


Modelling spatially distributed surface runoff generation using SWAT-VSA: a case study in a watershed of the north-west Himalayan landscape

Suresh Kumar¹  · A. Singh¹ · D. P. Shrestha²

Received: 21 October 2016 / Accepted: 31 October 2016 / Published online: 12 November 2016
© Springer International Publishing Switzerland 2016

Abstract Soil and Water Assessment Tool (SWAT) and Soil and Water Assessment Tool-Variable Source Area (SWAT-VSA) models were employed to predict surface runoff generation in a watershed of the Himalayan landscape in GIS environment. Both the models differed in term of defining hydrological response units (HRUs) that serves as basis in assigning curve number for surface runoff estimation. HRUs in SWAT was derived by combination of hydrological soil groups based on soil types and land use/land cover (LULC) whereas in SWAT-VSA, it was based on soil wetness index derived from digital elevation model (DEM) and LULC. Both models were calibrated to predict surface runoff at watershed scale. SWAT-VSA predicted quite well [Root Mean Square Error (RMSE) = 3.88, Nash–Sutcliffe coefficient of efficiency (NSE) = 0.75] than the SWAT (RMSE = 4.12, NSE = 0.72) model. Paddy (rice) cropland in the watershed generated highest surface runoff. Integration of topographic wetness index derived from DEM with SWAT model helped in estimating spatially distributed surface runoff generation in the watershed. Study revealed that saturation excess as the dominant runoff process in the Himalayan landscape and SWAT-VSA provide more representative results than the SWAT based on infiltration excess.

Keywords Surface runoff · Watershed · SWAT · SWAT-VSA · DEM · Himalayan landscape

Introduction

Soil erosion due to accelerating runoff in various land cover types pose a serious threat to the long term sustainability of the fragile Himalayan landscape (Tiwari 2000). Runoff generation and soil erosion varies both spatially and temporarily. Few areas of the watershed are critical and witness high amount of soil loss caused by surface runoff. Knowledge of these critical source areas of soil erosion are necessitated for adopting suitable soil and water conservation measures in the watershed. Surface runoff generation plays an important role in delimiting these areas. Thus, effective control of non-point source of sediment loss transported by runoff requires information about these areas (Frankenberger et al. 1999) to develop management strategies for controlling soil degradation and controlling runoff.

The process of transformation of rainfall into runoff over a watershed is very complex, highly nonlinear, and exhibits both temporal and spatial variability (ASCE 2000). Either infiltration or saturation-excess processes may predominate temporarily and spatially within a watershed. Infiltration excess or Hortonian flow occurs when rainfall intensities exceed the rate at which water can infiltrate into the soil. Hortonian flow is primarily controlled by soil type, land cover and rainfall intensity whereas the saturation excess runoff is generated by direct precipitation on or exfiltration from saturated areas in the watershed (Ward 1984). Most commonly models used in predicting surface runoff are Soil and Water Assessment Tool (SWAT) (Arnold et al. 1993), General Watershed Loading Function (GWLF) (Haith and Shoemaker 1987), Agricultural Non-point Source Pollution (AGNPS) (Young et al. 1989), Areal Non-point Source Watershed Environment Simulation (ANSWERS) (Beasley et al. 1980) and Chemicals,

✉ Suresh Kumar
suresh_kumar@iirs.gov.in

¹ Indian Institute of Remote Sensing, 4 Kalidas Road, Dehradun, Uttarakhand 248001, India

² Faculty of Geo-Information Science and Earth Observation (ITC), University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands

Runoff and Erosion from Agricultural Management Systems (CREAMS) (Knisel 1980). These models are semi-distributed and usually based on Hortonian overland flow generation mechanisms following Soil Conservation Service Curve Number (SCS-CN) (USDA-SCS 1972) method. They represent relatively large portions of watersheds as lumped hydrological units and, therefore, cannot be used to identify discrete, saturated areas in the watershed. These models are based on NRCS curve number (CN) equations to predict surface runoff from watershed. The way the CN is applied in these models implicitly assumes infiltration-excess (Hortonian) response to rainfall (Walter and Shaw 2005). In Humid and well vegetated area, especially with soils underlain by a shallow restricting layer or shallow water tables witness saturation-excess process of runoff generation on variable source area (VSAs) (Srinivasan et al. 2002; Needelman et al. 2004).

SCS-CN based SWAT model is widely used infiltration excess surface runoff prediction (McCuen 1982; Jain et al. 2010; Qiu et al. 2012) at basin, catchment and watershed scale due to its simplicity and reliability. This model does not account variable source area (VSAs) of runoff generation. It predicts surface runoff considering hydrological response units (HRUs) which do not allow water flows among HRUs and therefore, cannot simulate the formation of VSAs. Easton et al. (2008) proposed topographic wetness index (TWI) to redefine HRUs to predict VSAs for the watersheds dominated by saturation-excess runoff (Lyon et al. 2004; Schneiderman et al. 2007). Steenhuis et al. (1995) and Schneiderman et al. (2007) showed how CN models can be used to predict the distribution of VSAs and explicitly simulated saturation-excess runoff from VSAs. Thereafter, Easton et al. (2008) re-conceptualized SWAT to model which integrates topographic parameter to simulate the spatial distribution of runoff based on saturation excess within the watershed.

Topography of watershed plays a dominant role in spatial distribution of soil properties and hydrological processes (McKenzie and Ryan 1999; Bell et al. 1995; Beven and Wood 1983) and thus controlling runoff generation processes in the hilly terrain (Krause and Flügel 2001). In recent years, digital terrain models (DTMs) demonstrated potential application in predicting soil hydrological parameters and their spatial distribution (Park et al. 2001; Romano and Palladino 2002; Martinez et al. 2010) and it had helped in improving runoff estimation in the hilly landscape (Lyon et al. 2006). TOPMODEL (topography based hydrological model) (Beven and Kirkby 1979) was the earliest model that provided the model structure to integrate DEM as (TWI) to simulate variable source area (VSA) hydrology and thereafter it had been applied outside of TOPMODEL. TWI has been found effectively in predicting (VSA) for watersheds dominated

by saturation-excess runoff (Western et al. 1999; Lyon et al. 2004; Agnew et al. 2006; Schneiderman et al. 2007). While modeling surface runoff in the data scarce hilly and mountainous landscape DTM derived terrain indices can be used to represent spatial distribution of soil hydraulic properties with limited field observations, since soil hydraulic conductivity data may not be available for most of the inaccessible areas. Moreover, the soil variability strongly correlates with the topographic features, because of the relation of the soil genesis to topology and hydrology (Page et al. 2005; Sharma et al. 2006). In spatial hydrological modeling, runoff generation seems to be very sensitive to the variation of soil hydraulic conductivity (Herbst et al. 2006) and tends to vary widely in space.

Himalayan landscape is characterized as mountainous and hilly topography with complex slope. The soils in the region are dominantly shallow to moderately deep underlain by lithic rock. The area witness high rainfall and characterized by humid to sub-humid climate. They are composed of hillslopes where surface water flows from upper to lower slopes develops sub-surface flow and saturation of sub-soils which facilitates saturation-excess runoff. Agriculture field lying at lower hillslopes cultivated mainly for paddy crop and remain saturated with water. Thus, the watershed witnesses variable source area (VSA). It requires incorporating VSA hydrology concept into models employing CN-type functionality to capture spatial variability of saturation excess runoff source area (Easton et al. 2008). Therefore, the present study aims to study performance of SWAT and SWAT-VSA in predicting surface runoff at watershed scale and to identify spatially distributed runoff source area in the watershed of Himalayan landscape.

Materials and methods

Study area

The watershed located in the outer Himalayan landscape in Dehra Dun district Uttarakhand state, India (Fig. 1). It is located between 30°28'15"–30°28'44" and 30°28'15"E latitude and 77°54'46"–77°55'45"E longitude covering an area of 57 hectare and the elevation ranges from 920 to 1480 m in the watershed. The watershed is characterized by moderately steep to very steep sloping hills which drains by an ephemeral channel that runs from north-west to south-west. The mean annual rainfall is 1753 mm of which about 60% (about 1000 mm rain) is received during monsoon season (June–September) and the remaining 40% during the winter season (December–April). Soils belong to soil taxonomy family of Loamy skeletal Typic Udorthents, Coarse loamy and Fine loamy Typic Hapludepts.

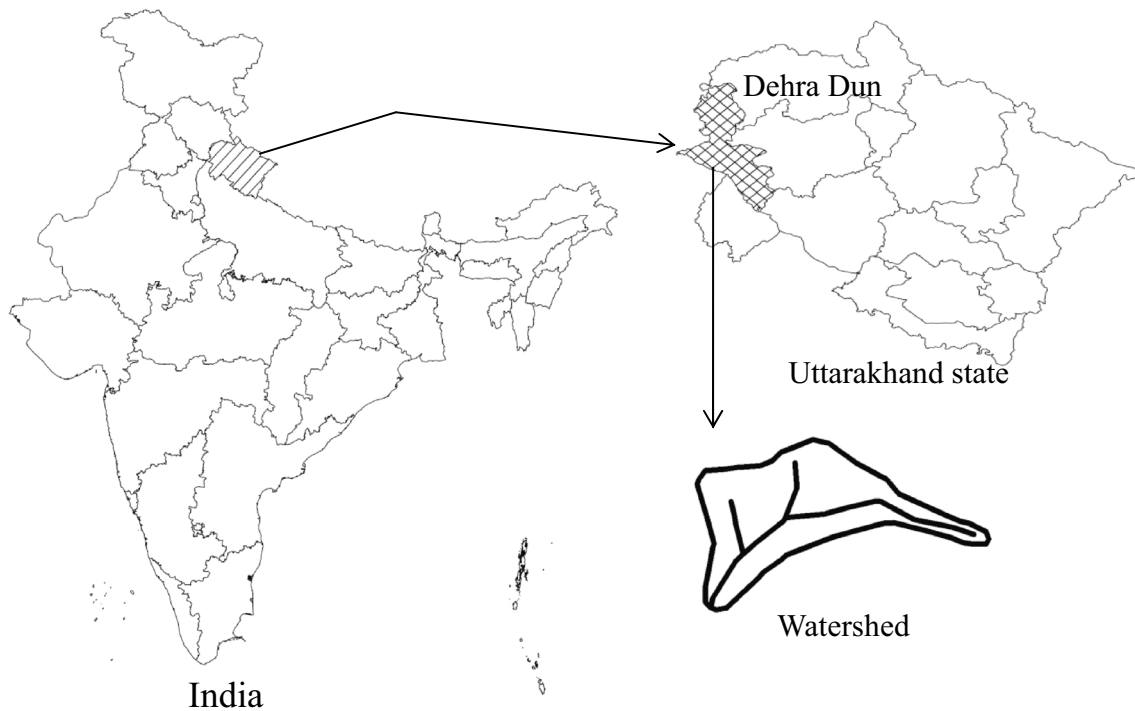


Fig. 1 Location of watershed in Dehra dun district, Uttarakhand, state, India

Maize and paddy (rice) crops are grown in the rainy season (kharif) and wheat and mustard in winter (rabi) season. The natural vegetation cover comprises of Sal forest (*Shorea robusta*), shrubs (*Lantana camera*, *Ipomoea batata*) and grasses (*Saccharam spontanium*) and barren lands at the higher elevation regions on steeper slopes.

Runoff modelling

Watershed in Himalayan landscape characterized by rugged terrain that develops variable source area (VSA) which is controlled by topography for runoff generation. SWAT and the SWAT-VSA models were tested in order to find suitable method for runoff estimation at watershed scale as well as to identify spatially distributed area of surface runoff generation. The description of the models as follows:

SWAT model

Soil and Water Assessment Tool (SWAT) model (Arnold et al. 1998) is a distributed, continuous model operating on a daily time step to predict runoff, erosion, sediment and nutrient transport from agricultural watersheds under different management practices (Arnold et al. 1996). SWAT uses the CN method to partition precipitation into either infiltration, which can then reach a stream by several flow paths, or to overland runoff, which flows

directly to a stream (Neitsch et al. 2002). The model simulates surface runoff volumes for each HRU using the SCS-CN (curve number) method. The CN equation was originally developed by Rallison (1980) and estimated total watershed runoff depth Q (mm) for a stream (USDA-SCS 1972). The runoff prediction with SCS curve number equation is given by:

$$Q = \frac{Pe^2}{(Pe + Se)} \quad \text{for } Pe > Ia \quad (1)$$

$$Se = (25,400/CN) - 254$$

where, Q is the surface runoff depth (mm), Ia is the initial abstraction (mm), Pe is effective rainfall (mm) computed by subtracting Initial abstract ion (Ia) from rainfall (P), Se is the depth of effective available storage within the watershed in mm, and CN is the curve number which originally derived as function of soil and land use types. Ia is estimated as an empirically derived fraction of available watershed storage (USDA-SC 1972).

The curve number is a function of the soil's permeability, land use and antecedent soil moisture (AMC) conditions. Soil was classified in one of the four hydrological soil groups (HSGs) according to its runoff potential. Other than soil properties and land use, AMC conditions also affect the curve number. SWAT model adjusts the CN according to the antecedent moisture condition calculated from daily rainfall data.

SWAT-VSA model

The model simulates surface runoff volumes using SCS-CN equation. The significant difference in SWAT-VSA lies in the redefining of the HRUs in terms of CN-VSA (variable source area) hydrology. In SWAT model, HRUs were defined by land-use and soil types whereas in SWAT-VSA, soil wetness index (SWI) was used in combination with land use to define the HRUs. Thus, contrary to SWAT where primary mechanism is assumed to be infiltration excess, the SWAT-VSA takes into account saturation excess response to rainfall. In SWAT-VSA, the CN equation was re-interpreted in terms of a saturation-excess runoff process.

The SCS-CN equation (Eq. 1) is an empirical relationship between rainfall and runoff, and is therefore independent of the underlying runoff generation mechanism. Steenhuis et al. (1995) differentiated this equation to express the saturated fraction (A_f) contributing runoff as:

$$A_f = 1 - \frac{S^2}{(P_e + S_e)^2} \quad (2)$$

where, P_e is the effective precipitation and defined as $P - I_a$, or the amount of water required to initiate runoff. It is assumed that runoff only occurs from areas that have local effective storage, σ_e , less than P_e . Therefore, by substituting σ_e for P_e in Eq. 2, the relationship for the fraction of the watershed area, A_s , that has local effective storage $\leq \sigma_e$ for a given overall watershed storage of S_e becomes (Schneiderman et al. 2007):

$$A_s = 1 - \frac{S_e^2}{(\sigma_e + S_e)^2} \quad (3)$$

here, S_e and I_a are watershed properties while σ_e is defined at local level. Solving for σ_e gives the maximum effective local soil moisture storage within any particular fraction, A_s , of the watershed area (Schneiderman et al. 2007):

$$\sigma_e = S_e \left(\sqrt{\frac{1}{1 - A_s}} - 1 \right) \quad (4)$$

For a given storm event with precipitation P , the fraction of the watershed that saturates first ($A_s = 0$) has local storage $\sigma_e = 0$, and runoff from this fraction will be $P - I_a$. Successively drier fractions retain more precipitation. Runoff q_i (mm) for an saturated area, can be expressed as (Schneiderman et al. 2007):

$$q_i = P_e - \sigma_e \quad \text{for } P_e > \sigma_e \quad (5)$$

And for the unsaturated area

$$q_i = 0 \quad \text{for } P_e \leq \sigma_e \quad (6)$$

To avoid changing any SWAT code, Eq. 5 can be approximated with CN equation (Easton et al. 2008)

$$q_i = \frac{P_e^2}{P_e + \sigma_e} \quad (7)$$

q_i predicts the fractional area of the watershed contributing to runoff without indicating important information about where that area is located in a watershed. To determine this, soil topographic index was used (Lyon et al. 2004)

$$\text{Soil wetness index} = \ln \left(\frac{\alpha}{T \tan \beta} \right) \quad (8)$$

where, α is the upslope contributing area for the cell per unit of contour line (m), $\tan \beta$ is the topographic slope of the cell, and T is the soil transmissivity (soil depth \times saturated soil hydraulic conductivity) of the uppermost layer of the soil (m^2 per day).

The effective value of σ_e can be defined linearly on the basis of wetness value obtained from the soil wetness index, the value of σ_e is set to minimum for unsaturated zone (low index) and to maximum for saturated zone (high index) (Lyon et al. 2004; Schneiderman et al. 2007; Zachary et al. 2008).

Data processing

AVSWAT-2000 interface of SWAT model was used for the model calibration instead of AVSWAT-X interface of SWAT model, as it follows automatic calibration process. SWAT model requires several data ranging from soil, land use, topography and climate etc.

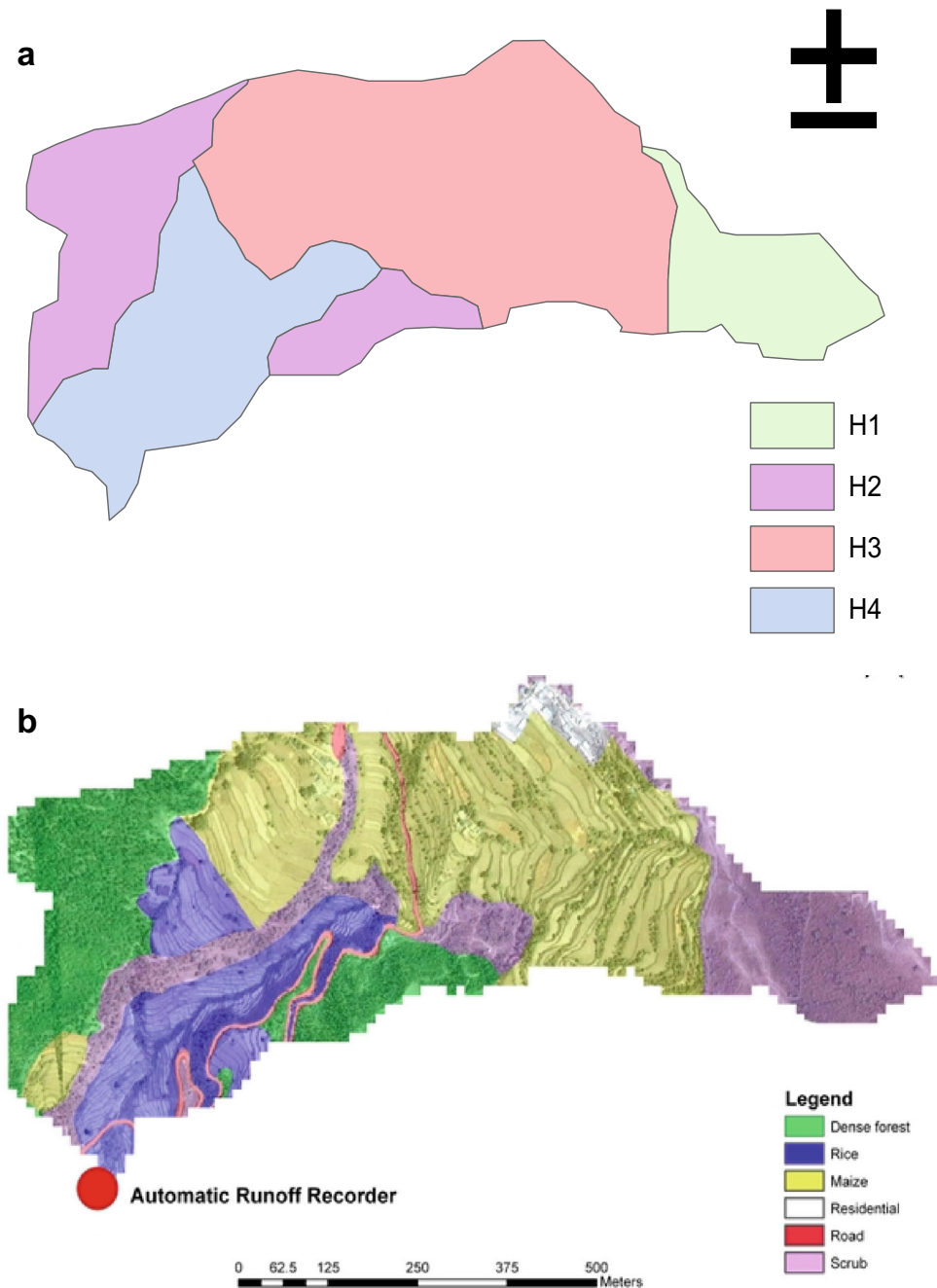
Land cover/land use data

IRS Resourcesat-1 LISS IV satellite data (5.8 m spatial resolution) was used to prepare land use/land cover by visual method. The watershed was traversed prior to rainy season in the months of May–June to record land use/land cover information at 21 sites with their geographic location using GPS. The FCC image characteristics of various land use/land cover were established and visual interpretation was carried out by on-screen digitization to prepare land use/cover map (Fig. 2) of the watershed. It revealed LULC classes of forest cover (30%), barren and scrub (18%), cropland (51%) and settlement (1%). Paddy and maize crops are grown in the rainy season (July–October). The information on average plant height and plant density of the crops was observed at 15 days interval during the months of July–15 October, 2008 at randomly selected 12 field sites of plot size of 1–2 m^2 in the watershed.

Soil characteristics

The watershed was delineated into land units of hilltop, upper, middle and lower hillslopes based on topography and dominant land use/land cover (Fig. 3). Soil types in the watershed

Fig. 2 **a** Soil map of the watershed, **b** land use/land cover map of the watershed



were found to be closely associated with land use/land cover types. The soils in the hilltops (H1) (6–8% slope) were gravelly loamy sand, shallow (<20 cm) in depth and containing coarse fragment of 40–45%. These soils easily got saturation condition due to its shallow depth. Upper hillslope (H2) having very steep (50–70%) slope and mid-hillslope (H3) with steep (30–35%) slope were characterized by moderately deep and deep soil depth, respectively. The soils are sandy loam in texture and contain 35–50% coarse fragments in the sub-surface layer. These soils are underlain by stones/weathered

rock fragments. The soils at lower hillslope (H4) are deep (80–110 cm), loam in texture, 10–15% graves/pebbles in surface and are moderately well drained. These soils occupy by the paddy fields and remain saturated or ponded with water due to traditional puddling and management practices. The upper hillslope (H2) are under dense forest cover and mid-hillslope (H3) is cultivated for maize crop. These soils are underlain by stones/weathered rock fragments or compacted C-horizons with large amount of coarse fragments which ceases the downward movement of water or reduces the

permeability of soils. The necessary input information namely soil texture, bulk density, HSG, soil depth, rock fragments, organic carbon content, soil erodibility factor (K) required by the SWAT model was extracted from the soil database for each soil type. Available water content (AWC) was calculated from soil–plant–air–water (SPAW) software based on soil texture and organic matter content.

During fieldwork (18 July–12 August 2008), soil moisture was measured in transects at hilltop, upper, mid and lower hillslopes using Theta Probe during 18 July to 12 August, 2008. In total 23 sites were observed for soil moisture. Saturated hydraulic conductivity (Ksat) was also measured in the dominant land use/cover types in the hillslopes using double ring infiltrometer.

Soil wetness index (SWI)

IRS stereo Cartosat satellite data was used to generate digital elevation model (DEM) with grid size of 5.8 m. The generated DEM had the vertical accuracy of RMSE 4.48 m. DEM was used to prepare slope (in radiance) and flow accumulation maps using ArcGIS. The flow accumulation map was generated following multiple flow algorithm (Quinn et al. 1991) embedded in the Arc-GIS.

Soil wetness index (SWI) was prepared using slope, flow accumulation, soil transmissivity (Ksat) and soil depth maps to derive SWI map by implementing Eq. 8 in ArcGIS 9.2, stated below:

$$SWI(map) = \text{Natural log}(\ln) \left[\frac{\text{Flowaccumulation}(map) \times \text{cellsize} \times \text{cellsize}}{\tan(\text{slopedmap}(\text{radians})) \times (\text{Ksat}(map) \times \text{soildepth}(map))} \right] \quad (9)$$

DEM was processed further to delineate sub-watershed by defining outlet point. First order stream/drainage lines from toposheet (1:50,000 scale) was provided to the SWAT model for better hydrographic segmentation and sub-watershed delineation (Neitsch et al. 2005). Topographic index concept effectively predicts VSAs for many watersheds dominated by saturation-excess runoff (Western et al. 1999; Lyon et al. 2004).

Weather data and surface runoff measurement

Daily rainfall data was obtained from the automatic tipping bucket rain gauge with HOB0 data logger installed in the watershed. Rainfall data for 2008 was processed in Box Pro 4.0 software to obtain the rainfall and number of rainy days in months from July to October. Weather data of the mean monthly maximum and minimum temperature, wind

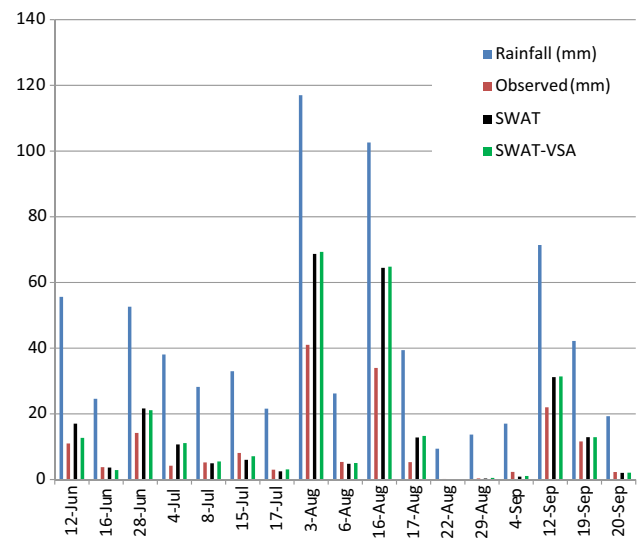


Fig. 3 Rainfall and modeled surface runoff from calibrated SWAT and SWAT-VSA models

velocity, and relative humidity were obtained from Automatic weather station (AWS) installed at 1 km. away from the sub-watershed outlet.

A rectangular weir structure was constructed at the outlet of the watershed to record surface run-off using automatic stage level runoff recorder. It records daily surface runoff at 15 min interval from a catchment of 57 ha. The total discharge was calculated using daily runoff-hydrographs in Excel. Daily Surface runoff measurements of selected rain

events of the year 2008 were used to calibrate and simulate the model for predicting surface runoff.

Soil moisture field measurement

Soil moisture variations are to an extent, dependent upon the topographic position in a landscape and has a linear relation with topography (Rohde and Seibert 1999; Sorensen and Seibert 2007). Soil moisture at the surface (0–10 cm) and sub-surface (10–20 cm) layers were measured in transect using Theta Probe during 18 July–12 August, 2008. During the field observations, soil moisture values of the sub-surface (10–20 cm) was observed very close to the surface layer (0–10 cm), thus indicating the saturation of the lower layer with progress of monsoons. High soil moisture content was observed at the hillslopes with the highest SWI values in the watershed. Slightly more variation in soil moisture (0–10 cm) was observed at

the upslope area (lower SWI) and less variation in the mid and lower hillslope (higher SWI) area indicating saturation of these area. Paddy fields were located at lower (toe) hillslope in the watershed remain saturated as they are flooded with water. These observations suggested variable source area of runoff generation and dominantly saturation excess surface runoff processes in the landscape. The watershed received continuous rains (21, 27 and 25 days rain in months of July, August and September of 2008, respectively) that have kept the soil moist and saturated in these months. It facilitated saturation-excess surface runoff generation.

Generating hydrological response units (HRUs)

The model predicts surface runoff for HRUs based on CN value following look up table. In SWAT, HRU is characterized by unique combination of land-use, management and HSG derived from soil map (Neitsch et al. 2002). AVSWAT model then automatically calculates CN values for each HRUs. In the SWAT-VSA model, the HRUs were defined by combination of SWI and land cover/land use classes. The CN was then assigned based on the HRUs. Once the initial CN defined, the management option is used to redefine the CN value. Important consideration in modelling was to define information pertaining to management for the various land use/land cover. For the main crops such as paddy and maize, plant growing season, tillage practices and harvesting period information were collected and based on this information management practices (P) factor were assigned. Priestley–Taylor method (Priestley and Taylor 1972) was chosen for estimating evaporation over the others methods because of its suitability for humid conditions and ability to generate daily values from average data (Neitsch et al. 2005). Skewed normal distribution method (Nicks 1974) was used to determine rainfall amount for the area based on the daily rainfall data.

Model calibration and validation

The hydrologic calibration was performed using daily runoff data at the outlet of the watershed. Models were run to predict the daily surface runoff on selected rain events and were calibrated by changing the sensitive parameters such as CN, AWC, USLE-P, ESCO, USLE-C and BIOMIX (Table 1). The calibration was carried out by changing the parameters until the runoff and predicted values obtained closely. These parameters were adjusted with trial and error adjustment to predict near to the observed values. CN, AWC and ESCO are basic water balance parameters recommended in the SWAT user manual (Neitsch et al. 2005). ESCO factor was not considered for the calibration

Table 1 Sensitive parameters of SWAT and SWAT-VSA models

S. no	Parameter	Change	SWAT Surface runoff	SWAT-VSA Surface runoff
1	CN	−4	−33.5	−31.5
2	CN	+4	59	56
3	AWC	−0.05	−8	−3.3
4	AWC	+0.05	−1.92	−5.5
5	ESCO	−76	0	0
6	ESCO	+76	0	0
7	USLE-C	−25	1.15	−
8	USLE-C	+25	1.15	−
9	USLE-P	−5	−45.23	−
10	USLE-P	+5	−45.23	−
11	SLOPE	−25	1.15	−
12	SLOPE	+25	1.15	−
13	SLSUBBS	−25	19.9	−
14	SLSUBBS	+25	19.9	−
15	BIOMIX	−50	−45.23	−
16	BIOMIX	+50	−45.23	−

process, since its effect on the model output was negligible due to humid climatic conditions in the area.

After the calibration, model was run to predict the surface runoff from each HRU on daily time step. The model performance was evaluated qualitatively using 1:1 plot of predicted and observed runoff. Selected rain events (22 nos.) of the year 2008 showing clear hydrographs were used for calibration (5 nos.) validation (17 nos.) of the model for surface runoff. Quantitatively, Nash–Sutcliffe coefficient of efficiency (NSE) (Nash and Sutcliffe 1970) and Root Mean Square Error (RMSE) were used to evaluate the goodness of fit of calibration.

Results and discussion

SWAT being lumped model implicitly ignore distribution of intra-watershed processes as they simulate integrated watershed response whereas SWAT-VSA captures the spatial distribution of runoff source area (Easton et al. 2008). In the study, SWAT and SWAT-VSA models were

Table 2 Evaluation of SWAT, SWAT-VSA and modified SWAT-VSA model performance

S. no.		Low to moderate rainfall events		With all rainfall events	
		SWAT	SWAT-VSA	SWAT	SWAT-VSA
1	r ²	0.97	0.97	0.89	0.89
2	RMSE	4.12	3.88	11.82	10.86
3	NSE	0.70	0.75	0.42	0.49

calibrated to predict runoff at watershed scale. There were 4 and 12 numbers of HRUs generated in SWAT and SWAT-VSA models, respectively. CN was assigned based on SWI classes (Easton et al. 2008) and land use/land cover in SWAT-VSA. HRUs generation in SWAT-VSA provided an opportunity for implementing the model as SWAT model without altering SWAT model structure. Thus, it facilitated for assigning CN values automatically as in SWAT model.

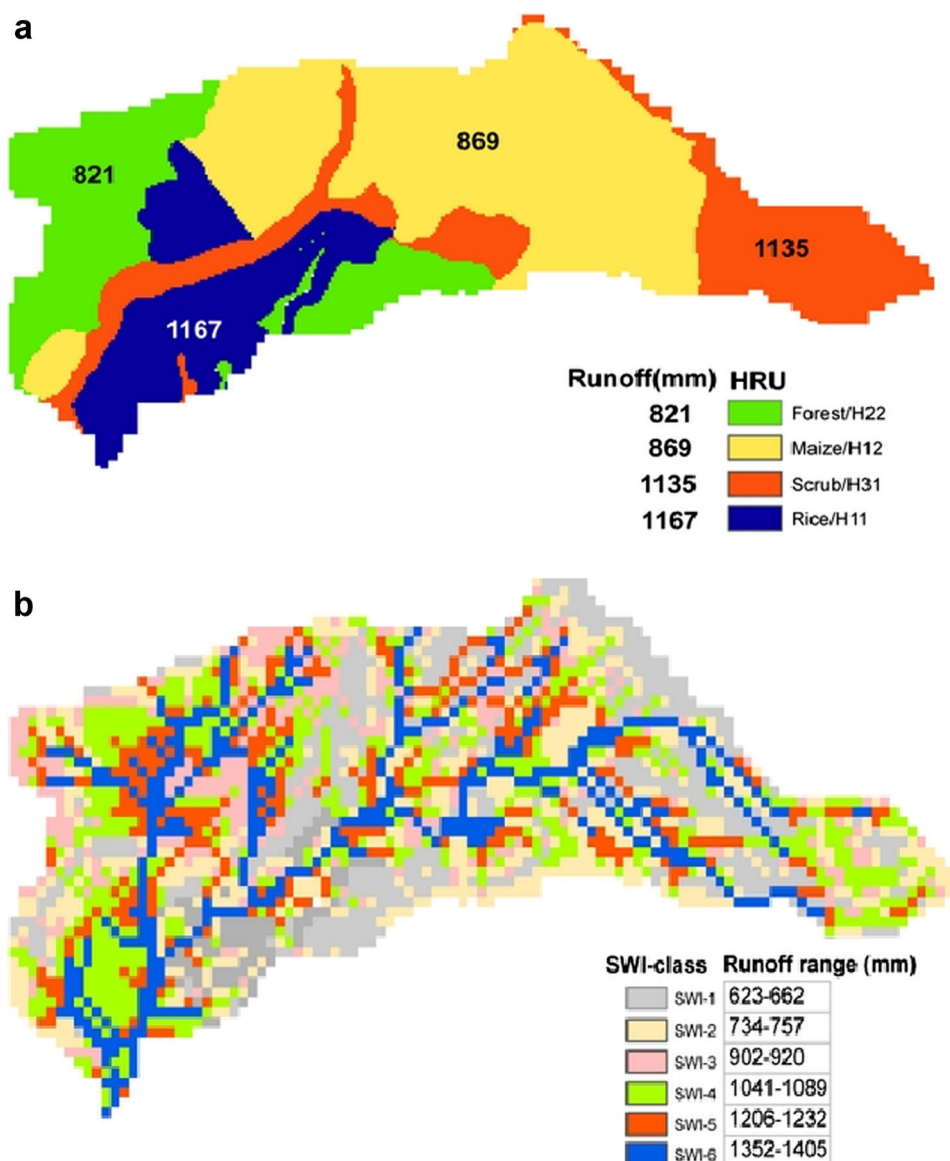
For analysing the sensitivity of the parameters used in runoff prediction, CN, AWC and USLE-P were altered by value, whereas ESCO, USLE C, SLOPE (steepness), SLSUBBSN (slope length), BIOMIX were modified by percentage. Curve number (CN) was found to be most sensitive parameters followed by available water capacity (AWC) for runoff prediction (Table 1). Positive and

negative change in AWC value resulted into decrease in runoff, because of the complex relationship of the AWC with antecedent rainfall. Surface runoff was not found sensitive to ESCO, because of the humid climatic conditions in the area.

Surface runoff modelling

Rainfall and predicted surface runoff of the watershed with SWAT and SWAT-VSA models is shown in Fig. 3. Among all 17 rain events, rainfall varied from 9.4 to 117 mm. Surface runoff predicted very well except of high rainfall events (>100 mm) with the models (Table 2). The study aims to spatial prediction of surface runoff in the watershed. SWAT model predicted highest amount of surface runoff from paddy fields (HRU1) followed by scrub (HRU4), maize (HRU2) and forest cover (HRU3) (Fig. 4a).

Fig. 4 **a** SWAT predicted surface runoff from various land cover types, **b** SWAT-VSA predicted surface runoff in SWI classes



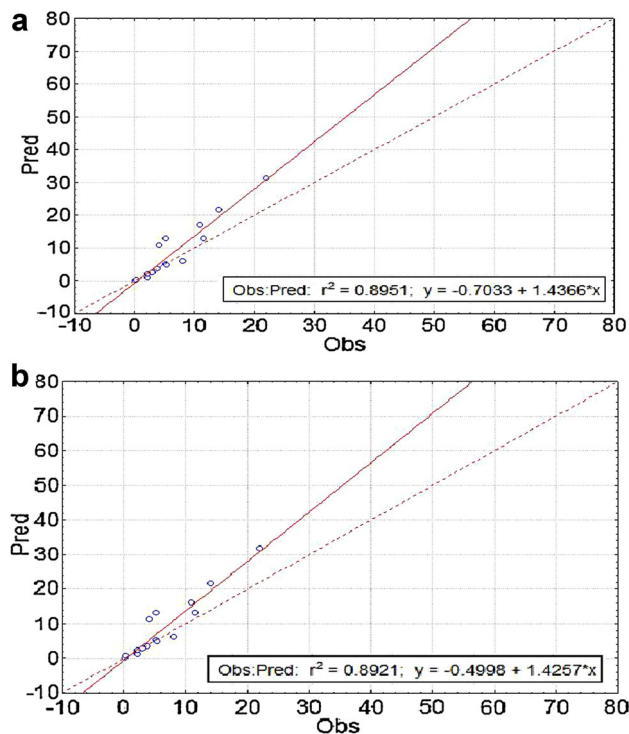


Fig. 5 Observed vs. predicted runoff (for all rainfall events). **a** SWAT, **b** SWAT-VSA

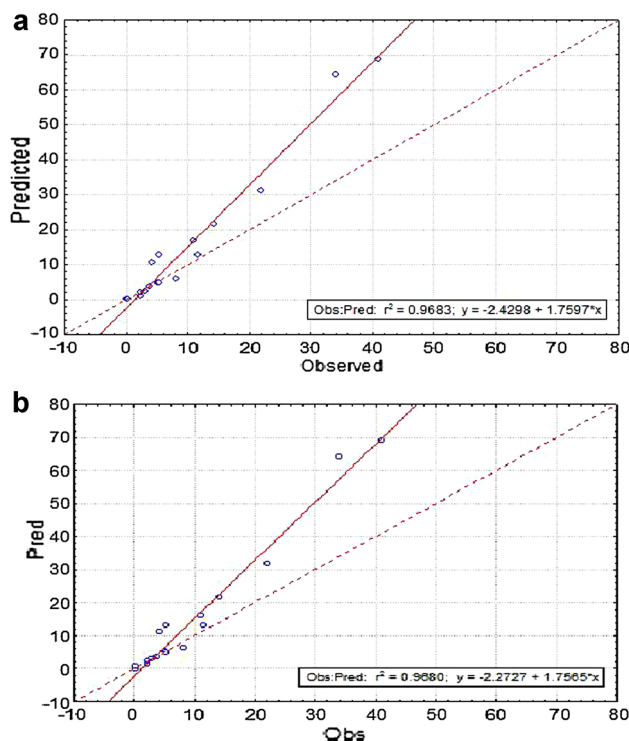


Fig. 6 Observed vs. predicted runoff (for low to moderate rainfall events). **a** SWAT, **b** SWAT-VSA

Rice crop and scrub areas located near the streams contributed same runoff to that located far away from the streams. In the SWAT-VSA, 11 HRUs were generated from the combination of three SWI classes and four major land uses. Surface runoff varied in SWI class according to the land use classes (Fig. 4b). The highest runoff was modelled from HRU created with SWI-VI (highest prone to saturation) having paddy area (land use having high runoff potential) followed by scrub land cover, of similar characteristics to that of former. Similarly the maize crop area in SWI-I accounted for low runoff in comparison to the maize located in SWI-III/III. The SWAT-VSA accounted soil wetness index (topography/soil transmissivity) and land use into consideration for modelling runoff, in other words the model took into account the degree of saturation along with effect of land use/land cover. Integration of SWI incorporated variable source area concept hence, improved the prediction of surface runoff with SWAT-VSA model.

The trend line (1:1 line) showed that the model overestimated the surface runoff for high rainfall volume (Fig. 5a, b). For low to moderate rainfall events surface runoff was well estimated (Fig. 6a, b) and similar observation was reported by Haregeweyn and Yohannes (2003). Evaluations of the model performance showed that the models predicted well (R^2 value of 0.89 when all rain events were considered and r^2 of 0.97 for low to moderate rain events excluding high rainfall events (Table 2). Runoff prediction was observed very well for low to medium amount of rainfall events whereas poor in case of high amount of rainfall events. Srinivasan et al. (2002) showed that for extremely large rain events both infiltration excess and saturation excess runoff processes may be possible which could result in high runoff. Simulation of runoff with these models is independent of rainfall intensity; this may be the reason for over estimation for large rain events (Arnold et al. 2000).

Nash–Sutcliffe coefficient of efficiency (NSE) (Nash and Sutcliffe, 1970) and Root Mean Square Error (RMSE) were used to evaluate the goodness of fit of observed and predicted data. The closer the NSE value to 1.0 the better is the estimation by the model. NSE more than or equal to 0.75 is considered to be an excellent estimate and NSE between 0.75 and 0.36 is regarded to be satisfactory (Motovilov et al. 1999). The closer the RMSE value to zero, the better is the estimation. For all rain events including high rainfall events, the RMSE for predicted to observed runoff was 11.82 and 10.86 for SWAT and SWAT-VSA, respectively. When the high rainfall event (for which models were still predicting high runoff) was neglected then the RMSE of 4.12 and 3.88 were estimated for SWAT and SWAT-VSA, respectively. NSE showed

that the SWAT-VSA ($NSE = 0.75$) performed better in predicting runoff as compared to SWAT ($NSE = 0.70$). The study clearly showed integration of SWI in SWAT model has improved the runoff prediction as well as provided spatially distributed surface runoff in the watershed.

Conclusion

SWAT model primarily considers infiltration excess runoff generation whereas SWAT-VSA accounts saturation excess runoff generation mechanism. Sub-humid climatic condition leading to continuous rains in rainy season supported the saturation of soils that caused saturation excess runoff generation process in dominance in the Himalayan landscape. Mid and lower hillslopes in the watershed showed saturation of the fields in large. The soil moisture varies with convergent topography suggested variable source area of runoff generation. Digital terrain model (DTM) derived soil wetness index (SWI) provided a unique opportunity to account spatial variability of soil hydrological condition that controls runoff generation. Highest surface runoff was predicted from HRU generated with SWI-III (highly prone to saturation) with paddy cropland and lowest from HRU with SWI-I lies in hill top area. Paddy croplands followed by scrub, maize and forest cover as most contributing area of surface runoff generation in the watershed. HRUs generation in SWAT-VSA provided an opportunity of predicting spatial distributed surface runoff generation without altering SWAT model structure. Study revealed that saturation excess as the dominant runoff process in the Himalayan landscape and SWAT-VSA models based on this method provide more representative results than the SWAT based on infiltration excess.

Acknowledgements Authors are thankful to the Director, Indian Institute of Remote Sensing for providing necessary facilities to carry out the research work. The financial support from Technology Development Project (TDP) from the ISRO, Department of Space is duly acknowledged.

References

- Agnew LJ, Lyon S, Gérard-Marchant P, Collins VB, Lembo AJ, Steenhuis TS, Walter MT (2006) Identifying hydrologically sensitive areas: bridging science and application. *J Environ Manag* 78:64–76
- Arnold JG, Allen PM, Bernhardt G (1993) A comprehensive surface-ground water flow model. *J Hydrol* 142:47–69
- Arnold JG, Williams JR, Srinivasan R, King KW (1996) SWAT: soil and water assessment tool. USDA-ARS, Grassland, Soil and Water Research Laboratory, Temple, Texas, USA
- Arnold JG, Srinivasan R, Muttiah RS, Williams JR (1998) Large area hydrologic modeling and assessment, part I: model development. *J Am Water Res Assoc* 34:73–89
- Arnold JG, Williams JR, Srinivasan R, King KW (2000) Soil and water assessment tool manual. USDA Agricultural Research Service, Texas
- ASCE (2000) Artificial neural networks in hydrology. I: preliminary concepts. *J Hydrol Eng* 5(2):115–123
- Beasley DB, Huggins LF, Monke EJ (1980) ANSWERS user's manual. Purdue University, West Lafayette
- Bell JC, Butler CA, Thompson JA (1995) Soil terrain modeling for site-specific agricultural management. In: Robert PC, Rust RH, Larson WE (eds) Site-specific management for agricultural systems. Am Soc Agron, Madison, pp 209–228
- Beven KJ, Kirkby MJ (1979) A physically-based, variable contributing area model of basin hydrology. *Hydrol Sci Bull* 24:43–69
- Beven KJ, Wood EF (1983) Catchment geomorphology and the dynamics of runoff contributing areas. *J Hydrol* 65:139–158
- Easton ZM, Fuka DR, Walter MT, Cowan DM, Schneiderman EM, Steenhuis TS (2008) Re-conceptualizing the soil and water assessment tool (SWAT) model to predict runoff from variable source areas. *J Hydrol* 348(3–4):279–291
- Frankenberger JR, Brooks ES, Walter MT, Walter MF, Steenhuis TS (1999) A GIS-based variable source area model. *Hydrol Process* 13(6):804–822
- Haith DA, Shoemaker LL (1987) Generalized watershed loading functions for stream flow nutrients. *Water Resour Bull* 23(3):471–478
- Haregeweyn N, Yohannes F (2003) Testing and evaluation of the agricultural non-point source pollution model (AGNPS) on Augucho catchment, western Hararghe, Ethiopia. *Agric Ecosyst Environ* 99:201–212
- Herbst M, Diekkruiger B, Vereecken H (2006) Geostatistical co-regionalization of soil hydraulic properties in a micro-scale catchment using terrain attributes. *Geoderma* 132:206–221
- Jain SK, Tyagi J, Vishal Singh V (2010) Simulation of runoff and sediment yield for a Himalayan watershed using SWAT model. *J Water Resour Prot* 2:267–281
- Knisel WG (1980) CREAMS: a fieldscale model for chemical, runoff, and erosion from agricultural management systems. Conservation Report No. 26. USDA, Washington, DC
- Krause P, Flügel WA (2001) A modelling system for physically based simulation of hydrological processes in large catchments. In: Proceedings of the MODSIM'01, Canberra, p 9–13
- Lyon SW, Walter MT, Gerard-Marchant P, Steenhuis TS (2004) Using a topographic index to distribute variable source area runoff predicted with the SCS curve-number equation. *Hydrol Process* 18:2757–2771
- Lyon SW, McHale MR, Walter MT, Steenhuis TS (2006) The impact of runoff generation mechanism on the location of critical source areas. *J Am Water Resour Assoc* 42(3):793–804
- Martinez C, Hancock GR, Kalma JD, Wells T, Boland L (2010) An assessment of digital elevation models and their ability to capture geomorphic and hydrologic properties at the catchment scale. *Int J Remote Sens* 31(23):6239–6257
- McCuen RH (1982) Guide to hydrologic analysis using SCS methods. Prentice-Hall, Inc, New Jersey, p 160
- McKenzie NJ, Ryan PJ (1999) Spatial prediction of soil properties using environmental correlation. *Geoderma* 89:67–94
- Motovilov YG, Gottschalk L, Engeland K, Rodhe A (1999) Validation of a distributed hydrological model against spatial observations. *Agric Meteorol* 98–99:257–277
- Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models. Part I a discussion of principles. *J Hydrol* 10:282–290
- Needelman BA, Gburek WJ, Petersen GW, Sharpley AN, Kleinman PJA (2004) Surface runoff along two agricultural hillslopes with contrasting soils. *Soil Sci Soc Am J* 68:914–923
- Neitsch SL, Arnold JG, Kiniry JR, Williams JR, King KW (2002) Soil and water assessment tool theoretical documentation version

2000. Grassland, soil and water research laboratory, GSWRL Report 02–01. Blackland Research and Extension Centre, Temple
- Neitsch SL, Arnold JG, Kiniry JR, Williams JR, King KW (2005) Soil and water assessment tool theoretical documentation grassland. Soil and Water Research Laboratory, Temple, p 506
- Nicks AD (1974) Stochastic generation of the occurrence, pattern, and location of maximum amount of daily rainfall. In: Proceeding of symposium on statistical hydrology, Tuscon, Department of Agriculture
- Page T, Haygarth PM, Beven KJ, Joynes A, Butler T, Keeler C, Freer J, Owens PN, Wood GA (2005) Spatial variability of soil phosphorus in relation to the topographic index and critical source areas: sampling for assessing risk to water quality. *J Environ Qual* 34:2263–2277
- Park SJ, McSweeney K, Lowery B (2001) Identification of the spatial distribution of soils using a process-based terrain characterization. *Geoderma* 103:249–272
- Priestley CHB, Taylor RJ (1972) On the assessment of surface heat flux and evaporation using large-scale parameters. *Mon Weather Rev* 100:81–92
- Qiu Lin-jing, Zheng Fen-li, Yin Run-sheng (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
- Quinn P, Beven K, Chevallier P, Planchon O (1991) The prediction of hillslope flow paths for distributed hydrological modeling using digital terrain models. *Hydrol Process* 5:59–79
- Rallison RE (1980) Origin and evolution of the SCS runoff equation. In: Symposium on watershed management. ASCE, New York, pp 912–924
- Rohde A, Seibert J (1999) Wetland occurrence in relation to topography: a test of topographic indices as moisture indicators. *Agric Meteorol* 98–99:325–340
- Romano N, Palladino M (2002) Prediction of soil water retention using soil physical data and terrain attributes. *J Hydrol* 265(1):56–75
- Schneiderman EM, Steenhuis TS, Thongs DJ, Easton ZM, Zion MS, Mendoza GF, Walter MT, Neal AL (2007) Incorporating variable source area hydrology into the curve number based generalized watershed loading function model. *Hydrol Process* 21(25):3420–3430
- Sharma SK, Mohanty BP, Zhu JT (2006) Including topography and vegetation attributes for developing pedotransfer functions. *Soil Sci Soc Am J* 70:1430–1440
- Sorensen R, Seibert J (2007) Effects of DEM resolution on the calculation of topographical indices: TWI and its components. *J Hydrol* 347:79–89
- Srinivasan MS, Gburek WJ, Hamlett JM (2002) Dynamics of storm flow generation—a hillslope—scale field study in east-central Pennsylvania USA. *Hydrol Process* 16(3):649–665
- Steenhuis TS, Winchell M, Rossing J, Zollweg JA, Walter MF (1995) SCS runoff equation revisited for variable-source runoff areas. *J Irrig Drain Eng* 121:234–238
- Tiwari PC (2000) Land-use changes in Himalaya and their impact on the plains ecosystem—need for sustainable land use. *Land Use Policy* 17(2):101–111
- USDA-SCS (1972) Design Hydrograph, chapter 21, section 4, Hydrology, National Engineering Handbook, NEH Notice, 4–104
- Walter MT, Shaw SB (2005) Discussion: “Curve number hydrology in water quality modeling: uses, abuses, and future directions” by Garen and Moore. *J Am Water Resour Assoc* 41(6):1491–1492
- Ward RC (1984) On the response to precipitation of headwater streams in humid areas. *J Hydrol* 74(1–2):171–189
- Western AW, Grayson RB, Blöschl G, Willgoose GR, McMahon TA (1999) Observed spatial organization of soil moisture and its relation to terrain indices. *Water Resour Res* 35(3):797–810
- Wigmosta MS, Vail LW, Lettenmaier DP (1994) A distributed hydrology-vegetation model for complex terrain. *Water Resour Res* 30(6):1665–1679
- Young RA, Onstad DD, Anderson WP (1989) AGNPS: a nonpoint source pollution model for evaluating agricultural watersheds. *Soil Water Conserv* 44(2):168–173
- Zachary M, Easton ZM, Fuka DR, Walter MT, Cowan DM, Schneiderman EM, Steenhuis TS (2008) Re-conceptualizing the soil and water assessment tool (SWAT) model to predict runoff from variable source areas. *J Hydrol* 348:279–291