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Estimation of runoff curve numbers using a physically-based approach of preferential flow modelling

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Abstract The Runoff Curve Number (CN) technique of the NRCS is the most widely used methodology for the computation of storm runoff. In this study colour dye-tracing experiments were used to derive soil macroporosity parameters from 11 common land use and land cover (LULC) classes of northeast India. The eco-hydrological model SWAP was calibrated using the soil macropore parameters and daily observed soil moisture contents for different LULC classes. Using 30 years of meteorological data, the calibrated SWAP model was run to obtain daily runoff from the 11 LULC classes. The scatter plot between the SWAP simulated runoff and observed rainfall clearly depicted upper and lower boundaries representing wet and dry antecedent runoff conditions, respectively. Following the NRCS-CN rainfall–runoff relationship, an optimization technique was used to fit the upper and lower boundaries of the scatter plot to different CN values. The derived CN values accounted for the effect of preferential flow characteristics.

Key words curve number; land use and land cover; rainfall–runoff relationship; macropores; preferential flow; SWAP model

INTRODUCTION

Estimation of storm runoff from the ungauged hilly watersheds of the wet tropical and sub-tropical regions is a critical task due to wide spatial and temporal variations in topography, soil properties, rainfall characteristics, and land use and land cover (LULC). However, in preferential flow path dominated hilly watersheds the infiltration and runoff generation processes are significantly controlled by the active soil macroporosity, which is often closely related to the existing LULC classes (Shougrakpam *et al.*, 2010; Sharma *et al.*, 2013). The NRCS-CN is a widely used, simple, and flexible conceptual method which incorporates the watershed parameters like soil type, LULC, and climatic factors in one entity called the Curve Number (CN). The NRCS-CN method of estimating runoff can be used as a stand-alone rainfall–runoff model or may be integrated as the internal runoff estimating component in complex watershed scale models. In humid tropical or sub-tropical regions, often a threshold phenomenon is exhibited by the watershed for the initiation of runoff (Williams *et al.*, 2002).

At the onset of the rainy season a critical rainfall depth is infiltrated completely before any runoff is generated. However, during the wet monsoon months more of the rainfall occurs as runoff. Such a threshold mechanism of runoff generation is often closely related to rainfall depth, soil wetness condition, and preferential flow characteristics associated with different LULC classes (Tromp-van Meerveld & McDonnell, 2005; Graham *et al.*, 2010; Penna *et al.*, 2011; Sharma *et al.*, 2013). The NRCS-CN method may be a useful tool for runoff computation if used in combination with a hydrological model that can simulate runoff from different LULC classes based on preferential flow, rainfall depth, and soil wetness condition, which are considered to be the major controlling factors for runoff generation from vegetated hillslopes. The present study aimed at estimating runoff curve numbers for all the major LULC classes in the ungauged hilly watersheds of northeast India considering their respective preferential flow characteristics. The relationship of the estimated CN with antecedent moisture condition, soil macroporosity, threshold rainfall depth, and initial abstraction should be useful for hydrologists investigating the rainfall–runoff processes in different watersheds of the region.

MATERIALS AND METHODS

The study area of the present investigation is located in the Brahmaputra River basin of northeast India. The landscapes are dominated by densely vegetated hillslopes and river floodplains. The climate of the region falls under humid sub-tropics with majority of the annual rainfall concentrated in the monsoon season (May–August). The average annual rainfall in the Brahmaputra basin is about 2300 mm and rainfall increases gradually from west to east (Sarma, 2005). Extreme hydrologic events like flash flood, landslides, and river bank failure are quite frequent in the region (Sarkar *et al.*, 2008; Sarkar & Dutta, 2012). But, from a hydrological point of view the area is still largely unexplored and has a vast scope for research. In the present investigation *in situ* experiments were conducted at seven different sites (Fig. 1) of the region representing 11 LULC classes.

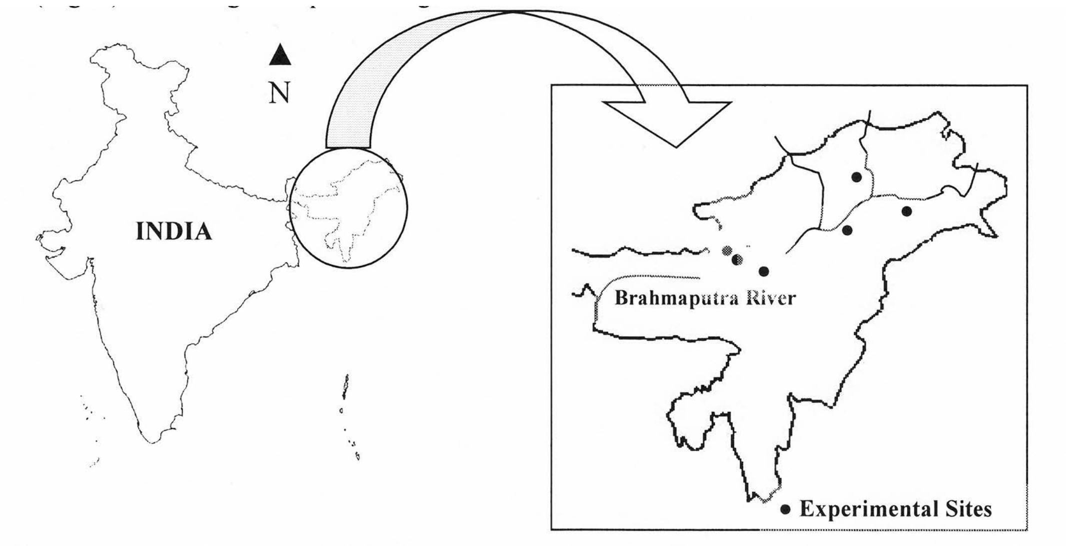

Fig. 1 Location of the experimental sites in the study area.

In order to calibrate the SWAP model (van Dam *et al.*, 2008) daily soil moisture contents were monitored in field plots having distinct LULC classes. Daily soil moisture measurements were taken from 1 May 2011 to 31 August 2011 at four locations in each plot at 100, 200, 300, 400, and 1000 mm depths below ground level using a profile probe soil moisture device. Depth averaged soil moisture contents in the root zone depth were estimated at daily time-steps for the observation period.

With the purpose of characterising soil macropore parameters colour dye-tracing experiments were conducted with soils under the selected 11 LULC classes using standard methodology available in literature (Stähli *et al.*, 2004; Weiler &Flühler, 2004; Shougrakpam, 2010; Lichner *et al.*, 2011). The observed dye patterns were analysed to obtain the following soil and macropore parameters viz. depth of the topsoil horizon (Z_{Ah}), depth of the discrete macropore domain or internal catchment (IC) domain (Z_{ic}), maximum depth of the macropores (Z_{st}), the volume fraction of macropores at the soil surface (V_{st}), the volume fraction of macropores in the IC domain (V_{ic}), the volume fraction of macropores in the main bypass (MB) domain (V_{mb}), the minimal soil polygon diameter (d_{mi}) and maximal soil polygon diameter (d_{ma}) estimated based on amount of stained spots in the excavated dye-tracer profiles, an optional shape parameter that represents the fraction of IC macropores that ends at the bottom of the A-horizon (R_{ZAh}), internal catchment volumetric proportion at the soil surface (P_{ic}), main bypass volumetric proportion at the soil surface (P_{mb}), and the shape factor exponent (m). The estimated macropore parameters for all the 11 LULC classes are enumerated in Table 1. It could be noted that the forest classes had more macropore connectivity and hence showed higher interconnected continuous macropores in the MB domain and fewer isolated macropores in the IC domain. Using the observed soil moisture data and soil macropore parameters the SWAP model calibration was done for different LULC classes.

The SWAP simulations were run for a period of 30 years from 1 January 1961 to 31 December 1990 for the 11 LULC classes. The daily rainfall data and temperature data were collected for the study area from the India Meteorological Department (IMD), Pune for the selected 30 year period. Detailed vegetation parameters, interception, and canopy storage for the selected LULC classes were adapted from the basic crop module files of the SWAP model. Collected soil physical properties (texture, structure, bulk density) from each LULC locations were used as input to the SWAP model. The soil hydraulic properties were estimated using the pedotransfer model ROSETTA (Schaap, 1999). The maximum rooting depths used for the simulations were invariably considered as the bedrock and the roots were assumed to decrease linearly from the soil surface down to the maximum depth. The depth wise root density was evaluated by fitting an exponential decay function on the dye-tracer patterns for each LULC class. As the experimental plots were located on hillslopes, a very low threshold ponding depth (1 mm) was considered in the simulations. In all cases a fine numerical discretisation grid (5 mm) was chosen along the soil profile.

Table 1 Soil macropore parameters derived from colour dye-tracer experiments.

Macropore parameters	BDF	BAM	SRB	PLN	TGN	BEF	NEF	JHM	ALP	GRS	CRP
Z_{Ah} (cm)	4	6	4	4	2	4	10	10	8	20	2
Z_{ic} (cm)	14	15	13	8	4	14	30	24	14	30	20
Z_{st} (cm)	30	30	30	10	10	38	42	50	25	50	30
d_{mi} (cm)	11.05	11.77	11.59	11.81	14.64	12.56	12.11	18.33	9.94	12.03	15.86
d_{ma} (cm)	36.15	33.37	34.04	33.20	22.29	30.32	32.07	8.04	40.46	32.39	17.59
R_{ZAh}	0.81	0.78	0.67	0.76	0.92	0.89	0.99	0.77	0.67	0.78	0.73
V_{st} (cm^3/cm^3)	0.09	0.09	0.06	0.05	0.04	0.08	0.06	0.02	0.07	0.06	0.03
V_{ic} (cm^3/cm^3)	0.08	0.07	0.06	0.04	0.03	0.07	0.05	0.01	0.06	0.05	0.02
V_{mb} (cm^3/cm^3)	0.013	0.01	0.01	0.009	0.009	0.01	0.01	0.009	0.007	0.01	0.008
P_{ic}	0.86	0.84	0.85	0.84	0.75	0.82	0.83	0.62	0.90	0.83	0.71
P_{mb}	0.13	0.17	0.15	0.16	0.25	0.18	0.17	0.37	0.09	0.16	0.29
m	0.80	0.63	0.93	0.97	1.19	0.80	1.52	1.07	0.93	1.19	1.12

BDF: Broad leaved deciduous forest; SRB: Shrub; TGN: Tea-garden; BAM: Bamboo; BEF: Broad leaved evergreen forest; ALP: Alpine Shrub; CRP: Cropland; PLN: Plantation; NEF: Needle leaved evergreen forest; GRS: Grassland; JHM: Jhum cultivation.

RESULTS AND DISCUSSION

Model calibration

The eco-hydrological model SWAP was calibrated using measured root zone soil moisture contents and observed soil macropore structures obtained from the colour dye-tracing experiments. Figure 2 shows the results of SWAP model calibration for the broad leaved deciduous forest plot. The model could predict the observed soil moisture variations reasonably well for the calibration period. The Nash-Sutcliffe coefficients for the different LULC classes varied in the range of 0.75 to 0.90. The simulated and observed root zone soil moisture content values were found to be comparable for low and medium rainfall events. However, for high rainfall events the SWAP model was found to overestimate the soil moisture contents. For all the LULC classes, such predictions could be observed after the high rainfall events on 3 August (69 mm) and 4 August (52 mm). Gurrapu (2005) also reported that the SWAP model overestimated soil moisture on days of heavy rainfall because high intensity rainfall events caused higher drainage but did not contribute to soil moisture storage.

Estimation of NRCS-CN for Different LULC Classes

In this study a new approach has been proposed for the estimation of CN values for different LULC classes by integrating the SWAP model simulations with the conventional NRCS-CN

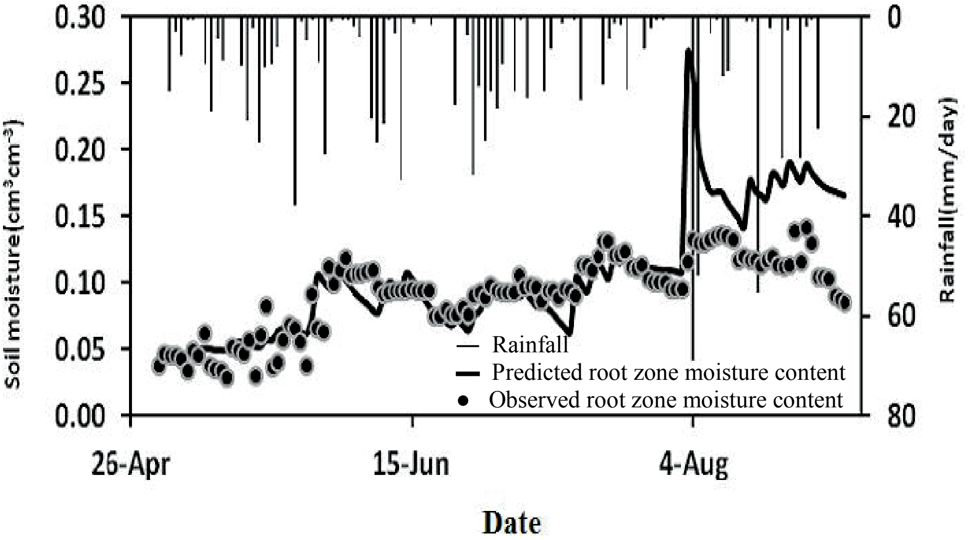

Fig. 2 Calibration of the SWAP model for the broad leaved deciduous forest.

methodology. Initially, for each LULC class the calibrated SWAP model was run with the 30-year daily rainfall (P_i) data to predict the daily runoff $Q(P_i)$. Then a scatter plot between the predicted daily runoff and observed daily rainfall was prepared. The scatter plot clearly depicted upper and lower boundaries representing wet and dry antecedent runoff conditions, respectively. The data points representing the upper and lower envelopes of the scatter plot were selected for optimisation. In the optimisation procedure depending on LULC and soil types, CN values representing dry and wet antecedent conditions were assumed. Then, using NRCS-CN methodology daily theoretical storage capacity or retention (S_e) for each selected data point was estimated using equation (1). For the given LULC class, a value of abstraction coefficient (λ) was assumed to compute the initial abstraction (I_a) from equation (2). Finally, the daily runoff, $Q_{CN}(P_i)$, was estimated following the NRCS-CN method using equation (3). The CN values for both wet and dry antecedent conditions were optimised separately following a least-square error (LSE) concept between the SWAP simulated daily runoff [$Q(P_i)$] and NRCS-CN estimated daily runoff [$Q_{CN}(P_i)$] for the selected number of data points. In the scatter plot if there were N data points in the wet or dry antecedent boundaries, then the representative CN value was optimised by minimising the objective function given in equation (4). Finally, in the scatter plot upper and lower boundary curves were fitted to represent the wet and dry antecedent CN values.

$$S_e = \left(\frac{25400}{CN}\right) - 254 \tag{1}$$

$$I_a = \lambda S_e \tag{2}$$

$$Q_{CN}(P_i) = \frac{(P_i - I_a)^2}{(P_i - I_a) + S_e} \quad \text{if} \, P_i > I_a \tag{3a}$$

$$= 0 \qquad\qquad \text{if} \, P_i < 0 \tag{3b}$$

$$LSE = Min \sum_{i=1}^{N} \left[Q(P_i) - Q_{CN}(P_i)\right]^2 \tag{4}$$

Figure 3 shows the scatter plot and optimised wet and dry antecedent CN curves for the LULC class shrub. Similarly, plots were obtained for all 11 LULC classes. The optimised wet and dry antecedent CN values, soil textural class, and hydrologic soil groups for all 11 LULC classes of the study area are summarised in Table 2. It could be observed that under dry antecedent condition broadleaved deciduous forests, shrubs, alpine shrubs, and grasslands exhibited lower CN values compared to croplands and *Jhum* cultivations. Similar results were also reported by Shougrakpam *et al.* (2010). However, in a few LULC classes, viz. bamboo plantation, broad leaved evergreen forest, needle leaved evergreen forest, and plantation, the CN values could only be generated for wet antecedent conditions. Under dry antecedent conditions no runoff was generated due to very high macroporosity and soil suction. Ebrahimian *et al.* (2012) reported average CN values for forests, cropland, plantation, and grassland as 55, 62, 65, and 63, respectively. Hernandez *et al.* (2000) reported average CN values for forest, oak (broad leaved evergreen forest), grassland, and cropland as 64, 66, 71, and 72, respectively. The variations of CN values in the present investigation may be attributed mainly to the influence of different preferential flow conditions.

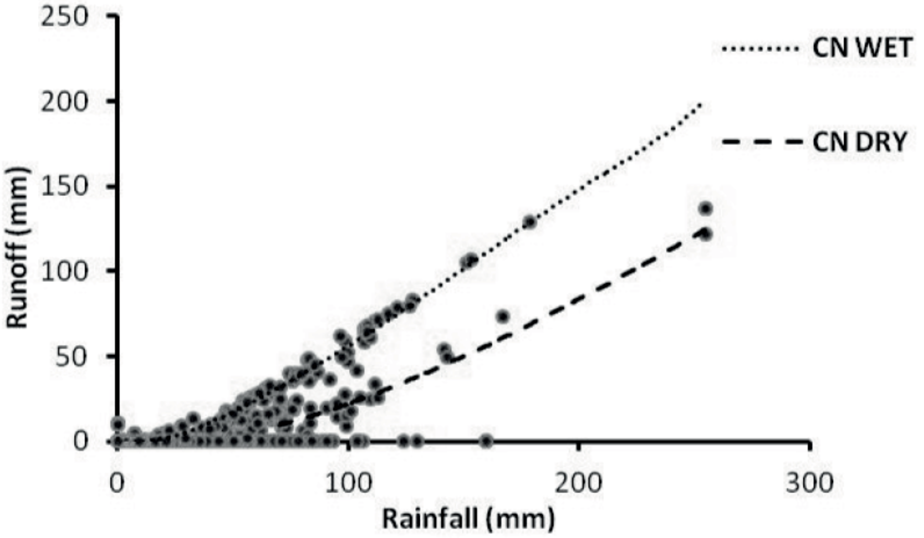

Fig. 3 Scatter plot between SWAP predicted daily runoff and observed daily rainfall showing optimised CN curves for wet and dry antecedent conditions.

Table 2 Optimized Curve Number (CN) estimated for different LULC classes.

LULC Classes	Soil textural classes	Hydrologic soil group	Wet antecedent condition CN	Dry antecedent condition CN
BDF	Sandy loam	B	82	54
BEF	Loam	C	52	–
NEF	Clay loam	C	67	–
BAM	Sandy clay	C	54	–
SRB	Sandy loam	B	84	55
ALP	Silty clay loam	C	82	56
GRS	Sandy loam	B	70	54
PLN	Loam	C	63	–
TGN	Silty loam	B	77	58
CRP	Silty loam	B	92	74
JHM	Sandy loam	B	87	72

CONCLUSIONS

The present investigation showed that by integrating SWAP model simulations with NRCS-CN technique for different LULC classes the CN values could be optimised. It was observed that the optimised CN values depend on soil properties, antecedent moisture condition, and most importantly the LULC classes. The results obtained by the proposed method were quite encouraging as in all the cases, the effects of landscape alterations in LULC classes like plantation, tea garden, cropland, and *Jhum* cultivation, were evident through higher CN values. On the other hand, lower CN values in LULC classes like broad leaved deciduous forest, broad leaved evergreen forest, needle leaved evergreen forest, bamboo plantation, shrub, alpine shrub, and grassland indicated higher infiltration rates and storage capacity. In humid catchments runoff is generated, even for low and moderate rainfall events, as during the wet season the soil remains invariably saturated. However, during dry periods runoff is generated only in cases of high rainfall events when the rate of absorption or retention is exceeded. Therefore, in highly macroporous soils under dry antecedent conditions no runoff was generated. The CN values were found to be dependent on the soil macroporosity associated with different LULC classes. The proposed method of optimising CN values successfully incorporated the effect of preferential flow in runoff generation from different LULC classes of northeast India.

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