https://doi.org/10.52151/jae2019562.1685

http://www.isae.in / journal_jae.aspx

Journal of Agricultural Engineering

Vol. 56 (2): April-June, 2019

Application of Soil and Water Assessment Tool for Runoff Simulation in a Data Scarce Himalayan Watershed

Tabasum Rasool[1] and Rohitashw Kumar[2]*

[1]Research Scholar, [2]Professor, College of Agricultural Engineering and Technology, Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir, Shalimar Campus, Srinagar-190025, Jammu and Kashmir. *Corresponding author e-mail address: rohituhf@rediffmail.com

Article Info

Manuscript received: September, 2018
Revised manuscript accepted: May, 2019

Keywords: Dal watershed, runoff, SWAT model, GIS, remote sensing

ABSTRACT

The present study was conducted to simulate runoff in the watershed of Dal (188.72 km^2) located in the temperate region of Kashmir using Soil and Water Assessment Tool (SWAT). The study watershed is characterized by significant climatic contrast, abrupt topography, and soil fragility, thereby resulting in flash floods and water erosion. Such situation requires interventions to preserve soil and water resources, and a decision tool for integrated watershed management. The SWAT was calibrated for the year 2010, and validated for the year 2011, based on a comparison of simulated and observed monthly runoff at the watershed outlet. The model performance was evaluated using coefficient of determination (R^2), Nash-Sutcliffe efficiency (E_{NS}), relative root means square error (RRMSE) and percent bias (PBIAS). During the calibration period, R^2, E_{NS}, RRMSE and PBIAS were 0.98, 0.87, 1.3 and (-) 26, respectively. During the validation period, the values of R^2, $E_{NS,}$ RRMSE and PBIAS were 0.97, 0.84. 1.1 and (-) 26.0, respectively. The modelled values showed reasonably good agreement with the observed values of runoff, both during calibration and validation periods. The runoff in the watershed was quantified under the prevailing land use conditions. The study demonstrated a satisfactory application of the SWAT model for quantification of hydrological processes in a watershed under data scarce condition.

India's land resources are under immense pressure as it shares only 2.3 % of the world's geographical area, but supports around 18 % of the world's population and 15 % of the world's livestock (Rao *et al*., 2015). The total geographical area of the country is 328 Mha, of which 120.7 M ha is the total degraded area. Out of the 120.7 M ha degraded land, 104.2 Mha (86.3 %) is arable land (Maji *et al*., 2010). Soil is an important resource for the economy and food security of a country, and runoff is a major factor for delimiting the erosion problem. Of the total degraded land area of 120.7 Mha, 73.3 Mha (60.7 %) is degraded by water erosion (Maji *et al*., 2010). Therefore, effective control of soil erosion and sediment loss occurring from non-point sources and transported by runoff requires information about the quantity and source areas of runoff (Frankenberger *et al.,* 1999; Tyagi *et al.,*2013; Panhalkar, 2014; Yen *et al.,* 2014, 2015). In mountainous watersheds, especially in the Himalayan region, the spatial and temporal variability in terms of soil, land use/cover, topography, rainfall and biotic forest cover, as well as young geologic materials have large interventions (Singh and Woolhiser, 2002; Guo *et al.,* 2016). Runoff data are scarcely available for the Himalayan watersheds, which are often required for operation and management of irrigation and hydropower projects. Simulation models can be partially used for hydrologic evaluation of watershed under limited and unavailable data conditions. Physically-based and spatially-distributed hydrological models like ANSWERS (Beasley *et al.*, 1980), CREAMS model (Knisel, 1980), SWRRB (Williams *et al*., 1985) and OPUS (Smith, 1992) are available in the literature for determination of hydrological parameters, estimation of watershed yield, and assessment of best management practices.

Soil and Water Assessment Tool (SWAT), a physically-based and spatially-distributed model, is being increasingly used to assess the hydrological behaviour of large and complex watersheds (Arnold *et al*., 1998; Neitsch *et al*., 2005). The main problem in the application of rainfall-runoff simulation models are the calibration and validation of the model due to lack of reliable data for comparing the model-simulated values with the actual values (Pandey *et al*., 2005; Odusanya *et al*., 2019). Further, application of the hydrological models requires input data of the topography, land use/cover, and soils, apart from hydro-meteorological data at multiple points in space and time to describe the spatial and temporal variability of watershed characteristics. In recent years, Geographic Information System (GIS) has proved as an excellent tool to aggregate and organize input data for distributed parameter hydrological modelling (Srinivasan and Arnold, 1994). Rapid parameterization of hydrologic models can be derived using Remote Sensing (RS) and GIS (Kumar *et al*., 2002; Huang, 2003). The GIS-based SWAT model has been widely used for hydrological modelling of a micro-watershed (Kim *et al*., 2009; Easton *et al*., 2010; Jadhao *et al*., 2010; Jain *et al*., 2010; Phomcha *et al*., 2011). Many researchers reported that the SWAT model is capable to simulate runoff and sediment yield, and hence, can be used as a tool for water resources planning and management (Qiu *et al*., 2012; Rao *et al*., 2012; Wang *et al*., 2017; Jinfeng and Wang, 2018).The SWAT was originally developed to operate in large-scale ungauged basins with little or no calibration efforts (Arnold *et al*., 1998), and has been applied in several ungauged and data scarce basins (Zhang *et al*., 2017; Mishra *et al*., 2017). Most SWAT parameters can be estimated automatically using the GIS interface and meteorological information combined with internal model databases (Zhang *et al*., 2008; Srinivasan *et al*., 2010). Srinivasan *et al*. (2010) reported that the SWAT model could satisfactorily predict the Upper Mississippi River basin (UMRB) hydrologic budget and crop yield without calibration. The un-calibrated SWAT model produced similar evaluation statistics to those calculated using calibrated SWAT models from three previous studies of the UMRB.

The present study aimed at calibration and validation of the SWAT model for simulating runoff under limited data conditions in the watershed of Dal lake catchment in Kashmir.

MATERIALS AND METHODS

Study Area

This study was conducted in a Himalayan watershed, of Dal lake catchment. It is located between the latitudes of 34°5.5´-34°13´N and longitudes of 74°48´-75°09´E in the Indus Water Resource Region of Jhelum basin, covering an area of 188.72 km^2 (Fig. 1). The study area is 1700 m above the mean sea level. The area falls in the temperate region, and experiences an irregular climate with large variation in annual precipitation. The average annual rainfall in the study area is 780 mm. The major landform of the watershed includes flat to gently sloping, undulating plains, hills and mountains. The major land of the flat areas of the watershed is under agriculture, horticulture and urban settlement. The mountainous area is under natural forest, grasslands and scrub lands, while most of the natural vegetation and barren land is under the hilly regions (Badar *et al.,* 2013). The soil types in the watershed are mountain soils, mountain meadow soils, pod soils and brown soils. The soils in the area are sandy loam to loam in texture, well-drained, with soil depth varying from shallow to deep underlain by boulders, pebbles, gravels, sand and silt strata.

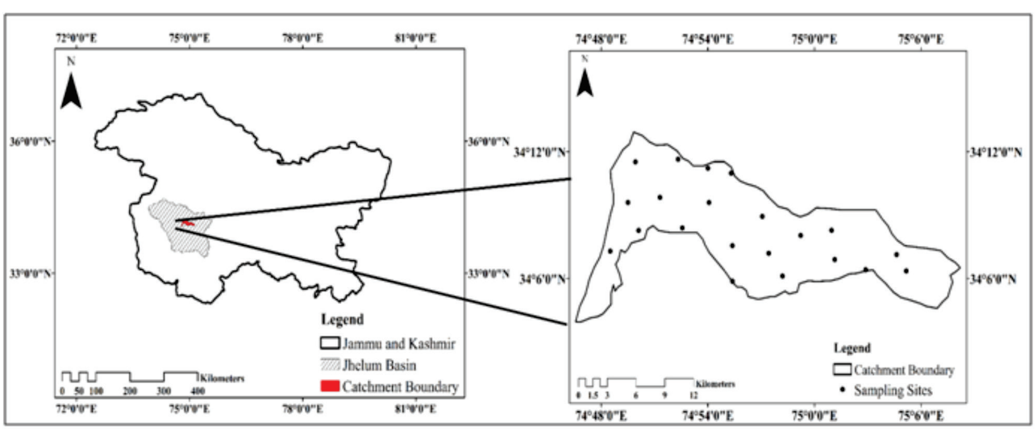

Fig. 1: Location map of study area depicting soil sampling sites

Data and Software Used

Daily data of maximum and minimum temperature and rainfall were collected for nine years (2003-2011) from the Weather Station, Division of Agronomy, Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir (SKUAST-Kashmir) provided by the India Meteorological Department (IMD), Pune under the project on Forecasting Agricultural output using Space Agro-meteorology and Land (FASAL). The long term weather statistics of rainfall, maximum and minimum temperature, relative humidity, wind speed and solar radiation was stored in SWAT weather database format. Runoff data in mm, monitored during the year 2010-2011 at the outlet of the watershed, were obtained from the Soil Conservation Department, Magarmalbagh, Srinagar, and the same were used for SWAT calibration and validation.

The Digital Elevation Model (DEM) of the study area at 30 m spatial resolution was downloaded from the dataset of U.S. National Aeronautics and Space Administration (NASA) Shuttle Radar Topography Mission (SRTM), (Fig. 2). Several reconnaissance field visits were conducted to collect information about the land use/cover in the area. Soil samples were collected randomly throughout the study area using the soil auger from 21 different sites at an average depth of 25 cm (Fig. 1) and location coordinates, i.e. latitude and longitude, of the sampling sites were recorded with the help of *Garmin Nuvi* Global Positioning System (GPS).

The RS data were processed and analysed in GIS for viewing and analysing multiple layers of spatially related information associated with a geographical location. Software used for processing of data included ERDAS imagine 9.1 for image processing; ArcGIS 9.3 for geospatial analysis; ArcSWAT for simulation of basin hydrology, and USDA-SPAW (United State Department of Agriculture – Soil-Plant-Air-Water) model for soil data analysis.

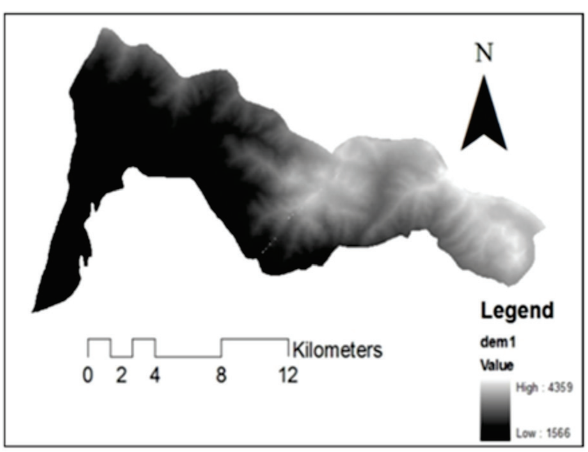

Fig. 2: Digital elevation model of study area

Soil and Water Assessment Tool (SWAT)

ArcSWAT software (SWAT model integrated with GIS) was used to simulate runoff. SWAT requires detailed information about weather, soil properties, topography, vegetation and land management practices in a watershed. In SWAT, a watershed is divided into a number of sub-basins, and each sub-basin contains at least one Hydrologic Response Unit (HRU), a tributary channel, and the main channel. Sub-basin possesses a geographical position and is spatially interconnected, and flow from one sub-basin enters into the other. These sub-basins are further partitioned into HRUs, which are comprised of a unique land cover, soil, and topographic elevation combinations.

SWAT uses Soil Conservation Service - Curve Number (SCS-CN) method for runoff estimation, which is given as (SCS, 1972):

$$Q_{surf} = \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)} \quad \ldots(1)$$

Where,

Qsurf = Accumulated runoff, mm,

R_{day} = Rainfall depth of the day, mm,

I_a = Initial abstractions, including surface storage, interception and infiltration prior to runoff, mm, and,

S = Retention parameter, mm.

The retention parameter (S) varies spatially due to changes in soils, land use, management and slope, and also temporally due to changes in soil water content. It is defined as (SCS, 1972):

$$S = 25.4\left(\frac{1000}{CN} - 10\right) \quad \ldots(2)$$

where, CN = Curve number for the day.

The initial abstraction I_a is estimated as 0.2*S*, and thus, the equation becomes:

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)} \quad \ldots(3)$$

In SWAT, the CN value for Antecedent Moisture Condition (AMC) II is provided to the model; subsequently, it adjusts the CN according to the AMC calculated from daily rainfall data.

Preparing Input Data for SWAT

The DEM was used to delineate the watershed boundary (Fig. 1), determine the potential surface flows, calculate the terrain slope, and determine the effect of meteorological stations in SWAT. For the preparation of land use/cover map, the field-surveyed land-use classes were digitized and converted into raster format. The SWAT land use/cover class codes were used for linking the land-use database to the land-use layer.

The soil textural and physicochemical properties required by the SWAT included soil texture, organic carbon, available water content and Hydrological Soil Group (HSG) for each soil type. Sieve and hydrometer methods were used for determining percent sand, silt and clay, and then the soil texture was determined using the United States Department of Agriculture (USDA) textural triangle.

Soil map was prepared using GIS, and authenticated by comparing it with soil map at 1:50,000 scale prepared by the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP), Nagpur. Organic carbon content was determined by Walkley and Black (1934) wet oxidation procedure. Available water content (AWC) was calculated using SPAW software (Saxton and Willey, 2006). For each soil series, the HSG required by the CN method was derived from the soil texture and permeability properties. The permeability codes for various textures were taken from USDA (1986). Calculated soil physical attributes were stored in SWAT's soil database through an ArcSWAT interface. The database was linked to soil map through the look-up table, which was again linked to the soil map and given as input.

The ArcSWAT interface was used for the setup and parameterization of the hydrologic model. The DEM was imported into the SWAT model. A masking polygon (in grid format) was loaded into the model to extract the area of interest, delineate watershed boundary and digitize stream networks. The streams were defined on the basis of drainage area threshold. Optimal threshold area (critical source area) of 55.96 ha was adjusted for the sub-basin delineation to get a sub-basin of approximate equal size. In addition to the outlets created by the interface at the sub-basins, outlets were defined manually at the gauging station. Land use/cover, soil and slope maps were overlaid for each sub-basin which forms the basis for the formation of HRUs.

The main set of input data for simulating the watershed parameters were all climatic data, which were required to run the SWAT Model. The input file menu contained items that allowed building database files containing the information needed to generate a default input parameter for the SWAT. The values were set automatically based on the watershed delineation and land use/soil/slope characterization. In the present study, the 'activate the write all command' of the write input tables menu option was selected, and simulation was done at a monthly time step.

Calibrating SWAT and Evaluating Performance

In this study, manual calibration based on the expert judgment as well as automatic calibration of SWAT was done to obtain an optimal fit of process parameters. The manual calibration was done by varying the input parameters, namely, CN, AWC, cover management (C-factor), and support practices (P-factor). Three-year (2003-2005) climatological data were used for model warm up. The model calibration and validation were performed using runoff data of years 2010 and 2011, respectively. Data availability was a limiting factor in this study as only two years' monthly runoff data were used for model calibration and validation purposes.

SWAT calibration adequacy test

Adequacy of the SWAT calibration was evaluated by adopting four statistical criteria, i.e. coefficient of determination (R^2), Nash-Sutcliffe efficiency (E_{NS}), relative root mean square error (RRMSE) and percent bias (PBIAS), which are briefly described below.

The R^2 is the proportion of variation explained by fitting a regression line and is viewed as a measure of the strength of a linear relationship between observed and simulated data (Gupta *et al.,* 1999, Moriasi *et al.,* 2007). It is computed as:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - O_m)(P_i - P_m)}{[\sum_{i=1}^{n}[(O_i - O_m)^2]^{0.5}[\sum_{i=1}^{n}(P_i - P_m)^2]^{0.5}}\right]^2 \quad \ldots(4)$$

where, O_i, P_i, O_m and P_m are observed, predicted, mean observed and mean predicted values, respectively. Parajuli (2010) categorized model performance based on R^2 for monthly streamflow as excellent (≥0.90), very good (0.75–0.89), good (0.50–0.74), fair (0.25–0.49), poor (0–0.24), and unsatisfactory (<0).

The E_{NS} is used to assess the predictive power of hydrological models, which indicates how well the plot of the observed versus simulated values fit to the 1:1

line (Nash and Sutcliffe, 1970). The closer the E_{NS} to 1, the more accurate the model is. The E_{NS} is defined as follows:

$$(E_{NS}) = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O_m)^2} \quad \ldots(5)$$

As per the model performance rating suggested by Moriasi *et al*. (2007), model simulation performance can be judged as "very good", "good", and "satisfactory" if $0.75< E_{NS} \leq 1.0$; $0.65< E_{NS} \leq 0.75$, and $0.50< E_{NS} \leq 0.65$, respectively.

The RRMSE, an index of the actual error produced by the model, is calculated by dividing RMSE with the average value of the observed data. The RRMSE value close to zero indicates the better model performance (Chu and Shirmohammadi, 2004; Singh *et al.,* 2004). The RRMSE is explained as:

$$\text{RRMSE} = \sqrt{\sum_{i=1}^{n}\frac{1}{n}(P_i - O_i)^2}\,\frac{1}{O_m} \quad \ldots(6)$$

The PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts, and is computed as (Gupta *et al.,* 1999; Moriasi *et al.,* 2007):

$$\text{PBIAS} = \frac{(\sum_{i=1}^{n} O_i - P_i))}{(\sum_{i=1}^{n} O_i)} \times 100 \quad \ldots(7)$$

The optimal value of PBIAS is 0, with low-magnitude values indicating accurate model simulation. Positive (or negative) values indicate model underestimation (or overestimation) bias. An absolute value for PBIAS <20 %, between ±20 % and ±30 %, and>±30 % are considered as good, satisfactory, and non-satisfactory, respectively (Gupta *et al.,* 1999). Moriasi *et al*. (2007) had suggested model simulation performance as "very good", "good", and "satisfactory" if PBIAS<±10.0; ±10.0<PBIAS≤±15.0, and ±15.0<PBIAS≤±25.0, respectively.

Validating SWAT and Simulating Watershed Runoff

After calibration, proper validation is equally essential for model testing before it could be used for varying conditions. In the validation process, the model was operated with input parameters set used during the calibration process, and the results were compared against an independent set of observed data to evaluate the performance of the model. The SWAT was validated adopting the four performance criteria, i.e. R^2, RRMSE, E_{NS}, and PBIAS, explained earlier. After validation, the model was simulated to generate runoff for four years (2006-2009).

RESULTS AND DISCUSSION

Model Input Parameters

Automatic delineation of the watershed boundary using the Arc-SWAT interface resulted in the generation of 70 sub-basins. Map depicting slope (in degrees) is presented in Fig. 3. The slope of watershed varied from <7° to >30°. About 21.96 % (41.44 km²) of the area has a slope less than 7° and 7.56 % (14.27 km²) of the area had very steep slope of >30°.The watershed areas under moderate slope (7-15°), high slope (15-20°), very high slope (20-25°) and steep slope (25-30°) categories occupied 14.73 %, 17.60 %, 20.73 %, and 17.42 % of the watershed area. The entire watershed was divided into eight land use classes as shown in Fig. 4. It is evident from Fig. 4 that the maximum area was covered by forest land (30.72 %), followed by snow cover (26.76 %). A total of eleven soil texture classes were identified in the study area, with sandy loam and loamy soils as the two major soil textural classes (Fig. 5). The AWC and HSG for soil textural classes are summarized in Table 1. It is evident from Table 1 that the maximum AWC was 0.175 mm of water per unit mm of soil for HSG C in sandy clay soil. The HSG for each soil class, required for the application of the CN method, was derived from the description of soil texture and permeability properties. The overlay of land use/cover, soil and slope maps resulted in the definition of 141 HRUs. The total runoff depends on the actual hydrologic condition of each land use/cover and soil present in the watershed.

Model Calibration Performance

The monthly runoff was simulated for the year 2010

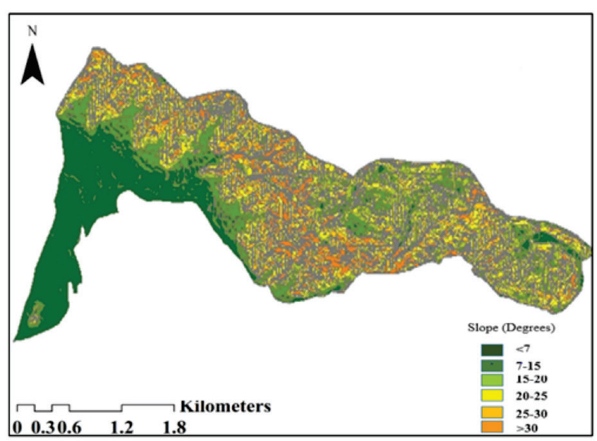

Fig. 3: Slope map of study area

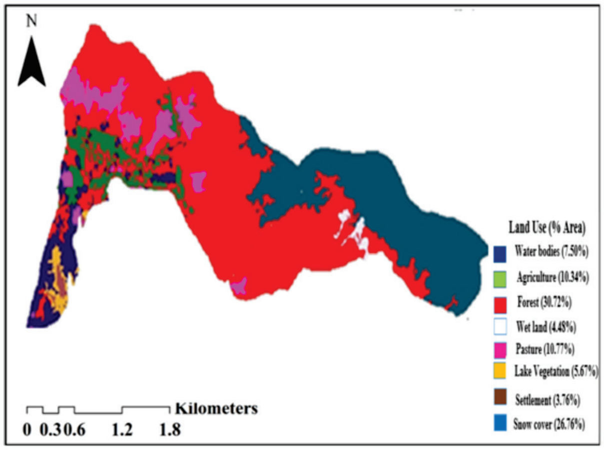

Fig. 4: Land use/cover map of study area

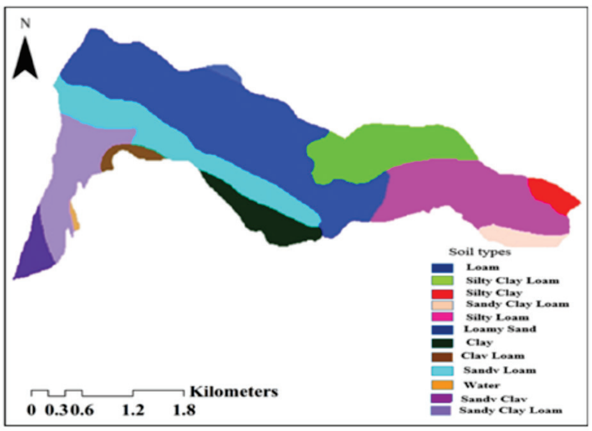

Fig. 5: Soil map of study area

Table 1. Available water content and hydrologic soil group of soil textural classes

Sl. No.	Soil type	Hydrologic soil group	Available water, mm water/ mm soil
1.	Loam	C	0.096
2.	Silty clay loam	C	0.150
3.	Silty clay	B	0.125
4.	Silt	A	0.142
5.	Silty loam	B	0.158
6.	Loamy sand	A	0.100
7.	Clay	D	0.116
8.	Clay loam	C	0.166
9.	Sandy loam	B	0.116
10.	Sandy clay	C	0.175
11.	Sandy clay loam	C	0.158

without calibrating the SWAT model. Distribution of the observed and simulated monthly runoff values over 12 months during the pre-calibration period is graphically presented in Fig. 6. It is evident from the Fig. 6 that the model overestimated the runoff as compared to observed runoff except during two winter months of November and December. The values of R^2, E_{NS}, RRMSE, and PBIAS during the pre-calibration were 0.98, 0.31, 3.0, and (-)58.0, respectively. The E_{NS} index value was less than 0.75 and PBIAS was greater than (±)30 %. The model performance was thus not good as the values of statistical indicators were not in satisfactory range, except of R^2 value. Hence, the model simulation was not satisfactory (Moriasi *et al.,* 2007) due to excessive overestimation of the runoff values during the pre-calibration period. Therefore, the SWAT model needed calibration and validation before using it for runoff simulation.

A graphical representation of observed and simulated monthly runoff values after SWAT calibration is shown in Fig. 7. It is seen that model-simulated values of runoff were overestimated as compared to their corresponding observed values. The overestimations were in all months, except during January and December months. Simulated month runoffs followed similar pattern as that of monthly runoffs. Monthly rainfall during calibration period varied from 0 mm (November) to 170 mm (May), and monthly simulated runoff varied from 2 mm (December /January) to 53 mm (May). In the month of November with no rainfall, the model simulated runoff was 5 mm against the observed runoff of 2 mm. This could be attributed to the contribution of base flow/delayed flow at the watershed outlet. The R^2, E_{NS}, RRMSE, and PBIAS values were 0.98, 0.87, 1.3, and (-) 26.0, respectively. It is apparent from the values of statistical indicators that the simulated and observed values of runoff were in good agreement. During the calibration period, values of the simulated monthly runoff matched well with the observed runoff values. The values of two statistical indicators (R^2>0.9; E_{NS}>0.75) clearly indicated that the model performance could be rated as "very good" (Moriasi *et al*., 2007; Parajuli, 2010). However, the value of PBIAS slightly deviated from the acceptable range (PBIAS < ±25.0) as suggested by Moriasi *et al.* (2007), but was well within the acceptable range (PBIAS< ±30.0) as suggested by Gupta *et al*.(1999). The total annual runoff computed by the model was 256 mm (32.8 % of the annual rainfall) against the observed annual runoff of 203 mm (26 % of the annual rainfall) due to the annual rainfall of 779 mm during the year 2010.

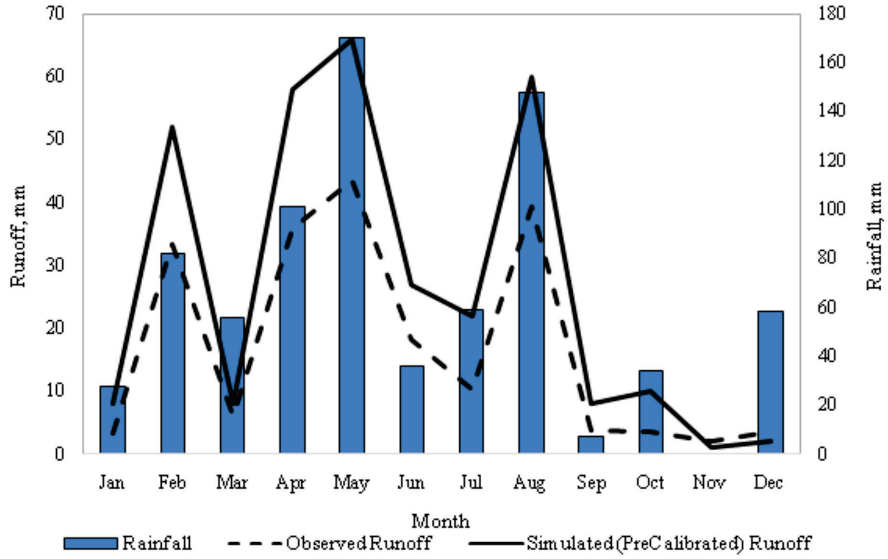

Fig. 6: Observed and simulated runoff during pre-calibration

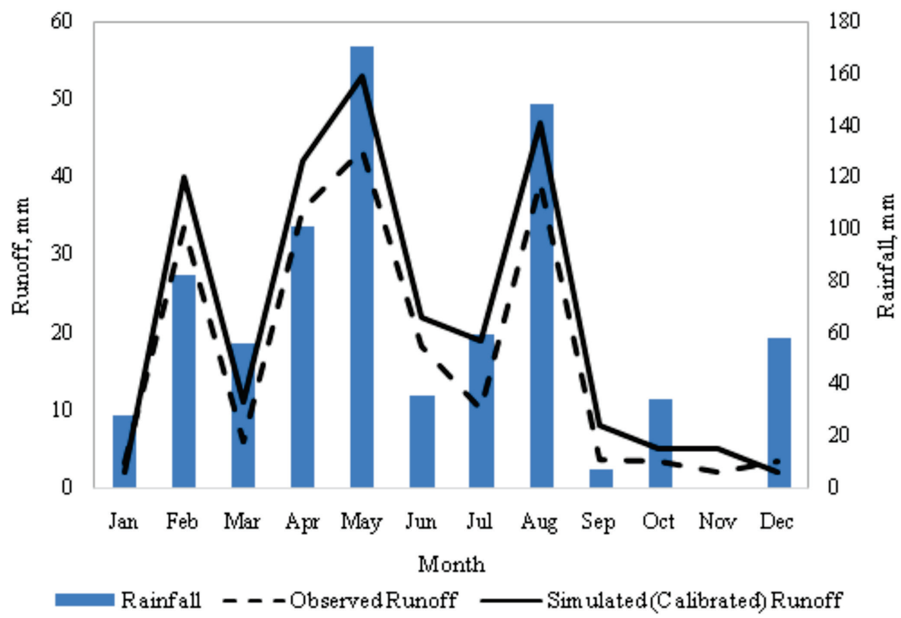

Fig. 7: Monthly observed and simulated runoff during calibration period

Model Validation and Simulated Runoff

For validation, the observed monthly runoff data for the year 2011 were utilized and compared with the model simulated values. The comparison between observed and model-simulated runoff values revealed that the model simulated runoff is 232 mm against the observed runoff of 184 mm, thus slightly overestimating the runoff values (Fig. 8). The overestimations were slightly higher in months of January and February, as simulated runoff was 39 mm and 33 mm against the observed runoff of 33 mm and 28 mm, respectively, which might be attributed to the occurrence of rainfall in temperate climate of the study area. Otherwise, the results showed that the simulated runoff values were in good agreement with the observed values (Fig. 8). Monthly rainfall during validation period varied from

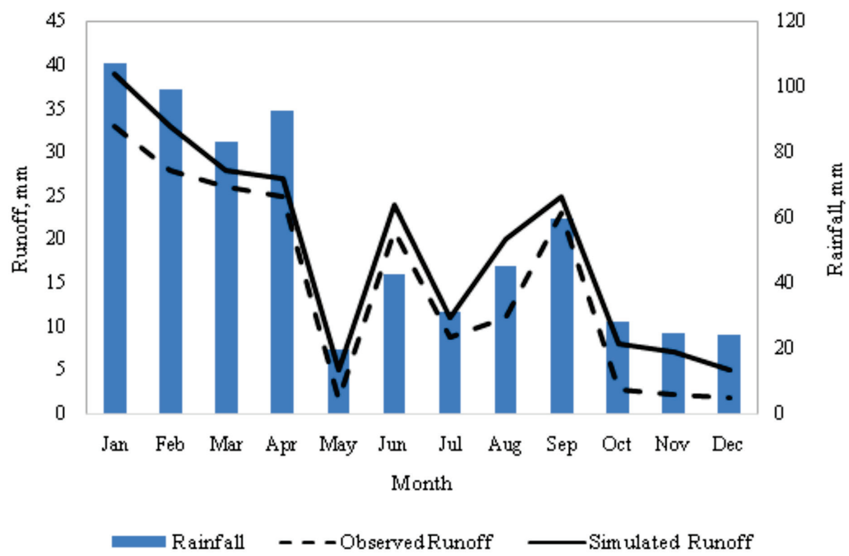

Fig. 8: Monthly observed and simulated runoff during validation period

20 mm (May) to 108 mm (January), and the simulated monthly runoff varied from 5 mm (May /December) to 39 mm (January). Overall 35 % of the annual rainfall was converted to runoff. The total annual runoff computed by the model was 232 mm (35 % of the annual rainfall) against the observed annual runoff of 184 mm (28 % of the annual rainfall) due to the annual rainfall of 659 mm during the year 2011.

Furthermore, the difference between the observed and model-simulated runoff values was found within the reasonable limits during the validation period. The values of statistical indicators, i.e. R^2, E_{NS}, RRMSE and PBIAS were 0.97, 0.84, 1.1 and (-) 26.0, respectively. Hence, the observed and model-simulated monthly runoff values matched well and the value of statistical indicators (R^2>0.9; E_{NS}>0.75) were within the acceptable range, and the model performance could be rated as "very good" (Moriasi *et al*., 2007; Parajuli, 2010). The PBIAS value was also within acceptable range (PBIAS< ±30.0) (Gupta *et al*., 1999). Therefore, the SWAT model is adequately validated.

After validation, the SWAT model was used for runoff simulation for 4 years (2006-2009). A comparison between the observed and simulated runoff values is shown in Table 2. It is seen that the annual rainfall was maximum in the year 2006 resulting in the maximum annual runoff of 193 mm. In contrast, the annual rainfall was minimum in the year 2007 resulting in the minimum annual runoff of 110 mm. Thus, the simulated runoff quantities were found to be directly proportional to the amount of annual rainfall. In general, the SWAT model performed well in simulating runoff values in the study watershed, and the results were acceptable as in most instances the simulated monthly runoff were close to the monthly observed runoff both during calibration and validation period, and also the different statistical indicators (R^2>0.9; E_{NS}>0.75; PBIAS < ±30.0) were within the acceptable range. Thus, SWAT was found to be a capable tool for runoff simulation, and might be used for further analysis of the hydrological responses in the watershed. The results of this study will be helpful in developing suitable water management adaptation plans for the study watershed.

Table 2. Simulated runoff during 2006-2009

Sl. No.	Year	Rainfall, mm	Runoff, mm
1.	2006	1020	193
2.	2007	577	110
3.	2008	706	138
4.	2009	612	130

CONCLUSIONS

In the present study, the performance of the SWAT model was evaluated using standard calibration and validation procedures and performance statistics under limiting data conditions. The total runoff computed by the SWAT model was 256 mm against the observed runoff of 202.9 mm during the calibration period. A good agreement between measured and simulated monthly runoff values was demonstrated by R^2, E_{NS}, RRMSE, and PBIAS values of 0.98, 0.87, 1.3, and -26, respectively, during the calibration period. The value of R^2, E_{NS}, RRMSE and PBIAS during validation were 0.97, 0.84, 1.1, and -26, respectively. The performances of the model can be further enhanced by integrating more reliable spatial representation of rainfall and other climatic data such as solar radiation, humidity and wind, and also including a greater number of runoff year data for model calibration and validation purposes.

ACKNOWLEDGEMENT

Authors are thankful to the College of Agricultural Engineering and Technology and Division of Soil Science, SKUAST-Kashmir for providing all necessary facilities.

REFERENCES

Arnold J G; Williams J R; Srinivasan R; King K W. 1998. SWAT: Soil and Water Assessment Tool. User's Manual, USDA Agriculture Research Service Grassland, Soil and Water Research Laboratory, 808 East Blackland Road Temple, TX 76502, pp: 190.

Badar B; Romshoo S A; Khan M A. 2013. Modelling watershed hydrological responses in a Himalayan Lake as a function of changing land use and land cover. J. Earth Syst. Sci., 122(2), 433-449.

Beasley D B; Huggins L F; Monke E J. 1980. ANSWERS: A model for watershed planning. Trans. ASAE, 23(4), 938-944.

Chu T W; Shirmohammadi A. 2004. Evaluation of the SWAT model's hydrology component in the piedmont physiographic region of Maryland. Trans. ASAE, 47(4), 1057-1073.

Easton Z M; Fuka D R; White E D; Awulachew S B; Ahmed A A; Steenhuis T S. 2010. A multi basin SWAT model analysis of runoff and sedimentation in the Blue Nile, Ethiopia. Hydrol. Earth Syst. Sci. Discuss., 7, 3837-3878.

Frankenberger J R; Brooks E S; Walter M T; Water M F; Steenhuis T S. 1999. A GIS-based variable source area hydrology model. Hydrol. Process., 13(6), 805-822.

Guo J; Su X L; Singh V P; Jin J M. 2016. Impacts of climate and land use/cover change on streamflow using SWAT and a separation method for the Xiying River Basin in north-western China. Water, 8 (192),1-14.

Gupta H V; Sorooshian S; Yapo P O. 1999. Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. J. Hydrol. Eng., 4(2), 135-143.

Huang Y F. 2003. GIS-based distributed model for simulating runoff and sediment load in the Malian River Basin. Hydrobiologia, 494(2), 127-134.

Jadhao V G; Jadhao A K; Tripathi M P. 2010. Estimation of monthly surface runoff and sediment yield from a small watershed by using simulation technique. Int. J. Agric. Eng., 2(2), 278-284.

Jain S; Tyagi J; Singh V. 2010. Simulation of runoff and sediment yield for a Himalayan watershed using SWAT Model. J. Water Resour. Prot., 2(3), 267-281.

Jinfeng W; Gao Y; Wang S. 2018. Assessing the response of runoff to climate change and human activities for a typical basin in the Northern Taihang mountain. China. J. Earth Syst. Sci., 127(37), 1-15.

Kim J G; Park Y; Yoo D; Kim N W; Engel B A; Lim K J. 2009. Development of a SWAT Patch for better estimation of sediment yield in steep sloping watersheds. J. Am. Water Resour. Assoc., 45(4), 963-972.

Knisel W G. 1980. CREAMS: A Field Scale Model for Chemicals, Runoff and Erosion from Agricultural Management Systems. Conservation Report No 26, U.S. Department of Agriculture, Washington DC, pp: 640.

Kumar S; Dhaimodkar S B; Pande L M. 2002. The assessment of potential land use in the proposed irrigation command using remote sensing and GIS. J. Indian Soc. Remote, 3(3), 157-166.

Maji A K; Reddy G P O; Sarkar D. 2010. Degraded and Wastelands of India: Status and Spatial Distribution. Indian Council of Agricultural Research, New Delhi, pp; 167.

Mishra H; Denis D M; Suryavanshi S; Kumar M; Srivastava S K; Denis A F; Kumar R. 2017. Hydrological simulation of a small ungauged agricultural watershed Semrakalwana of Northern India. Appl. Water Sci., 7(6), 2803-2815.

Moriasi D N; Arnold J G; Van Liew M W; Bingner R L; Harmel R D; Veith T L. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE, 50(3), 885-900.

Nash J E; Sutcliffe J V. 1970. River flow forecasting through conceptual models: Part 1. A discussion of principles. J. Hydrol., 10(3), 282-290.

Neitsch S L; Arnold J G; Kiniry J R; Williams J R. 2005. Soil and Water Assessment Tool Theoretical Documentation Version 2005. Grassland, Soil and Water Research Laboratory, Agricultural Research Service, Texas, USA, pp: 476.

Odusanya A E; Mehdi B; Schürz C; Oke A O: Awokola O S; Awomeso J A; Adejuwon J O; Schulz K. 2019. Multi-site calibration and validation of SWAT with satellite-based evapotranspiration in a data-sparse catchment in southwestern Nigeria. Hydrol. Earth Syst. Sci., 23, 1113-1144.

Pandey V K; Panda S N; Sudhakar S. 2005. Modelling of an agricultural watershed using remote sensing and a geographic information system. Biosyst. Eng., 90(3), 331-347.

Panhalkar S S. 2014. Hydrological modelling using SWAT model and geoinformatic techniques. Egypt. J. Remote Sens. Space Sci., 17(2), 197-207.

Parajuli P B. 2010. Assessing sensitivity of hydrologic responses to climate change from forested watershed in Mississippi. Hydrol. Process., 24(26), 3785-3797.

Phomcha P; Wirojanagud P; Vangpaisal T; Thaveevouthti T. 2011. Modelling the impacts of alternative soil conservation practices for an agricultural watershed with the SWAT model. Procedia Eng., 32,1205-1213.

Qiu L J; Zheng F L; Yin R S. 2012. SWAT-based runoff and sediment simulation in a small watershed, The loessial hilly-gullied region of China: Capabilities and challenges. Int. J. Sediment Res., 27, 226-234.

Rao C S; Lal R; Prasad J V N S; Gopinath K A; Singh R; Jakkula V S; Sahrawat K L; Venkateswarlu B; Sikka A K; Virmani S M. 2015. Potential and Challenges of Rainfed Farming in India. Adv. Agron., 133,113-181.

Rao E P; Prabhanjan A; Eldho T I. 2012. Sediment yield modelling using SWAT and Geo-Spatial technologies. In: Proc. International SWAT Conference, Indian Institute of Technology, Delhi, 647-658.

Saxton K E; Willey P H. 2006. The SPAW model for agricultural field and pond hydrologic simulation. In: Singh V P; Frevert D K (Eds.) Watershed models. CRC Press, Boca Raton, Fl, 401-435.

SCS (Soil Conservation Services). 1972. National Engineering Handbook, Section 4: Hydrology. Chapter 10, United States Department of Agriculture, Natural Resources Conservation Service, Washington, DC, 10.1-10.2.

Singh V P; Woolhiser D A. 2002. Mathematical modelling of watershed hydrology. J. Hydrol. Eng., 7, 270-292.

Singh J; Knapp H V; Demissie M. 2004. Hydrologic modeling of the Iroquois river watershed using HSPF and SWAT. ISWS CR 2004-08, Champaign, Ill.: Illinois State Water Survey. Available at www.sws.uiuc.edu/ pubdoc/CR/ ISWSCR2004-08.pdf. (Accessed on 8 September, 2005).

Smith R. 1992. OPUS, An integrated Simulation Model for Transport of Nonpoint Sources Pollutants at the Field Scale. Volume I: Documentation, ARS-98, U.S. Department of Agriculture, Agricultural Research Service, Washington, DC, pp. 120.

Srinivasan R; **Arnold J G.** 1994. Integration of basin scale water quality model with GIS. Water Res. Bull., 26(4), 611-620.

Srinivasan R; Zhang X; Arnold J G. 2010. SWAT ungauged: Hydrological budget and crop yield predictions in the upper Mississippi river basin. Trans. ASABE, 53(5), 1533-1546.

Tyagi J V; Rai S P; Qazi N; Singh M P. 2013. Assessment of discharge and sediment transport from different forest cover types in lower Himalaya using Soil and Water Assessment Tool (SWAT). Int. J. Water Res. Environ. Eng., 6(1), 49-66.

USDA. 1986. Urban Hydrology for Small Watersheds. Technical Release No. 55 (TR-55), United States Department of Agriculture (USDA), Natural Resources Conservation Service, Conservation Engineering Division, Washington DC, pp. 2.1-2.16.

Walkley A; Black I A. 1934. An examination of Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. Soil Sci., 37, 29-37.

Wang H; Sun F B; Xia J; Liu W B. 2017. Impact of LUCC on streamflow based on the SWAT model over the Wei river basin on the Loess Plateau in China. Hydrol. Earth Syst. Sci., 21, 1929-1945.

Williams J R; Nicks A D; Arnold J G. 1985. Simulator for water resources in rural basins. J. Hydraulic Eng.,111(6), 970-986.

Yen H; Wang X; Fontane D G; Harmel R D; Arabi M

A. 2014. Framework for propagation of uncertainty contributed by input data, parameterization, model structure, and calibration/ validation data in watershed modeling. Environ. Model. Softw., 54, 211-221.

Yen H; White M J; Jeong J; Arabi M; Arnold J G. 2015. Evaluation of alternative surface runoff accounting procedures using SWAT model. Int. J. Agric. Biol. Eng., 8(3), 54-68.

Zhang L; Lu J; Chen X; Liang D; Fu X; Sauvage S; Perez J M S. 2017. Stream flow simulation and verification in ungauged zones by coupling hydrological and hydrodynamic models: A case study of the Poyang lake ungauged zone. Hydrol. Earth Syst. Sci., 21, 5847-5861.

Zhang X; Srinivasan R; Van Liew M. 2008. Multisite calibration of the SWAT model for hydrologic modeling. Trans. ASABE, 51(6), 2039-2049.