ORIGINAL RESEARCH
PAPER

Watershed subdivision and weather input effect on streamflow simulation using SWAT model

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ABSTRACT

In watershed modeling research, it is practical to subdivide a watershed into smaller units or sub-watersheds for modeling purposes. The ability of a model to simulate the watershed system depends on how well watershed processes are represented by the model and how well the watershed system is described by model input. This study is conducted to evaluate the impact of watershed subdivision and different weather input datasets on streamflow simulations using the soil and water assessment tool model. For this purpose, Cuhai-Bakonyér watershed was chosen as a study area. Two climate databases and four subdivision variations levels were evaluated. The model streamflow predictions slightly effected by subdivision impact. The climate datasets showed significant differences in streamflow predictions.

1. INTRODUCTION

It is common practice to partition the watershed into smaller units for modeling purposes. Each sub-watershed is assumed to be homogeneous with the entire watershed. However, watershed subdivisions influence the principle of homogeneity, since larger sub-watersheds are more likely to have variable conditions. Smaller sub-watersheds increase the effort to prepare input data. The effect of the watershed subdivision on model simulation is directly related to sources of uncertainty [1] including stream channel, sub-watershed topography, soils, land use and climate inputs [2].

Reference [3] found that better accuracy of flow predictions resulted with the Soil and Water Assessment Tool (SWAT) model resulted from the decrease in the size of sub-watersheds. Another research [4] found that SWAT streamflow predictions were relatively insensitive to different combinations of sub-watershed. Reference [5] found that the effect of watershed subdivision on streamflow simulation had a little change after a specific threshold value. Reference [6] studied the appropriate size of watershed subdivision and he found that the simulated flow of various sub-watershed sizes is dependent on corresponding changes in topography characteristics within the sub-watersheds. However, none of the above considered the effect of weather input data. Weather data is always an important driver of rainfall-runoff processes [7] and many equations used in SWAT are affected by weather data, which in turn are dependent on its resolution. On another hand, the investigation of the accuracy of the Climate Forecast System Reanalysis (CFSR) dataset, which is the most widely used weather data in the SWAT model [8–9] on Hungarian watershed is still unknown [10–11]. This dataset has a resolution of 38 km with a near-global coverage [12]. In the Hungarian context, an alternative regional daily weather dataset Climate for Carpathian Region (CARPATCLIM) is available in gridded format this data is entirely derived from the network of regional weather stations and interpolated at a cell size of 10 km. The sensitivity of SWAT to CFSR vs. CARPATCLIM weather inputs in predicting streamflow has never been

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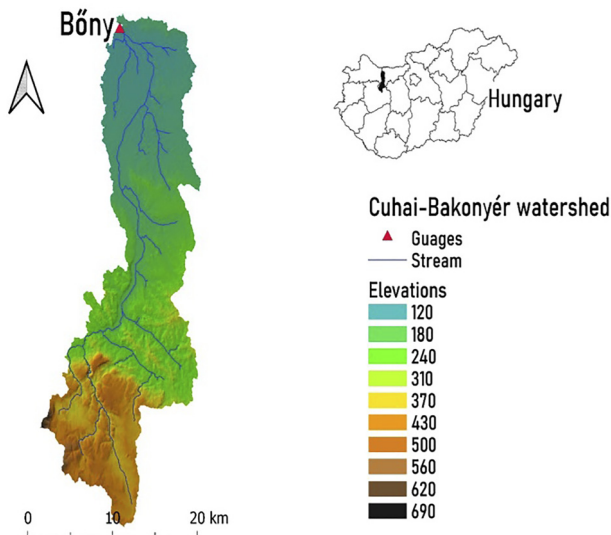E-mail: firas.alsilibe@hallgato.sze.hu

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Fig. 1. Study area

evaluated, especially in Hungarian watershed. Considering these factors, weather data is selected as a candidate to study the effect of input data accuracy on streamflow simulation besides the subdivision effect. In this study, the SWAT model was used to investigate the impact of watershed subdivision on streamflow simulation, for a watershed in Hungary. The objective is to develop a guideline for a threshold level of subdivision for accurate prediction of flow with SWAT and investigate the accuracy of weather datasets on streamflow simulation.

2. MATERIALS AND METHODS

2.1. SWAT model description

SWAT is a watershed-scale model and it was developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large complex watersheds with varying soils, land use, and management conditions over long period [1]. It is a semi-distributed physically-based model, computationally efficient, and capable of continuous simulation over long periods. In SWAT, the watershed is divided into sub-watersheds, and the sub-watersheds are connected by streams and rivers. The sub-watersheds are subdivided into Hydrological Response Units

(HRUs) where each unit has homogeneous land-use, land-cover, slope, and soil properties. There are two major hydrological processes in the watersheds, the land component that transports water to the channel, and the channel component, that transports water to the outlet point. The land component of the hydrological model determines precipitation, and then divides the precipitation into canopy storage, surface runoff, and infiltration. Surface runoff is relatively fast and arrives at the channels first. With infiltration, the water enters the soil profile, and movement to the stream occurs through interflow and baseflow. Options exist in SWAT for estimating surface runoff from HRUs: the Natural Resources Conservation Service Curve Number (CN) method [13] or the Green and Ampt method [14]. Three methods for estimating potential evapotranspiration are also provided: Priestly-Taylor [15], Penman-Monteith [16] and Hargreaves [17]. The option is also provided for the user to estimate EvaTranspiration (ET) values outside of SWAT and then read them into the model for the simulation run.

2.2. Watershed description

The study area, the Cuhai-Bakonyér watershed, is located in the North-Western part of Hungary, in the Kisalföld region as it is shown in Fig. 1. The total area of the watershed is 475 km^2. The upstream area of the watershed is hillier, and mostly covered by forests (30%), the downstream area is more flat and mostly cultivated land (55%) with 10% of the watershed area cover with cropland and a low percentage of urban settlements (5%). The elevations range is from 120 m.a.s.l to 690 m.a.s.l.

2.3. Input data

Data used in this study include (Table 1):

1. 25 m resolution Digital Elevation Model (DEM) from North Transdanubian Environmental Protection and Water Management Directorate (ÉDUVIZIG) [18];
2. 100 m resolution Corine Land Cover (CLC 2018) datasets [19];
3. 25 m resolution stream network layer from ÉDUVIZIG [18];
4. 1:5,000,000 scale Harmonized World Soil Database [20];
5. Two weather datasets
   a) The CARPATCLIM climate dataset [21];
   b) CFSR dataset [22].

Table 1. The sources of input data used in SWAT model

Data Type	Scale/Resolution	Source
DEM	25 m	ÉDUVIZIG [18]
Soil data	1:5 000 000 map	Food and Agriculture Organization (FAO) [20]
	30 arc-second raster database	Harmonized World Soil Database [20]
Stream network	25 m	ÉDUVIZIG [18]
Land use map	100 m	CLC2018 [19]
Weather data	12 stations, 10 × 10 km^2, Daily 1960–2010	CARPATCLIM climate dataset [21]
	1 station, 38 × 38 km^2, Daily 1979–2016	CFSR [22]
Flow stream data	Daily 1961–2012 (m^3 s^{-1})	ÉDUVIZIG [18]
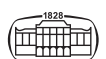
The methods used for these simulations included:

1. CN method for estimating surface runoff from precipitation [13];
2. The Penman-Monteith method for calculating the Potential EvapoTranspiration (PET) [16];
3. The variable storage method to simulate channel water routing [23]; and
4. Setting the channel dimensions to an inactive status [23].

2.4. Watershed subdivision

Watershed subdivision in the SWAT model occurs at two levels. First, a watershed is divided into several sub-watersheds based on threshold drainage area and is specified as a percentage of total watershed area [5]. Different minimum threshold drainage areas were used to generate different numbers of sub-watersheds (Table 2). The drainage network varied within each subdivided scenario, as it is shown in Fig. 2. Higher threshold drainage areas results in a less dense stream network, and consequently fewer numbers of sub-watersheds. Second, the sub-watersheds were further subdivided into HRUs by fixing a threshold area for land use and soil types in each sub-watersheds [24]. To study the effect of watershed subdivision on streamflow simulation four configurations are created corresponding to 0.1, 0.25, 0.5, and 0.75% of the total watershed area. In this study, the threshold levels were set at 0 percent, which allowed all soil categories and land uses within each sub-watershed to be presented in the model simulation.

Table 2. The results of different subdivision levels

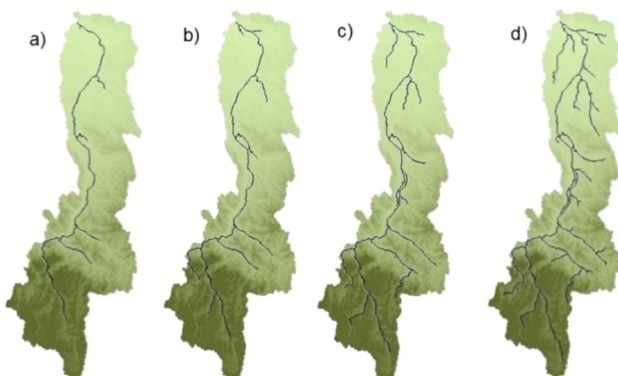| Minimum drainage area	sub-watersheds	HRU	% watershed area
$5\,km^2$	57	1,052	0.1%
$10\,km^2$ *	27	713	0.25%
$20\,km^2$	17	499	0.5%
$30\,km^2$	11	385	0.75%
$40\,km^2$	1	–	1%

* Default value that given by SWAT model.

Fig. 2. Drainage network resulting from applying different minimum drainage area in SWAT model, a) $30\,km^2$, b) $20\,km^2$, c) $10\,km^2$, d) $5\,km^2$

2.5. Weather dataset description

After defining the appropriate level of subdivision, streamflow sensitivity to two weather datasets was examined. The CARPATCLIM climate data was assumed to be more reliable than CFSR as the former was exclusively derived from gauged records and is available from the official page of Climate for Carpathian Region Project [21]. On the other hand, CFSR weather data sets are produced on a large spatial scale, assimilating the ground observation and remotely sensed measurements to provide estimates of atmospheric variables worldwide with a continuous based record for several decades is available from the SWAT homepage [25] in a format readily usable in SWAT. When a gridded climatic data is used into SWAT, the grid with its centroid nearest to the centroid of a sub-basin is taken into consideration as the climatic data for that sub-basin. SWAT is a semi-distributed hydrological model and hence lumps the climatic data at the sub-basin level.

2.6. Model evaluation and calibration

Model calibration procedure plays an important step in watershed modeling. A detailed procedure for calibration of SWAT was presented by [26]. The Percent BIAS index (PBIAS), coefficient of determination (R^2), and Nash-Sutcliffe Efficiency (NSE) [27] were used to evaluate model predictions. R^2 was calculated to evaluate the degree of correlation between the observed and simulated discharges, values range from 0 to 1, with an R^2 value equal to 1 means a perfect correlation between observations and model predictions. NSE vales range from 1 to $-\infty$, and higher values indicate a better prediction. If NSE is negative or very close to zero, the model prediction is considered unacceptable [26]. The coefficient of efficiency is an indication of how well the plot of observed versus predicted values fit a 1:1 line. Bias index measured the average tendency of the simulated values to be smaller or larger to their observed value, acceptable values under $-\backslash+$ 10. The calibration procedure was performed manually on a monthly basis. Streamflow component of the model was calibrated for a 60-month period, from January 1998 to Dec 2005 with three years as a warm-up period to prepare the model for the simulation.

3. RESULTS AND DISCUSSION

3.1. The effect of watershed subdivision on streamflow simulation

Using model default values with the CARPATCLIM climate data as weather input, first, the response of the streamflow components to the uncalibrated model subdivisions impact was examined. It was found that a threshold drainage area corresponding to 0.25% of Cuhai-Bakonyér Watershed area, which corresponding to subdivision of 17 watershed was the appropriate percentage that generate the closet model responses to the measured streamflow (Table 3).

Predicted annual average streamflow results that occurred at Bony gauge located at the outlet of the watershed

Table 3. Evaluation result of the comparison between SWAT model monthly, yearly prediction streamflow and the observation at Bony gauge

Configuration	Monthly			Yearly		
	NSE	PBIAS	R^2	NSE	PBIAS	R^2
11 sub-watershed	−0.97	−104.52	0.28	−3.7	−119	0.56
17 sub-watershed	0.188	−38.87	0.46	−3.6	−119	0.6
27 sub-watershed	−1.102	−105.84	0.27	−3.7	−120	0.5
57 sub-watershed	−1.006	−105.71	0.272	−3.77	−120	0.55
17 – CARPATCLIM *	0.188	−38.87	0.46	−3.6	−119	0.6
17 – CFSR	−1.17	−111.34	0.33	−5.01	−121	0.56

* This refer to the configuration corresponding with 17 sub-watersheds and CARPATCLIM weather database as input.

corresponding with four different configurations, ranging from 11 sub-watersheds at the coarsest level to 57 sub-watersheds for the most refined scenarios (Table 2) are presented in Fig. 3. The streamflow increased by less than 1 percent between the coarsest and finest watershed delineations, the total number of HRUs simulated for the four configurations increased in the same trend across the different sub-watershed delineations (Table 2). The scenario of subdivision corresponding to 17 sub-watershed showed different behavior with closer streamflow discharge to the observation (Table 3), in other hand, the error analysis (Table 3) shows that all configuration have the same statics with slightly better result corresponding to 17 sub-watershed with R ^{2} value of 0.6, which is the better among the rest results means good correlation between the simulated and measured annual discharge. Other criteria did not show differences between the four scenarios. Figure 4 shows comparison between the four configurations and the observation; it is appear that SWAT's annual streamflow was relatively insensitive to changes in the number of sub-watersheds.

3.2. Effect of weather input dataset

After the comparison between the subdivision configurations, two dataset (CARPATCLIM, CFSR) were applied. Table 3 shows the results of comparison between the two weather dataset configurations with the observations. In monthly predications, both scenarios overestimated the flow over the simulation period (Fig. 5). Generally,
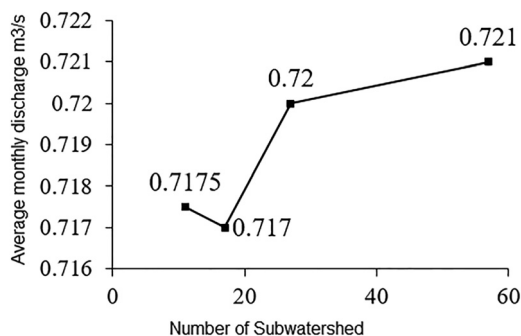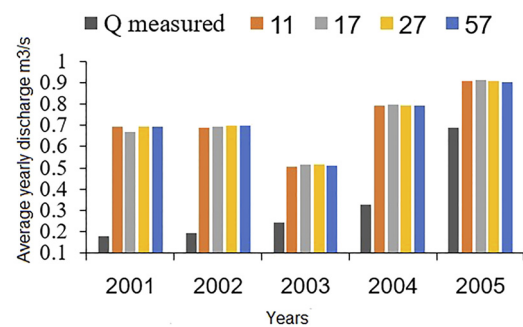
Fig. 4. Comparison between the averages annual predict streamflow for the four configuration at Bony station with measured flow between 20012005 (Numbers referee to the number of sub-watershed)
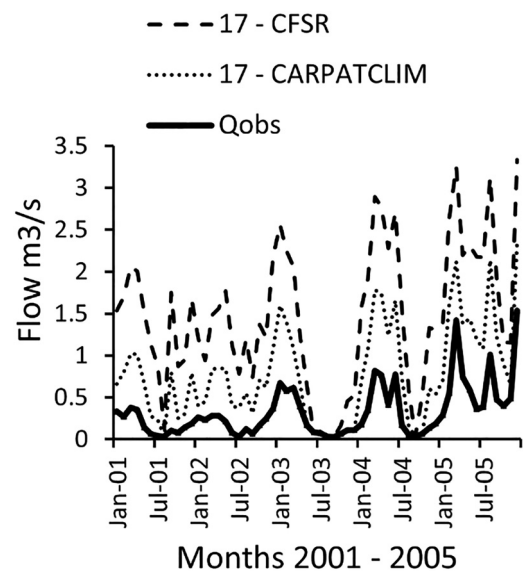
Fig. 5. Comparison of average monthly flow predictions of CARPATCLIM and CFSR scenarios with the observation

CARPATCLIM gave better result based on the error criteria evaluation with value of 0.46 for R^2 comparing to 0.33 for the CFSR scenario. NSE and PBPIAS criteria were not satisfied for the monthly predictions. Yearly predictions between the scenarios follow the same trend with better performance for the CARPATCLIM dataset with R^2 of 0.6

Fig. 3. Average annual predicted streamflow using SWAT model between 2001 and 2005 as a function of total sub-watersheds
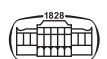
comparing with 0.56 for CFSR dataset. The other criteria were slightly different with unacceptable values.

3.3. Model calibration

Calibration procedure was done using the best scenario corresponding to subdivision level of 17 watersheds and CARPATCLIM weather dataset as model input result of calibration process found in (Table 4). The uncalibrated model overpredicted the average monthly streamflow over the calibration period (2001–2005). During calibration, calibration criteria and the ranges of parameter variations were obtained from [28]. Before calibration, the model was incapable of simulating the highest value (Fig. 6) and shows poor NSE = 0.188. After calibrating the model, with the help of parameters adjustments, the model performed well to capture streamflow in calibrating period (Fig. 6). The calibrating period showed an NSE of 0.52 above 0.5, which indicates the acceptability of the model. Calibrated results showed an R factor of 0.56. Visual comparison of simulated and observed monthly flows, throughout the calibration period is shown in Fig. 6. It shows significant improvement to capture the observed value comparing with before calibration (Fig. 6).

Table 4. The result of monthly calibration for SWAT streamflow simulation

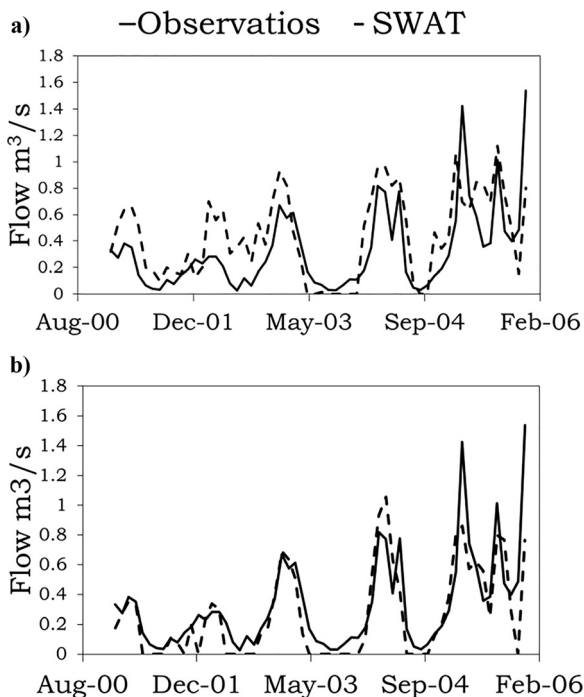|	Before calibration	After calibration
NSE	0.188	0.52
PBIAS	−38.87	−2.66
R^2	0.4616	0.56

Fig. 6. Show comparison of observed and simulated average monthly stream flow using SWAT model at Bony gauging station for the period 2001–2005, a) before calibration, b) after calibration

4. CONCLUSION

In this paper, the study conducted a study to investigate the effect of watershed subdivision and two weather inputs datasets on streamflow simulation for small watershed in Hungary. It found that in general, the result indicated that the SWAT model streamflow predictions for the Cuhai-Bakonyér watershed not sensitive to watershed subdivision. Moreover, for this watershed with an area of 475 km^2, it was found that the appropriate level of subdivision corresponding to 0.5% of the watershed area. Streamflow predictions showed significant sensitivity to the variations in weather inputs data and CARPATCLIM dataset gave better results comparing with the CFSR dataset.

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