used to simulate the daily streamflow at the Shakou hydrological station in the Upper Huai River Basin with a total drainage area of 5803 km^2. Both daily and sub-daily rainfall observations at 28 rainfall stations were used as the model inputs to evaluate the impacts of the temporal resolution of rainfall on the daily simulation performance of the SWAT model in this large-sized basin. Projections of daily and sub-daily rainfall till 2050 by a regional climate model were then used as inputs to the SWAT models to examine the impacts of the temporal resolution of rainfall on the forecasts of future streamflow.

2 Study region and methodology

2.1 Study region

Located above the Shakou hydrological station of the upstream Huai River, the Ru River Basin drains a total area of 5803 km^2 (Fig. 1). With hills in the west and plains in the east, surface elevation in the basin ranges from 41 m to 977 m. Situated in the transition zone between the northern subtropical and warm temperate climate, the basin is characterized with four distinct seasons. Its annual mean temperature falls between 14.6℃ and 15℃, annual precipitation between 860mm and 980 mm, and annual solar radiation between 112 and 120 kcal/cm^2. Most of its precipitation occurs in the summer months from June to August.

The Ru River Basin is predominantly an agricultural watershed, with farmland, woodland, and grassland accounting for 65.6%, 14.5%, and 5.1% of its land coverage, respectively. Nearly 90% of the basin is dominated by three soil types, which are yellow-cinnamon soil, lime concretion black soil, and calcareous fluvo-aquic soil in an order of decreasing distribution area (Fig. 2). All of the three types of soils are generally high in clay and silt contents with poor soil permeability. Meanwhile, they also tend to have low contents of organic matters and soil nutrients such as nitrogen and phosphorous. Despite the less ideal soil properties for agricultural cultivation, the availability of sufficient moisture and heat allows the widespread double-cropping practice (mainly wheat-corn rotation) in the basin, and the region has long been recognized as one important "granary" of China.

2.2 Data sources

Topographic, land use/land cover (LULC), soil, and hydro-meteorological data used for developing the SWAT model in the Ru River Basin were summarized in Table 2. The 25 m Digital Elevation Model (DEM) data was obtained from the National Geomatics Center of China. The 2005 LULC map (1:100,000) was derived from the classification of the Landsat-TM images by Chinese Academy of Science according to the Chinese National Standard of Land Use Classifications, which was further classified into the standard LULC categories of SWAT. The spatial distribution of soil types as well as some physical and chemical properties of the soil layers was extracted from the soil databases of Nanjing Institute of Soil Science (Shi et al. 2004; Yu et al. 2007a; Yu et al. 2007b; Shi et al. 2010). In addition, the SPAW(Soil – Plant – Atmosphere – Water) software was used to estimate the available water capacity and soil carbon content of the soil layers (Saxton and Willey 2005), and the nutrient contents (nitrate, organic nitrogen, labile phosphorous, and organic phosphorous) of the soil layers were obtained from local soil survey reports (Henan Province Soil Survey Office, 1995).

To collect information on local crop management practices, face-to-face interviews with

116 farmers in 16 villages were conducted in the Ru River Basin based on a pre-constructed questionnaire. The interview results showed that the local farmers had been mostly practicing the wheat-corn rotation with rather homogeneous crop management practices. Generally, corn is planted in early June and harvested at the end of September, while wheat is planted in early October and harvested at the end of May. For corn, around 750 kg/ha of compound fertilizers and 188 kg/ha of urea are applied during planting, and an additional 150 kg/ha of urea is applied in July. For wheat, around 750 kg/ha of compound fertilizers and 94 kg/ha of urea are applied during planting, and an additional 94 kg/ha of urea is applied in the subsequent February.

Daily meteorological records on precipitation, maximum and minimum temperature, sunshine hours, relative humidity, and wind speed at the Zhumadian weather station from 1961 to 2011 were acquired from Chinese Meteorological Administration. Based on the historical weather data, the statistical parameters required by the SWAT weather generator were then calculated. The observed daily sunshine hours were also used to calculate daily solar radiation using the Angstrom-Prescott equation (Prescott 1940) whose empirical parameter values were obtained from Zuo et al. (1963). In addition, data on daily rainfall throughout the year and hourly rainfall in the flood season (May to September) at 28 rainfall stations from 2001 to 2011 were extracted from the annual reports on the Huai River Basin by Chinese Ministry of Water Resources. Daily streamflow at three hydrological stations (Lixin, Luzhuang, and Shakou) and daily outflow from three major reservoirs (Banqiao, Boshan, and Suyahu) from 2005 to 2011 were also extracted from the annual reports (Fig. 1).

Hydrological models including SWAT have been frequently used to assess the potential impacts of climate change on the hydrological cycles of global and regional scales by using the projections of future climatic conditions as their weather forcings (Jha and Gassman 2014; Li et al. 2014; Praskievicz and Bartlein 2014). There are a variety of methods to obtain the downscaled rainfall projections suitable for regional impact studies. For the Huai River Basin, some studies downscaled the monthly GCM precipitation projections to daily resolution using weather generators such as BCC/RCG-WG (Du et al. 2014) and LARS-WG (Duan and Mei 2014), while other studies utilized the outputs from regional climate models such as the CCLM (COSMO Model in Climate Mode) (Gao et al. 2014) and PRECIS (Providing Regional Climates for Impacts Studies) (Lu et al. 2013; Hu et al. 2014) models.

Nevertheless, most of these studies only utilized the projected rainfall data of daily resolution.

In this study, projections of future precipitation and temperature till 2050 for the study region were extracted from the HadGEM3-RA outputs provided by the CORDEX (Coordinated Regional Climate Downscaling Experiment) -East Asia. The CORDEX initiative was created by the Task Force for Regional Climate Downscaling (TFRCD) of the World Climate Research Program to generate regional climate change projections for various terrestrial regions within the timeline of the IPCC Fifth Assessment Report and beyond. CORDEX-East Asia is the East-Asian branch of the CORDEX initiative that produces ensemble climate simulations based on multiple dynamical and statistical downscaling models forced by various global climate models.

The HadGEM3-RA model is based on the global atmospheric HadGEM3 of the Met Office Hadley Centre (MOHC). The number of grid points in the HadGEM3-RA model is 220 (west-east) by 183 (north-south), with a horizontal resolution of 0.44 degree (approximately 50km). Configuration of HadGEM3-RA is almost same as the HadGEM3-A, except that the dynamic settings were taken from the operational limited area model. Detailed descriptions of the HadGEM model could be found in Davies et al. (2005) and Martin et al. (2006). In this study, the daily and three-hour outputs of precipitation, and the daily outputs of minimum and maximum temperature of the HadGEM3-RA model under the Representative Concentration Pathways (RCP) 4.5 scenario were used.

2.3 Spatiotemporal variability of precipitation

There have been large spatial and temporal variations in precipitation in the Ru River Basin between 2001 and 2011 (Fig. 3). Annual mean precipitation of the 28 rainfall stations in the wettest year of 2003 was 1317 mm, more than twice the amount of 583 mm in the driest year of 2001. The range of annual precipitation among the 28 stations remained above 320 mm throughout the 11-year period, with its coefficient of variation fluctuating between 0.1 and 0.2. Fig. 4 showed the spatial distribution of the average annual precipitation between 2001 and 2011. Generally, annual precipitation tended to be the lowest in the eastern and northwestern parts of the basin, higher in the southwestern part, and the highest in the middle.

Despite the considerable variability in the spatiotemporal distribution of precipitation in the Ru River Basin, its monthly precipitation exhibited a consistent pattern of concentration in the so-called flood season of May to September (Fig. 3). On the average, monthly precipitation from May to September was 92, 121, 255, 141, and 70 mm between 2001 and 2011, which together could account for 73.8% of annual precipitation. Meanwhile, there was much more variability in precipitation in the flood season.

2.4 SWAT model setup

For this study, the latest version of SWAT2012 was used. In SWAT, the Penman–Monteith equation was used to calculate potential evaportranspiration, the rainfall-runoff routing was computed using the SCS curve number method in the daily model and the Green & Ampt infiltration method in the sub-daily model, and the channel routing was calculated according to the variable storage coefficient method.

The Arc SWAT 2012 interface was used to prepare the input files for SWAT. The 25m DEM was used to delineate the sub-basins and river networks. Due to the continuing and extensive modifications to the study region's natural drainage system, the river burn-in option was used to generate the river networks based on the 1:250,000 river network dataset obtained from the Computer Network Information Center of Chinese Academy of Science. Using a threshold area of 8000 ha, a total of 55 sub-basins were delineated (Fig. 1), which were further divided into 394 hydrological response units (HRUs) with similar characteristics of LULC, soils, and slopes.

There are three major reservoirs in the Ru River Basin: Banqiao, Boshan, and Suyahu. The Suyahu reservoir is the biggest with a maximum storage capacity of 1.66 billion m^3, compared to 0.66 billion m^3 of the Banqiao reservoir and 0.40 billion m^3 of the Boshan reservoir. In SWAT, a reservoir is simulated as a water body with inflow, outflow, and change in storage. Although not suitable for real-time reservoir operation, the reservoir module of SWAT does provide sufficient accuracy for water balance assessment, especially when data on the reservoir outflows are available (Wang and Xia 2010). In this study, the three reservoirs were all simulated with their measured daily outflow rates.

The SWAT models for the Ru River Basin were set up with daily and hourly rainfall inputs, respectively. Since they were only available for the flood season (May to September), hourly rainfall data were estimated by assuming a uniform distribution in daily rainfall for the other seven months. The SUFI-2 algorithm built in the Soil and Water Assessment Tool

Calibration and Uncertainty Procedure (SWAT-CUP) (Abbaspour 2011) was used for both the calibration and validation of the SWAT models. After a four-year warming-up period, daily stream flow records at the three hydrological stations from 2005 to 2008 were used for calibration, while the records from 2009 to 2011 were used for validation.

2.5 Model uncertainty analysis

Hydrological models are subjected to many types of uncertainties such as conceptual model uncertainty, input uncertainty, and parameter uncertainty. Different methodologies and algorithms have been developed to assess uncertainties in hydrological modeling, such as the Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), Sequential Uncertainty Fitting (SUFI2), and Markov chain Monte Carlo (MCMC) methods, which have been applied and sometimes compared in Chinese river basins such as the Chaohe Basin (Yang et al. 2008), Lake Dianchi Basin (Zhou et al. 2014), and Wenjing River Watershed (Wu and Chen 2015).

The SUFI-2 algorithm uses the Latin hypercube sampling procedure, along with a global search algorithm that examines the behavior of the objective function by analyzing the Jacobian and Hessian matrices to progressively reduce the uncertainty in model parameters (Abbaspour et al. 2004). It accounts for all sources of uncertainties (including the conceptual model uncertainty, input uncertainty, and parameter uncertainty) for hydrological modeling by two measures known as the P-factor and the R-factor. The P-factor refers to the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU), which is calculated at the 2.5% and 97.5% levels of the cumulative distribution of the output variable obtained through Latin hypercube sampling. The R-factor refers to the average thickness of the 95PPU band divided by the standard deviation of the measured data. Theoretically, the P-factor ranges from 0 to 1, and the R-factor ranges from 0 to infinity. The goodness of calibration and prediction uncertainty is judged on the basis of closeness of the P-factor to 1 (i.e. all observations bracketed by the 95% prediction uncertainty) and the R-factor to 1 (i.e. achievement of rather small uncertainty band). A larger P-factor can often be achieved at the expense of a larger R-factor, and a balance must be reached between the two.

3 Results and discussion

3.1 Parameter comparison between the daily and sub-daily SWAT models

Table 3 listed the 16 parameters included in the calibration and validation of both the daily and sub-daily SWAT models of the Ru River Basin. For the parameter *Alpha_BF*, its calibration bounding limits were estimated based on the historical daily discharge records of the hydrological stations using the baseflow filter program (Arnold and Allen 1999). Based on the daily discharge records at the three hydrological stations, the SWAT-CUP program was used to calibrate both the daily and sub-daily models with several iterations of 1000 simulations. Because of its proximity to the massive and highly controlled Suyahu reservoir with a storage capacity of 1.66 billion m^3, discharge at the downstream Shakou station is much influenced by the outflows from the reservoir. To avoid the potential bias caused by the reservoir-influenced station, much more weight was given to the two upstream stations of Lixing and Luzhuang during calibration.

Table 4 compared the parameter calibration results between the daily and sub-daily models. At the beginning of the calibration, the same parameter ranges were used in the calibration of both models. Generally, parameters showed more sensitivity in the sub-daily models than the daily models. At the beginning of the calibration, seven parameters (*CN2_URML*, *CANMX_FRST*, *GW_DELAY*, *GWQMN*, *REVAPMN*, *SOL_K*, *CH_N2*) were not significantly sensitive at the 0.10 level in the daily model compared to two parameters (*CANMX_AGRR* and *CH_N1*) in the sub-daily model. After calibration, all parameters were still sensitive except *GWQMN* and *CH_N2* in the sub-daily model, while only six parameters (*CN2_FRST*, *SURLAG*, *EPCO*, *ALPHA_BF*, *ESCO*, *CH_N1*) remained significantly sensitive in the daily model.

Comparing the calibrated parameter values between the daily and sub-daily models indicated that their differences mainly lay in the parameters related to surface runoff and groundwater. In the calibrated sub-daily model, its larger moisture condition II curve numbers led to higher surface runoff potentials; its larger *GW_DELAY* value caused more delay for soil water to reach the shallow aquifer; and its larger *GW_REVAP* and lower *REVAPMN* values enabled more groundwater to diffuse upward and evaporate. These parameter differences seemed to indicate that the sub-daily model would predict more surface runoff and less baseflow contributing to river discharge than the daily model. However, water balance analysis of the Ru River Basin based on the two models yielded opposite results. The daily model estimated that 34% of the streamflow was contributed by baseflow compared to a larger estimate of 58% by the sub-daily model. The counterintuitive simulation results could be due to the different runoff estimation methods used by the two models. The daily model used the SCS curve number method, while the sub-daily model used the Green & Ampt infiltration method. In addition, the baseflow filter program (Arnold and Allen 1999) gave an estimated range of 0.47-0.64 for baseflow contribution, which coincided with the sub-daily model results.

3.2 Model performance comparison between the daily and sub-daily SWAT models

Table 5 compared the performances of the daily and sub-daily SWAT models at the three hydrological stations for both the calibration (2005-2008) and validation (2009-2011) periods. As mentioned above, since the discharge at the Shakou station is highly influenced by the Suyahu reservoir, whose daily outflow rates were used as model inputs, both the daily and sub-daily models were able to simulate its discharge rates well with both R^2 and NSE above 0.90 during the calibration and validation periods. At the upstream Lixin and Luzhuang stations, however, the sub-daily model has yielded much better performance than the daily model during both calibration and validation. At the Luzhuang station, for example, the R^2 of the sub-daily model is 0.75 and 0.70 during the calibration and validation period, respectively, much higher than 0.47 and 0.27 of the daily model.

Fig. 5 showed the observed and simulated amount of daily discharge at the Lixin and Luzhuang stations throughout the modeling period. Fig. 6 compared the observed and simulated amount of peak flow for all of the 99 percentile stream discharge events at the two stations. Generally, the sub-daily model was able to simulate the peak flow rates better than the daily model, especially at the Luzhuang station. For example, on July 16 of 2010, daily discharge was simulated to be 14.8 m^3/s and 27.8 m^3/s by the daily and sub-daily model, respectively, compared to the observed amount of 31.3 m^3/s at the Lixin station. Likewise, at the Luzhuang station, daily discharge was simulated to be 25.1 m^3/s and 38.3 m^3/s by the daily and sub-daily model, respectively, compared to the observed amount of 39.8 m^3/s on July 18 of 2010. The better performance of the sub-daily model could be due to its ability to incorporate the highly concentrated rainstorm events. For example, the daily rainfall on July 16, 2010 was 113.4 mm at the Lixin rainfall station, 72.8% of which occurred in a four-hour period between 3 and 7 am. With hourly rainfall as inputs, the sub-daily model was able to pick up the high rainfall variability and encompassed it in its simulation of streamflows.

In addition, the poorer streamflow simulation performance during the days with rainfalls of low to medium intensity also contributed to the low NSE and R^2 of the daily model at the Luzhuang Station. Fig. 7 compared the observed and simulated amount of daily streamflow at the Luzhuang station on all of the raining days when daily streamflow observations fell between 1 and 50 m^3/s. It can be seen that the daily model tended to be more sensitive to low and medium rainfall events, hence yielding significantly higher streamflow estimates than observed in many cases. A close examination of the HRUs of the sub-basin contributing to the Luzhuang station showed that around half of its land was covered by forests on steep slopes (>10%) and soils with high runoff potentials. Due to their conflicting impacts on runoff, the counterbalance among forestland, steep slope, and impermeable soils led to a complex pattern of rainfall-runoff responses under the rainfall of enormous variability in the sub-basin. Both Fig. 6 and Fig. 7 indicated that the daily SWAT model fell short of capturing the complex rainfall-runoff dynamics of the sub-basin by under-predicting streamflows during heavy storm events and over-predicting during the rainfall events of lower intensity.

While the sub-daily model yielded better simulations of daily streamflow, especially peak flow during the flood season, than the daily model, it incurred larger modeling uncertainties. At the beginning of the calibration when the parameter range was the same, the P-factor and R-factor were 0.39 and 0.34 for the Lixin Station in the sub-daily model compared to 0.53 and 0.39 in the daily-model. Likewise, the P-factor and R-factor were 0.71 and 0.40 for the Luzhuang Station in the sub-daily model compared to 0.92 and 0.43 in the daily-model.

3.3 Peak flow projection comparison between the daily and sub-daily SWAT models

Since the daily and sub-daily SWAT models have yielded considerable difference in the simulation of historical daily streamflow, especially peak flow, in the Ru River Basin, the two models were compared in their projections of peak flows till 2050 using the downscaled HadGEM3-RA outputs provided by the CORDEX-East Asia. In the HadGEM3-RA model, seven grid points were located either within or adjacent to the boundary of the Ru River Basin, whose precipitation and temperature projections were used as the inputs to the daily and sub-daily SWAT models. The weather generator of SWAT was used to generate the values for the other weather variables of solar radiation, relative humidity, and wind speed.

Since future reservoir outflow rates were not available, the three reservoirs were all simulated with the option of simulated target release in SWAT. Both the daily and sub-daily SWAT models were run with the HadGEM3-RA weather data from 2006 to 2050 with a five-year warming-up period. Due to the enormous impact of the Suyahu reservoir on the discharge at the outlet of the whole river basin, daily streamflow simulation results at the outlet of the sub-basin located along the River Ru and just above the Suyahu reservoir were used to make comparison between the daily and sub-daily models.

Fig. 8 compared the projected amount of monthly maximum daily discharge during the flood season (May to September) from 2011 to 20150 by the daily and sub-daily SWAT models. Both models have predicted a large intra-annual as well as inter-annual variation in monthly maximum daily discharge during the next few decades. The projected amount of monthly maximum daily discharge largely corresponded between the two models, except that the sub-daily model tended to project higher peak flows during the relatively wet years. For example, the simulated amount of maximum daily discharge in July by the sub-daily model surpassed the amount simulated by the daily model by 240, 164, 142, 137, and 126 m^3/s in 2028, 2018, 2039, 2023, and 2034, respectively. This tendency of predicting higher peak flow by the sub-daily model was consistent with what was observed during the simulation of historical streamflow between 2005 and 2011.

4 Conclusion

SWAT model has been increasingly used to make daily simulations of the hydrological processes in basins of a wide range of scales. Despite the significant role of precipitation in the hydrological cycle, few studies have been conducted to examine the impacts of the temporal resolution of rainfall inputs on the SWAT model's performance in large-sized river basins. By comparing between the SWAT models with daily and hourly rainfall inputs, this study has demonstrated that the temporal resolution of rainfall inputs could have much impact on daily streamflow simulations by SWAT in the large-sized Ru River Basin. Generally, the sub-daily SWAT model was better at simulating peak flows during the flood season, which is a critical factor in the formulation of sound strategies and programs for flood control and water security in river basins. In addition, the daily and sub-daily models have also depicted different hydrological processes in the study region. For example, the sub-daily model estimated that 58% of streamflow was contributed by baseflow while the daily model gave an estimate of 34%. The differences in hydrological process simulations could also have significant impact on using the SWAT model to simulate the pollutant transport and transformation processes in the river basin such as the nitrification and denitrification of nitrogen, which surely merits more in-depth investigations in the future.

Despite its overall better performance in daily streamflow simulation in the Ru River Basin, the sub-daily SWAT model has exhibited higher parameter sensitivity and more prediction uncertainty. Due to the limited availability of sub-daily rainfall projection results in China, this study has not compared and evaluated the uncertainty associated with the SWAT model projections of future streamflow. In view of the limited SWAT studies utilizing the sub-daily rainfall inputs and their potentially significant impacts on the simulations of hydrological process, streamflow, and pollutant transport, there is an imperative need for more SWAT studies incorporating precipitation data of higher temporal resolution in river basins of different environmental conditions, so as to comprehensively assess the impacts of the temporal resolution of rainfall inputs on SWAT modeling results and the implications to the sustainable management of the river basin's water resources as well as non-point source water pollution control. Meanwhile, reliable techniques for the downscaling, evaluation, and bias-correction of GCM outputs to the sub-daily resolution are needed for studying the impacts of climate change in river basins where sub-daily models are more applicable.

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Table 1 Selected recent SWAT applications on daily streamflow simulation

Reference	Watershed	Drainage Area (km^2)	Time Period		Calibration		Validation	
			Calib.	Valid.	R^2	NSE	R^2	NSE
Akhavan et al. (2010)	Hamadan–Bahar watershed (Iran)	2460	2000–2008	1992–1999	0.38-0.83	0.27-0.77	0.27-0.75	-0.01-0.70
Bekele and Knapp (2010)	Fox River （U.S.）	6885	1960-1969	1950-1959		0.55-0.65		0.46-0.67
Cerro et al. (2014)	Alegria Watershed (Spain)	53	2009-2010	2010-2011	0.72	0.68	0.52	0.49
Dessu and Melesse (2013)	Mara River (Kenya/Tanzania)	13750	1978–1982	1988–1992	0.69	0.68	0.44	0.43
Fohrer et al. (2014)	Kielstau Watershed (Germany)	50	2003–2005	2006–2009	0.84	0.83	0.77	0.76
Geza and McCray (2008)	Turkey Creek (U.S.)	126	1998–2001		0.61-0.74	0.27-0.77		-0.01-0.70
Glavan et al. (2011)	River Axe (England)	400	1988-1997	1998-2005	0.62	0.62	0.53	0.47
Gong et al. (2012)	Daning River (China)	2010	2000-2003	2004-2007		0.68-0.85		0.44-0.80
Mishra and Kar (2012)	Banha Watershed (India)	16.95	1996	2000, 2001	0.93	0.70	0.76-0.83	0.62-0.70
Oeurng et al. (2011)	Save River (France)	1110	1999-2009		0.56	0.53		
Oliver et al. (2014)	Big Haynes Creek (U.S.)	44	2003-2006	2007-2010	0.50	0.49	0.46	0.37
Rouhani et al. (2007)	Grote Nete River (Belgium)	383	1986–1989	1990–1995	0.82	0.67	0.81	0.66
Saha et al. (2014)	Yass River (Australia)	1597	1993–2002	2003–2011	0.55	0.56	0.81	0.71
Zhang et al. (2007)	Luohe River (China)	5239	1992 -1996	1997 -2000	0.82	0.65	0.74	0.54

Table 2 Data inputs for the SWAT model

Data Category	Scale/Extent	Data Sources
DEM	1:50,000	Chinese National Geomatics Center
2005 Land Use/ Land Cover	1:100,000	Chinese Academy of Science
Soil types and soil properties	1:1000,000	Nanjing Institute of Soil Science; Henan Province Soil Survey Office (1995); SPAW software
River networks	1:250,000	Chinese Academy of Science
Daily weather (1960-2011)	1 Station (Zhumadian)	Chinese Meteorological Administration
Daily and hourly rainfall (2001-2011)	28 Stations*	Chinese Ministry of Water Resources
Daily streamflow (2005-2011)	3 Stations (Lixin, Luzhuang, and Shakou)	Chinese Ministry of Water Resources
Daily reservoir outflow (2005-2011)	3 Reservoirs (Banqiao, Boshan, and Suyahu)	Chinese Ministry of Water Resources
Crop management practices	116 farmers	Field Survey

*The 28 rainfall stations are Banqiao, Boshan, Caibukou, Daheiliuzhuang, Guizhuang, Hexiaodian, Hezhuang, Houmiao, Jialou, Laojun, Linzhuang, Lixin, Luodian, Mayigou, Quesan, Shahedian, Shakou, Shizhuang, Suiping, Taohuadian, Wulizhuang, Xiachen, Xiangheguan, Xiasong, Xiatun, Zangji, Zhugou, and Zhumadian.

Table 3 Parameters for calibrating the daily and sub-daily SWAT models

Category	Parameter	Description
Runoff	*CN2*	Moisture condition II curve number
	SURLAG	Surface runoff lag coefficient
Plant	*EPCO*	Plant uptake compensation factor
	CANMX	Maximum canopy storage
Groundwater	*ALPHA_BF*	Baseflow alpha factor
	GW_DELAY	Groundwater delay
	GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur
	REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur
	GW_REVAP	Groundwater "revap" coefficient
Soil	*SOL_AWC*	Available water capacity of the soil layer
	SOL_K	Saturated hydraulic conductivity of the soil layer
	ESCO	Soil evaporation compensation factor
Channel	*CH_N1*	Manning's "n" value for the tributary channels
	CH_N2	Manning's "n" value for the main channel
	CH_K1	Effective hydraulic conductivity in tributary channel alluvium
	CH_K2	Effective hydraulic conductivity in main channel alluvium

Table 4 Comparison of parameter values and sensitivities between the daily and sub-daily SWAT models

Parameter	Initial Models			Calibrated Models					
	Range	P Value		Daily			Sub-Daily		
		Daily	Sub-Daily	Value	Range	P Value	Value	Range	P Value
CN2_AGRR	67-99	0.00	0.00	68.6-90.6[a]	68.5-92	0.22	75.8-97.8[a]	75-98	0.00
CN2_FRST	43-87	0.00	0.00	45.2-84.2[a]	43 - 85	0.06	46.6-85.6[a]	45-86	0.00
CN2_URML	62-92	0.89	0.06	64.1-79.1[a]	62 - 81	0.79	73.3-88.3[a]	67-89	0.00
SURLAG	1-10	0.00	0.00	2.3	1-5	0.00	5.1	4.3-10.7	0.00
EPCO	0.85-1	0.00	0.00	0.9	0.88-0.9	0.00	0.9	0.89-0.92	0.00
CANMX_AGRR	1-10	0.00	0.72	6.5	4-7	0.54	7.4	5.5-7.7	0.00
CANMX_FRST	5-25	0.13	0.00	10.5	4-13	0.19	23.3	16-25	0.00
ALPHA_BF	0.03-0.1	0.00	0.00	0.03	0.02-0.06	0.09	0.06	0.03-0.07	0.00
GW_DELAY	10-300	0.36	0.00	43.9	20-45	0.45	215.8	195-245	0.00
GWQMN	10-150	0.46	0.00	54.1	39-57	0.40	83.8	75-115	0.29
REVAPMN	10-200	0.34	0.00	141.6	125-145	0.50	69.1	45-70	0.02
GW_REVAP	0.02-0.2	0.05	0.00	0.03	0.02-0.04	0.73	0.16	0.13-0.17	0.00
SOL_AWC	0.12-0.36	0.00	0.00	0.15-0.34[b]	0.14-0.35	0.48	0.15-0.35[b]	0.14-0.36	0.00
SOL_K	1.6-901.3	0.13	0.00	2.0-895.1[b]	1.9-895.1	0.74	1.8-801.9[b]	1.7-808.1	0.00
ESCO	0.85-1	0.00	0.00	0.94	0.93-0.97	0.00	0.99	0.95-0.99	0.00
CH_N1	0.19-0.32	0.00	0.23	0.29	0.27-0.31	0.02	0.26	0.23-0.26	0.02
CH_N2	0.035-0.049	0.41	0.07	0.047	0.046-0.048	0.38	0.043	0.042-0.046	0.49
CH_K1	0-50	0.00	0.00	1.0	0-3	0.15	4.5	2.7-8.1	0.02
CH_K2	0-50	0.00	0.00	12.3	0-15	0.90	5.4	0-8.4	0.00

[a] Show the range of the calibrated values for different hydrological groups.

[b] Show the range of the calibrated values for different soil types and soil layers.

Table 5 Model evaluation statistics for the calibration and validation periods at the three hydrological stations

Station	Calibration (2005-2008)				Validation (2009-2011)			
	Daily		Sub-Daily		Daily		Sub-Daily	
	R^2	NSE	R^2	NSE	R^2	NSE	R^2	NSE
Lixin	0.59	0.59	0.74	0.74	0.70	0.70	0.85	0.85
Luzhuang	0.47	0.47	0.75	0.76	0.27	0.29	0.70	0.71
Shakou	0.93	0.93	0.92	0.92	0.96	0.96	0.92	0.94