Water Resour Manage (2009) 23:2455–2473
DOI 10.1007/s11269-008-9390-1

Estimation of the Runoff Curve Number via Direct Rainfall Simulator Measurements in the State of Iowa, USA

Mohamed Elhakeem · Athanasios N. Papanicolaou

Received: 16 January 2008 / Accepted: 12 December 2008 /

Abstract This study was the first to provide detailed methodological steps to estimate in-situ runoff curve number (*CN*) for selected agricultural fields in the State of Iowa via rainfall simulators. Representative fields in six counties were chosen to identify the effects of the following variables on runoff *CN*: rainfall intensity, soil type, soil moisture condition, tillage practice, and residue cover. The study also re-evaluated the range of the existing *CN* values for the different hydrologic soil groups in Iowa, and revised the equations describing the *CN* method to consider variables such as residue cover and soil moisture in a more detailed manner than the existing USDA method. The findings of this investigation showed that rainfall simulators are useful instruments for estimating in-situ runoff *CN* because rainfall intensity was adjustable during an experimental run. Further, the simulators eliminate the need of natural storm events. The range of the estimated *CN* values in summer agreed well (deviation less than 6%) with the reported *CN* values. However, the range of the estimated *CN* values in fall was generally less the reported *CN* values (deviation of about 40%) due to the high residue levels found in the fields after harvest. The effects of tillage practice and crop type were insignificant compared to residue cover and soil moisture. The study has also shown that the initial abstraction I_a is not linearly proportional to the potential maximum retention S, which agrees with the available literature.

Keywords Runoff curve number · Rainfall intensity · Soils · Residue cover · Tillage practice · Soil moisture · Non-linear regression

---

M. Elhakeem · A. N. Papanicolaou (✉)
100 Hydraulics Laboratory, IIHR—Hydroscience & Engineering, Department of Civil and Environmental Engineering, The University of Iowa, Iowa City, IA, 52242-1585 USA
e-mail: apapanic@engineering.uiowa.edu

1 Introduction

Surface runoff is function of many variables including rainfall intensity and duration, soil type, soil moisture, land use, cover, and slope. In view of the numerous variables and uncertainties governing surface runoff, lumped-conceptual models are useful approaches of analysis (e.g., Beven 1983; Ponce 1989; McCuen 2003; Mishra and Singh 2003). However, these models must be calibrated and verified using field measurements (Papanicolaou et al. 2008). Among the lumped models developed for predicting surface runoff in small agricultural watersheds, the curve number (CN) method (USDA 1986) is a widely accepted method because of its simplicity, and the limited number of parameters required for runoff prediction (e.g., Graf 1988; Ponce and Hawkins 1996; Bhuyan et al. 2003). The CN method is a two-parameter model to predict surface runoff depth from rainfall depth of individual storm events. The model parameters are the potential maximum retention (S) and the initial abstraction (I_a) expressed in terms of the runoff curve number CN. CN is considered to be a function of soil type, land use, cover, and antecedent runoff condition (USDA 1986).

The CN method has been the focus of much discussion in agriculture and hydrologic literature (e.g., Hawkins 1975, 1978, 1981, 1993; Rallison 1980; Bales and Betson 1981; Hjelmfelt et al. 1982; Mishra et al. 2004, 2005), and critically reviewed by many investigators clarifying its conceptual and empirical basis (e.g., Rallison and Miller 1981; Bondelid et al. 1982; Hjelmfelt 1991; Ponce and Hawkins 1996; Yu 1998; Mishra and Singh 1999; McCuen 2002, 2003). The method has been used successfully in ungauged rural watersheds and has evolved well beyond its original objective to be adopted for surface runoff prediction in urbanized and forested watersheds (USDA 1986). In addition, it has been integrated into many hydrologic, erosion, and water-quality models such as CREAMS (Knisel 1980), SWRRB (Williams et al. 1985; Arnold et al. 1990), AGNPS (Young et al. 1987, 1989, 1994), EPIC (Sharpley and Williams 1990), PERFECT (Littleboy et al. 1992), and WEPP (Risse et al. 1994; Nearing et al. 1996).

2 Objectives

Although the CN method has been applied successfully throughout the United States with few adjustments to account for regional differences in climate and soil texture (Ponce and Hawkins 1996), its predictive capability has not been tested in detail for US Corn Belt States (Wehmeyer 2006). The US Corn Belt States are facing an increase in water demands for corn production to meet rising ethanol needs as an alternative biofuel. Thus, proper CN estimates are needed to accurately evaluate water availability and close the water budget of agricultural fields. The use of singular tabulated CN values in states like Iowa, where humid and semiarid environments are present can result in large errors in surface runoff prediction (Brezonik et al. 1999). Careful measurements of runoff volume are needed to systematically evaluate the role of key variables such as rainfall intensity, soil moisture condition, tillage practice, and land cover on CN values (SUDAS 2004).

The main objective of the study was to provide statistically defendable runoff CN estimates for Iowan agricultural fields through direct field measurements with the following ultimate goals: 1) to provide detailed methodological steps to estimate CN

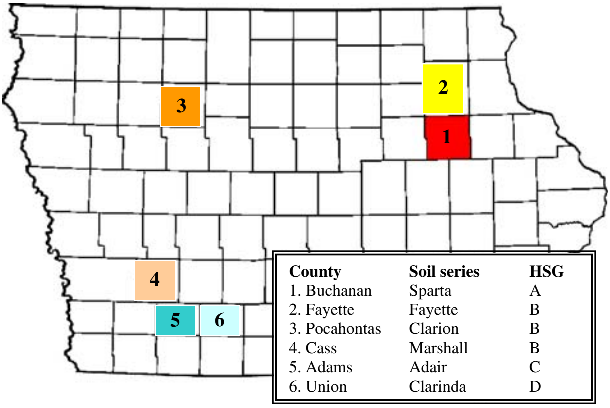
values from field measurements using rainfall simulators; 2) to identify the effects of soil type, soil moisture condition, tillage practice, and land cover on *CN*; 3) to investigate the effect of rainfall intensity on surface runoff and *CN*; 4) to evaluate the range of existing *CN* values for selected agriculture fields in Iowa under different hydrologic soil groups; and 5) to revise the equations describing the *CN* method by considering variables such as soil moisture, tillage practice, and land cover.

3 Methodology

A multifaceted approach was required to provide a range of *CN* values for selected agricultural fields in Iowa. This approach involved establishing a test-bed matrix for field measurements and data collection, developing methodological steps to estimate *CN* from in-situ measurements of surface runoff, employing an established runoff model (the *CN* method), and revising the *CN* equation through regression analysis of the collected data.

3.1 Test-bed Matrix

An important element of the field design was the development of an experimental test-bed matrix that identified field locations based on soil type, dominant tillage practice, and land cover. Based on a preliminary assessment and the recommendations of local NRCS offices, test beds were selected in the following counties: Buchanan, Fayette, Pocahontas, Cass, Adams and Union (Fig. 1). These counties have different soil textures varying from sandy to heavy clays representing the four Hydrologic Soil Groups (HSGs). Specifically, Buchanan County with Sparta soil is HSG A, Fayette County with Fayette soil, Pocahontas County with Clarion soil, and Cass County with Marshall soil are HSG B, Adams County with Adair soil is HSG C, and Union County with Clarinda soil is HSG D. Iowa soils are predominately HSG B; therefore, three counties with HSG B were selected (Table 1). Soil cores of 0.1 m diameter and 2.0 m depth were collected from representative fields via a truck-mounted Giddings Probe to confirm the soil series and related HSG of each field with the reported series in USDA (1986). The physical properties of



County	Soil series	HSG
1. Buchanan	Sparta	A
2. Fayette	Fayette	B
3. Pocahontas	Clarion	B
4. Cass	Marshall	B
5. Adams	Adair	C
6. Union	Clarinda	D

Fig. 1 Selected counties representing the four different soil types in the state of Iowa, USA

Table 1 Summary of the core sampling results according to the USDA (1993) classification

Core	County											
	Buchanan (Sparta soil type) (A reported HSG)		Fayette (Fayette soil type) (B reported HSG)		Pocahontas (Clarion soil type) (B reported HSG)		Cass (Marshall soil type) (B reported HSG)		Adams (Adair soil type) (C reported HSG)		Union (Clarinda soil type) (D reported HSG)	
	ST	HSG	ST	HSG	ST	HSG	ST	HSG	ST	HSG	ST	HSG
1	S	A	SiL	B	CL	B/C	SiCL	B/D	CL	C	SiCL	D
2	S	A	SiL	B	CL	B/C	SiCL	B/D	CL	C	SiCL	D
3	SL	A	SiL	B	L	B			SiCL	C/D	SiCL	D
4	SL	A	SiL	B	SCL	B			SiCL	C/D	SiCL	D
5	S	A	SiL	B	L	B			CL	C	SiCL	D
6	S	A	SiCL	B/D	SCL	B			CL	C	SiCL	D
7			SiCL	B/D								
8			SiL	B								

ST surface texture, *HSG* hydrologic soil group, *S* sand, *SL* sandy-loam, *SCL* sandy-clay-loam, *SiL* silty-loam, *Si* silt, *CL* clay-loam, *SiCL* silty-clay-loam, *SiC* silty-clay the soil (e.g., texture, color, and structure) were described in the field to identify the soil series using standard methods (USDA 1993). For most of the cores, surface soil textures were in the appropriate ranges for the predetermined HSG in each county (Table 1).

In order to examine the effect of tillage practice on CN estimates, three Soil Tillage Intensity Ratings (STIRs) were examined per county, which represented the conditions of long-term no-till (STIR I), rotational tillage (STIR II), and conventional tillage (STIR III). The crop rotations for these test fields were corn–soybean. According to NRCS, the STIR index for long-term no-till is 0–5; for rotational tillage is 5–30; and for conventional tillage is >60. NRCS utilizes the various operations database parameters in RUSLE-2 to quantify a STIR value (http://stir.nrcs.usda.gov/). Four factors considered by RUSLE-2 in quantifying a STIR value, namely: the operating speed of the equipment, the tillage type, the tillage depth, and the relative surface area of the field disturbed by the practices. The STIR value was calculated by applying the weighting factor approach (http://stir.nrcs.usda.gov/). Higher STIR values reflect either more intense disturbance or more frequent operations.

Field measurements were conducted in summer during the growing season and in fall after harvest to identify the effect of land cover (i.e., crops vs. residue). Four soybean fields and fourteen corn fields were considered in the study. The number of test sites was weighted towards corn to anticipate the expected increases in corn production to meet ethanol production needs.

3.2 Field Measurements

3.2.1 Equipment

The University of Iowa has three Norton Ladder Multiple Intensity Rainfall Simulators (Fig. 2) manufactured by the USDA-ARS National Soil Erosion Research Laboratory in W. Lafayette, IN (Norton 2006). The simulators were used for runoff measurement and *CN* estimates because rainfall intensity can be adjusted during an experimental run (Auerswald and Haider 1996). Further, the simulators eliminate the need of natural storm events. The basic unit of each simulator has an aluminum frame 2.5 m long, 1.5 m wide, and 2.7 m high. The frame has 4-telescopic legs so that the simulator maintains stability and vertical orientation of the nozzles. The frame is a self-contained unit that includes 2-nozzles spaced 1.1 m apart, piping, an oscillating mechanism, and a drive motor. The nozzles provide a median drop size of 2.25 mm, an exit velocity of 6.8 m s^{-1}, spherical drop shape, and a maximum rainfall intensity of 135 mm h^{-1} (Fig. 2). The simulators rainfall intensity can be changed instantaneously from a controller during a simulation event. The simulators were equipped with storage tanks and water pump connected to a system of valves that allowed internal water pressure to be adjusted for each simulator independently. Galvanized steel sheets (Fig. 2) were used for plot borders. Wind shields (Fig. 2) of slightly porous-fabric sheets were used to allow wind to be retarded.

3.2.2 Calibration

The simulators were calibrated at the University of Iowa via M300-disdrometer manufactured by Parsivel (Fig. 3a) against natural rainfall considering drop size

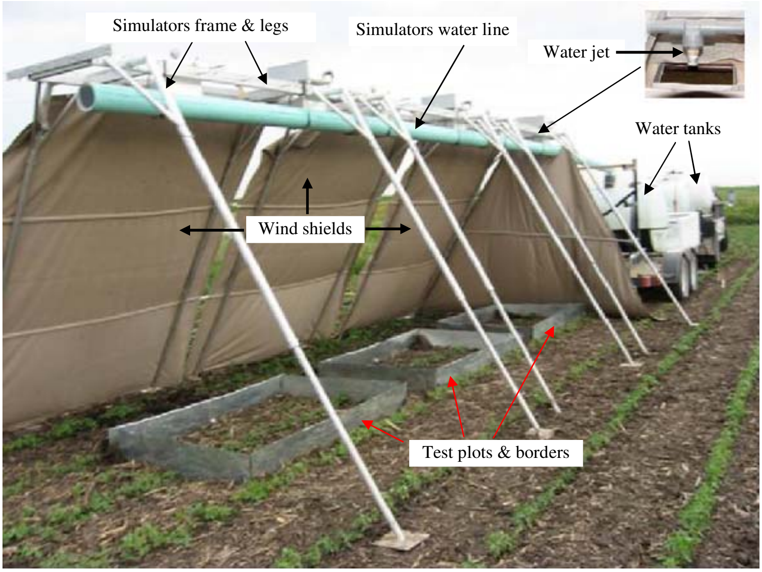


Fig. 2 General view of the rainfall simulators. On the *right top* the simulator nozzle

distribution, spatial uniformity, and fall velocities. The size distribution of the raindrops generated by the rainfall simulators for the selected intensities was compared to the Marshall-Palmer distribution (Marshall and Palmer 1948) (Fig. 3b), which is a commonly accepted distribution for natural raindrop sizes (Frasson 2007). In Fig. 3b, the solid line depicts the Marshall-Palmer distribution, while doted line represents the measured distribution. The close agreement between the measured and simulated values demonstrates the ability of the rainfall simulators to simulate

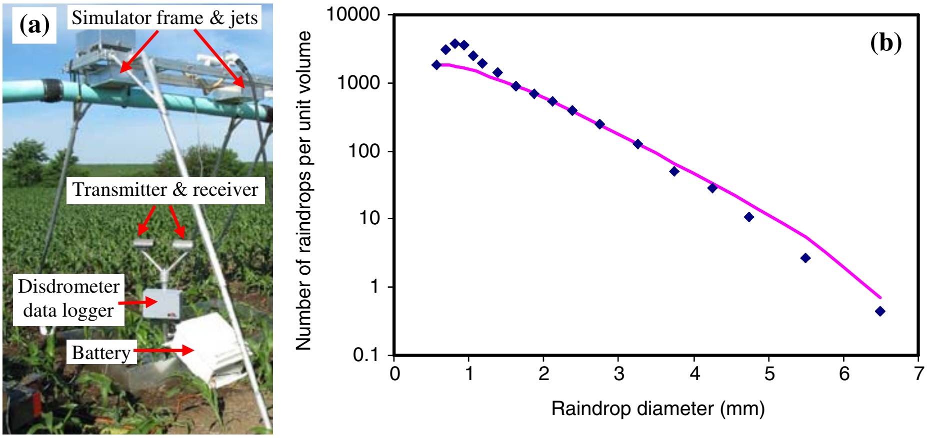


Fig. 3 Simulators calibration: **a** Disdrometer components; **b** Comparison between the rainfall simulators raindrops distribution (*dots*) and the Marshall-Palmer distribution (*solid line*), rainfall intensity was 80 mm/h

Table 2 Rainfall depths for different return periods in Iowa

	Return period (years)					
	2	5	10	25	50	100
24-h rainfall depth (mm)	84	102	114	140	152	160
3-h rainfall depth (mm)	50	61	68	83	90	95

natural rainfall. The terminal velocities of almost all drops from the Veejet nozzle were nearly found equal to the terminal velocities of those from natural rainstorms when the nozzle is at least 2.4 m above the soil surface. Therefore, the simulators were installed so that the nozzles were at least 2.5 m above the soil surface.

Previous studies with rainfall simulators have shown that rainfall events with 3-h duration are sufficient to guarantee steady-state condition for field measurements of surface runoff (Auerswald and Haider 1996). The maximum 3-h rainfall depths of different return periods for Iowa (Table 2) were obtained from the US rainfall distribution maps and the SCS 24-h–Type II rainfall distribution (Fig. 4a). Iowa is located in the Type II rainfall distribution zone (USDA 1986). The 24-h rainfall distribution (Fig. 4a) was normalized for 3-h period (Fig. 4b). The curve in Fig. 2b was approximated by a solid broken line given three rainfall intensities. It has the same distribution of 24-h rainfall distribution but for a 3-h period. Figure 2a shows that the maximum 3-h rainfall depth is about 60% of the 24-h rainfall depth. Rainfall depths varying from 19 to 107 mm were considered in this study, which covered the 3-h rainfall depths of return periods varying from 1-year to 100-years. This wide range of rainfall depths was important for *CN* estimation because of the nonlinearity between runoff Q and rainfall P relationship (see Eq. 1a in the results section). Although the *CN* method requires only the cumulative depth of rainfall at the end of the storm event (rainfall intensity, duration, and distribution are not required), the use of Type II rainfall distribution (S-curve shown in Fig. 4) mimic better natural rainstorm events, which typically start with a low-intensity, followed with a higher-intensity, and end with a lower-intensity.

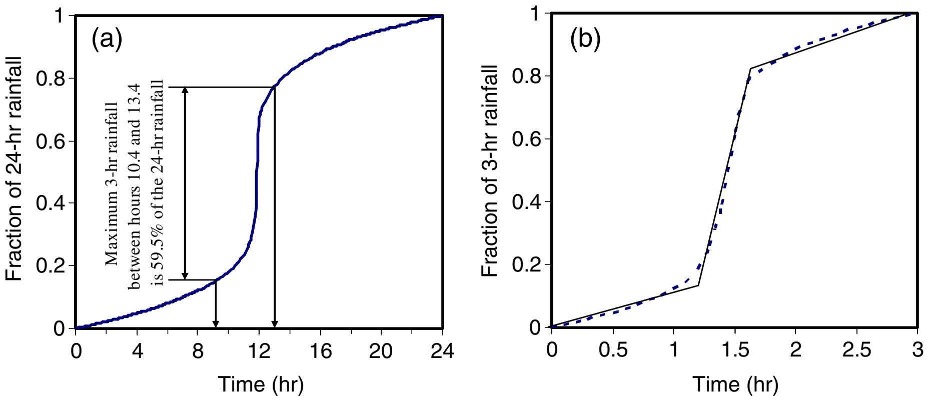


Fig. 4 Type II rainfall distribution: **a** 24-h; **b** 3-h

3.2.3 Procedure

In conducting the experiments, the dependent variable was surface runoff whereas the independent variable was the rainfall intensity for a set of runs of a specific soil, soil moisture, tillage practice, and land cover (i.e., crops vs. residue). The slope effect on surface runoff was controlled by selecting fields having almost the same slope. This was confirmed via surveying. Further, measurements were conducted in agricultural fields of very mild slopes (~0.5%) which are representative of the average condition found in Iowa. The role of soil moisture condition was minimized by using 3 plots per field in the summer instead of a single plot (Fig. 3). Six runs were conducted in each experimental plot. Based on the summer runs findings, the runoff condition (no runoff vs. ponding) of each test plot was identified, and thus the number of runs was lowered in the fall to 6 allowing for the use of a single plot per field. Soil moisture was also measured for further consideration in the data analysis (more details is given in the results section).

The field experiments were performed for periods of stable weather conditions, i.e., minimal variation in temperature and soil moisture during the day. Periods of freeze–thaw cycle were avoided to minimize errors resulting from soil aggregates breaking. Samples of the supply water used for the field experiments were collected and analyzed for pH and metals, which may affect the cohesion and porous structure of soil altering infiltration rate, and hence surface runoff (Ravisangar et al. 2001). The water quality analysis showed that the properties of the supply water were close to natural rainfall water properties of Iowa. The experiments were conducted in the summer and fall of 2006 to identify the residue effect (Fig. 5a, b).

The experimental procedure to conduct the rainfall simulator experimental runs was as follows. Three rainfall simulators were installed at the selected fields with minimum disturbance. The experimental plots (1.5 m ×2.5 m each) were installed

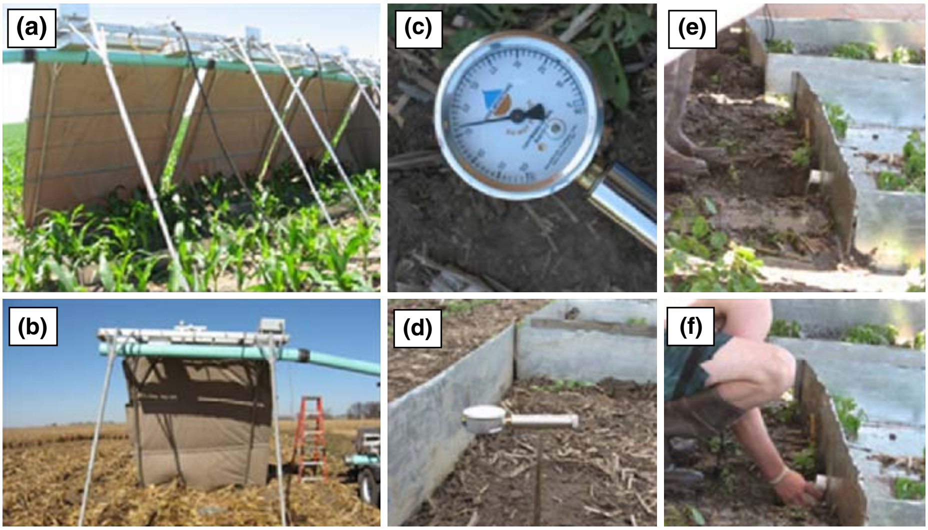


Fig. 5 Field measurements of surface runoff

adjacent to one another to limit spatial variability in soil properties (Fig. 2) and to allow for simultaneous measurements of 3-different rainfall intensities. This minimizes the differences in the soil moisture of each plot by having less number of runs. Initial soil moisture in each plot was measured via a tensiometer (Fig. 5c, d) at 0.5 and 1.0 ft depths before each run. The variation was less than 10% between the two depths. After measuring soil moisture, each simulator was set to a certain rainfall intensity following the rainfall distribution curve shown in Fig. 4b starting with a low-intensity, followed with a higher-intensity, and end with a lower-intensity. During the experimental run, runoff was collected from the outlet of the plot via small calibrated bottles of known volume (Fig. 5e, f). After each run, the rainfall simulator was stopped to allow the plots to drain before starting the next run.

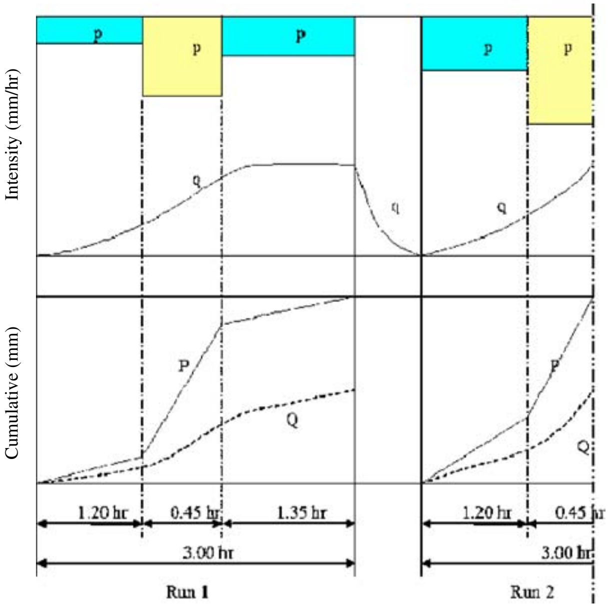
The following steps describe the experimental procedure:

1. Three rainfall simulators were installed at the selected fields with minimum disturbance. The experimental plots (1.5 m ×2.5 m each) were installed adjacent to one another to limit spatial variability in soil properties (Fig. 2) and to allow for simultaneous measurements of 3-different rainfall intensities. This minimizes the differences in the soil moisture of each plot by having less number of runs.
2. Initial soil moisture in each plot was measured via a tensiometer (Fig. 5c, d) at 15 and 30 cm depths from the soil surface before each run. The depth affected by the tillage practice ranges typically between 5 and 25 cm, depending on the tillage practice (e.g., no-till vs. conventional tillage). An intermediate value between the tillage practices depths (15 cm) was selected to measure the moisture condition. The second value was selected just below the distributed soil layer (30 cm), to check if there is variability in the moisture condition due to the tillage practice. The variation was less than 10% between the two depths. After measuring soil moisture, each simulator was set to a certain rainfall intensity following the rainfall distribution curve shown in Fig. 4b. During the experimental run, runoff was collected from the outlet of the plot via small calibrated bottles of known volume (Fig. 5e, f).
3. After each run, the rainfall simulator was stopped to allow the plots to drain before the next run starts. The time required for the plot to drain varies from 15 to 45 min, depending on the tested soils texture and residue. Figure 6 shows a conceptual sketch explaining our methodology for measuring surface runoff. The figure shows the distribution of the rainfall intensity (p) and corresponding runoff rate (q) in mm/h. The accumulated volumes of rainfall (P) and runoff (Q) in mm are also shown in Fig. 6.

4 Results

CN is an index representing the soil-cover complex that reflects the response of a specific soil under certain conditions (i.e., soil moisture, tillage practice, and land cover) to a rainstorm event through runoff and infiltration. *CN* is a non-dimensional index having theoretically a value between 0 (no runoff) and 100 (no infiltration). For a specific soil soil-cover condition, *CN* can be obtained from a range of rainfall

Fig. 6 Conceptual sketch explaining the methodology during tests. The sketch shows the rainfall–runoff trends in one plot for two subsequent runs



depths and corresponding runoff depths (Fig. 7) by solving for S and I_a using the following CN equations:

$$Q = \frac{(P - I_a)^2}{P + S - I_a} \tag{1a}$$

$$S = \frac{25400}{CN} - 254 \tag{1b}$$

where, Q is the direct runoff depth (mm), P is the rainfall depth (mm), S is the potential maximum retention (mm), and I_a is the initial abstraction (mm). The relationship between rainfall and runoff described by Eq. 1a requires the use of non-linear regression analysis methods (e.g., Shahin et al. 1993; Draper and Smith 1998) to obtain S and I_a values, which provide the best fit of Eq. 1a to the measured data. Figure 6 provides an example of the measured rainfall and runoff values, shown in dots, for sites 1 to 3 found in Fayette County. The solid lines represent the best-fit of Eq. 1a to the measured data. The intercept of the fitted line with the x-axis gives I_a. The CN value was obtained from Eq. 1b. There was no family of curves for different rainfall intensities of a single plot (Fig. 7b), which indicates that CN is not a function of rainfall intensity. For the summer runs (Fig. 7a), a single curve was also sufficient to fit the measured data from the 3 adjacent plots.

A summary of the CN data for the different fields is given in Table 3. The county name, sites per county, STIR, and crop type are shown in the first 4 columns. Columns 5–9 and 9–13 summarize the data for the summer and fall seasons, respectively. S and I_a values in columns 5, 6 and 9, 10 provide the best fit of Eq. 1a to the measured data. Columns 7 and 11 provide the ratio of S to I_a, which is defined as N. The CN values in columns 8 and 12 were estimated via Eq. 1b. Columns 9

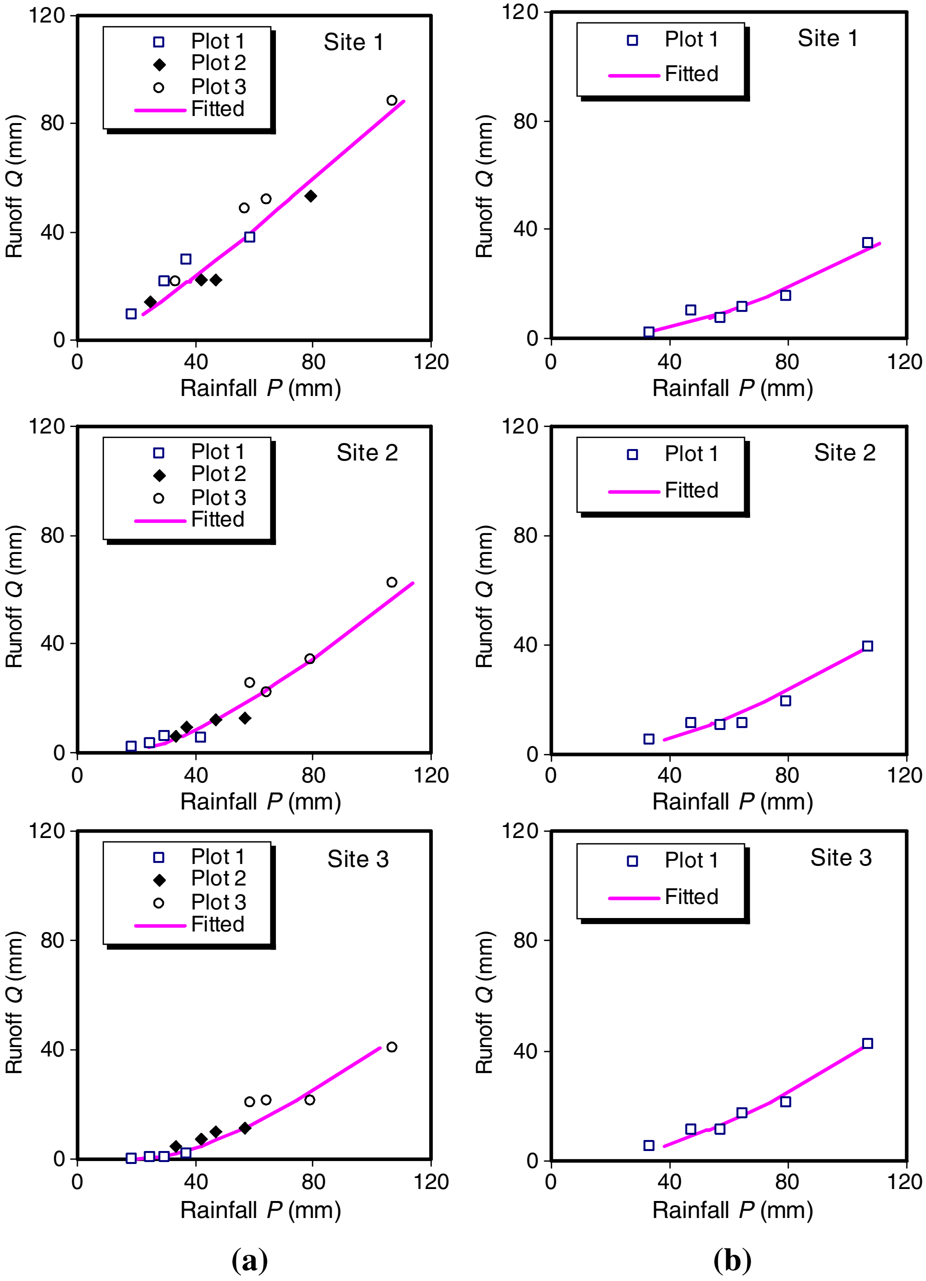


Fig. 7 Method of *CN* estimate from data obtained from the rainfall simulators. Rainfall depth versus runoff depth for Fayette County, Iowa: **a** summer measurements; **b** fall measurements

and 13 provide the measured percentage of the volumetric soil water content (M) obtained via the tensiometer. M theoretically varies between 0 for dry soil and 100 for a saturated soil.

Table 3 Summary of the *CN* results

(1) County	(2) Site	(3) STIR	(4) Crop	Measured summer data					Measured fall data				
				(6) S (mm)	(7) I_a(mm)	(8) I_a/S	(9) CN	(10) M %	(11) S (mm)	(12) I_a(mm)	(13) I_a/S	(14)CN	(15) M %
Buchanan	1	II	Corn	148	21	0.144	63	30	148	13	0.088	63	70
	2	II	Corn	170	23	0.105	60	40	767	53	0.069	25	46
	3	II	Corn	257	65	0.251	50	26	1285	101	0.079	17	36
Fayette	1	III	Corn	25	1	0.086	91	93	178	13	0.096	59	60
	2	II	Corn	64	13	0.196	80	44	152	7	0.048	63	64
	3	I	Corn	85	20	0.230	75	41	135	8	0.058	65	70
Pocahontas	1	I	Corn	142	33	0.234	64	31	204	17	0.081	56	60
	2	III	Soybean	17	2	0.134	94	70	52	3	0.060	83	90
	3	II	Soybean	61	5	0.082	81	52	86	5	0.053	75	82
Cass	1	I	Corn	63	7	0.113	80	52	107	7	0.069	70	70
	2	III	Corn	34	3	0.098	88	55	51	3	0.055	83	90
	3	II	Corn	71	13	0.178	78	46	71	5	0.068	78	90
Adams	1	III	Soybean	67	15	0.225	79	36	84	5	0.064	75	82
	2	I	Corn	45	6	0.141	85	48	114	9	0.078	69	70
	3	II	Soybean	29	3	0.099	90	61	71	6	0.079	78	82
Union	1	III	Corn	13	1	0.096	95	90	82	6	0.069	76	79
	2	II	Corn	48	8	0.166	84	41	87	5	0.062	75	77
	3	I	Corn	6	1	0.088	98	97	38	2	0.060	87	95

The *CN* values were generally lower in the fall compared to the summer (Table 3). The difference between fall and summer values (deviation of about 20%) was attributed to the amounts of residue found on the test plots at those times (Fig. 5), which control surface runoff (Rawls and Onstad 1978; Rawls et al. 1980). In fall, higher residue cover levels (0.85 and 0.77 for corn and soybean, respectively) reduced surface runoff and the *CN* values due to added roughness effects (Papanicolaou and Abaci 2008). In summer, residue levels dropped to 0.2 and 0.17 for corn and soybean, respectively, allowing more surface runoff. Papanicolaou and Abaci (2008) have shown that failure to adjust *CN* values for the presence of residue will overestimate annual surface runoff of Iowa agricultural fields. Thus, *CN* should be treated as a dynamic variable throughout the year (McCuen 2002; Schneider and McCuen 2005).

Higher soil moisture (M) conditions were also observed in fall compared to summer (Table 3). This was attributed to lower temperature and higher residue cover, which minimized evaporation from the soil surface (Linsley et al. 1986). In summer, lower residue cover, and higher temperature increased evapotranspiration rates during the growing season, thereby decreasing soil moisture.

Figures 8 and 9 showed S as a function of M and CN, and I_a as a function of S and M, respectively. These figures showed distinct non-linear trends based on season only as there was no family of curves for different STIRs or crop types. This season-based separation signifies the importance of residue cover on *CN* calculations compared to tillage practice (STIR) and crop type. Sets of non-linear empirical relationships were developed between the variables expressed as:

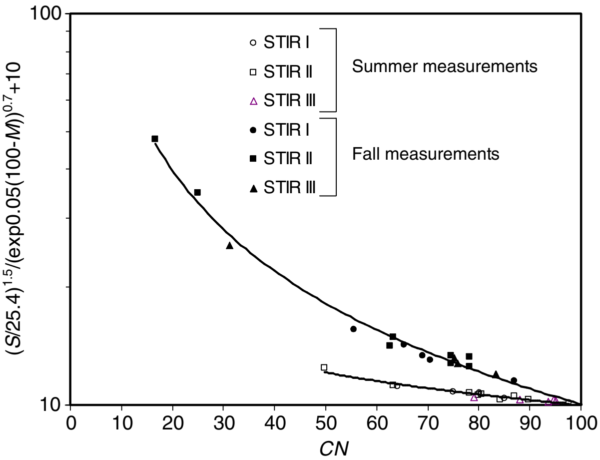
$$S = 25.4\left[\left(35.53CN^{-0.275} - 10\right)\left(e^{0.05(100-M)}\right)^{0.7}\right]^{2/3} \quad for\ summer \tag{2A}$$

$$S = 25.4\left[\left(515.18CN^{-0.855} - 10\right)\left(e^{0.05(100-M)}\right)^{0.7}\right]^{2/3} \quad for\ fall \tag{2B}$$

$$I_a = 0.0436S^{1.3} \ for\ summer;\ I_a = 0.0427S^{1.1} \ for\ fall \tag{3A, B}$$

$$I_a = (0.01133M)^{-3.322} \ for\ summer;\ I_a = (0.00837M)^{-4.052} \ for\ fall \tag{4A, B}$$

Fig. 8 Relationship between *S*, *CN*, and *M* for summer and fall measurements



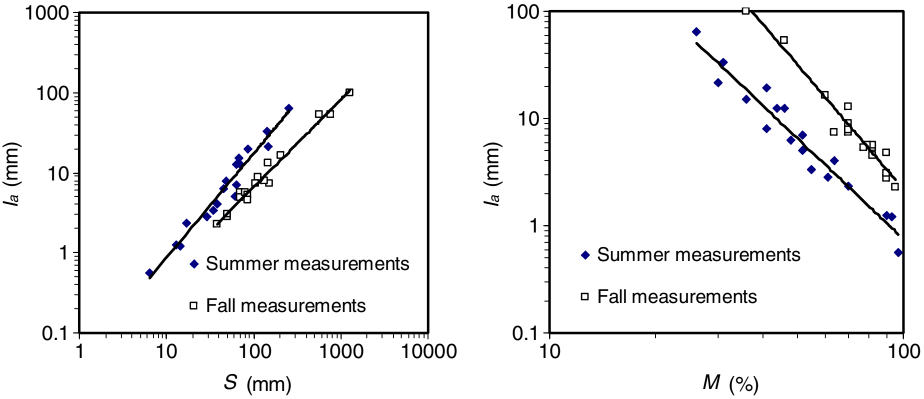


Fig. 9 Relationships between S, M, and I_a for summer and fall measurements

5 Applications

In order to compare the estimated CN values from the rainfall simulators with the reported CN, denoted as CN_R, the estimated CN values were adjusted based on the ratio $N = I_a/S$ and the antecedent runoff condition (ARC). Reported CN_R values were assumed to have $N_R = I_a/S = 0.2$, and average antecedent runoff condition (ARC II). USDA defines three antecedent runoff conditions, namely, ARC I (dry), ARC II (average), and ARC III (wet). CN values of an average soil moisture ($M = 50\%$), defined here as CN_{II}, and were considered equivalent to CN of ARC II. The following steps summarize the calculations used to adjust the estimated CN values:

1) Adjust S values of Table 3 as $S_{0.2} = (N_R/N)S$
2) Adjust I_a values of Table 3 as $I_{a0.2} = N_R S_{0.2}$
3) Calculate Mvalues for $I_{a0.2}$ using Eq. 4
4) Calculate $CN_{0.2}$ from equation 1B using $S_{0.2}$
5) Calculate CN_{II} from M and $CN_{0.2}$values obtained from step 3 and 4, respectively using the following equation:

$$CN = \frac{3.0646\, e^{0.0235M} CN_{II}}{10 + \left(0.030646\, e^{0.0235M} - 0.1\right) CN_{II}} \tag{5}$$

Equation 5 was developed from Eqs. 1a and 2 using graphical and multi-regression analysis methods. Equation 5 provides CN values for ARC other than average (ARC II) as a function of CN_{II} and M.

Table 4 summarizes the reported and adjusted CN values for different fields. The range of the adjusted summer CN_{II} values agreed well with the reported CN_R values (deviation less than 6%). However, the range of the adjusted fall CN_{II} values was generally below the reported CN_R (deviation of about 40%). The deviation of adjusted fall CN_{II} values from the reported CN_R values was attributed to the residue cover. The reported CN_R values combine the cumulative effects of residue

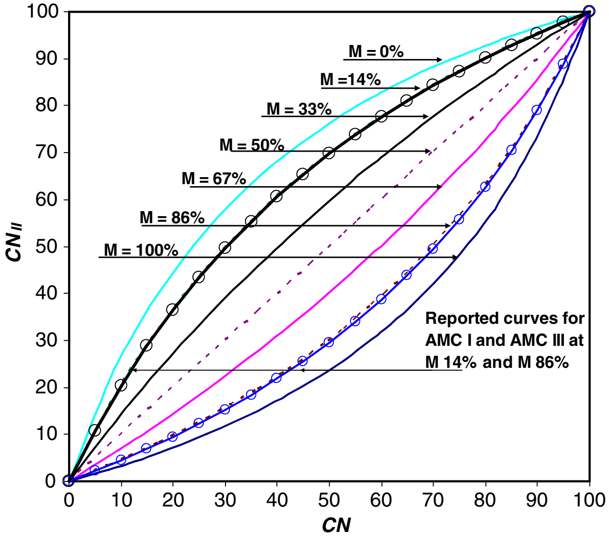
Table 4 Comparison between reported and estimated *CN* values adjusted for $I_a/S = 0.2$ and ARC II

County	Site	STIR	Crop	Reported Average CN_R	Summer $CN_{0.2,II}$	Fall $CN_{0.2,II}$
Buchanan	1	II	Corn	68 ± 4	67	47
	2	II	Corn	68 ± 4	82	16
	3	II	Corn	68 ± 4	67	12
Fayette	1	III	Corn	78 ± 4	89	25
	2	II	Corn	78 ± 4	83	35
	3	I	Corn	78 ± 4	82	41
Pocahontas	1	I	Corn	78 ± 4	75	40
	2	III	Soybean	78 ± 4	90	59
	3	II	Soybean	78 ± 4	72	48
Cass	1	I	Corn	78 ± 4	77	49
	2	III	Corn	78 ± 4	82	58
	3	II	Corn	78 ± 4	81	56
Adams	1	III	Soybean	84 ± 4	84	52
	2	I	Corn	84 ± 4	83	50
	3	II	Soybean	84 ± 4	84	58
Union	1	III	Corn	88 ± 3	90	54
	2	II	Corn	88 ± 3	84	50
	3	I	Corn	88 ± 3	93	64

cover level and many other variables into the ARC factor, where there are no methodological steps to separate the residue cover effect from other variables for *CN* correction.

Figure 10 shows family of curves developed from equation 5 between CN_{II} and *CN* as a function of *M*. The figure shows that *M* values higher than 50% provide *CN* values higher than CN_{II} and vise versa. It should be noted that for $M = 50\%$, the *CN* would be equal to CN_{II}. Figure 10 also shows that the reported CN_R for

Fig. 10 *CN* as function of CN_{II} and *M*



ARC I and ARC III relative to CN_{II} (ARC II) correspond to M = 14% and M = 86%, respectively. Figure 10 allows for interpolation of CN values other than the traditionally reported ones for the three ARC conditions (I, II, and III), which involve some ambiguity and subjectivity (Hjelmfelt 1991; Silveira et al. 2000).

In making the results useful for practical application, the following steps utilizing Table 4, and Eqs. 3 and 5 were proposed for surface runoff prediction:

1. Select an appropriate value for CN_{II} with respect to soil type, STIRs, and season using Table 4.
2. Assume or measure soil moisture M.
3. Calculate CN from Fig. 10 or Eq. 5 using CN_{II} and M determined from steps 1 and 2.
4. Calculate S from Eq. 1b using the CN value obtained from Fig. 10 or Eq. 5.
5. Calculate I_a from Eq. 3.
6. Use S and I_a to obtain Q from Eq. 1a for a specified rainstorm P.

6 Conclusions and Summary

This study was the first to provide detailed methodological steps to estimate in-situ runoff curve number (CN) for selected agricultural fields in Iowa using rainfall simulators. Representative fields in six counties were chosen to identify the effects of the following variables on CN value: soil type, soil moisture, rainfall intensity, tillage practice, and residue cover. The study estimated a range of CN values for the summer and fall seasons, and revised the equations describing the CN method to consider variables such as residue cover and moisture condition of the soil in a more detailed manner than the existing method.

The following points summarize the findings of this research:

1. Rainfall simulators were reliable instruments for estimating in-situ runoff CN because rainfall intensity was adjustable during an experimental run. Further, the simulators eliminate the need to wait for natural storm event.
2. A range of CN values was established for the summer and fall seasons. The range of the estimated CN_{II} values in summer agreed with the reported CN_R values. However, the range of the estimated CN_{II} values in fall was generally less than the reported CN_R values. This was attributed to the extensive residue cover found in the fields after harvest.
3. The influences of rainfall intensity, tillage practice, and crop type were insignificant compared to soil moisture and residue cover.
4. Initial abstraction I_a was not linearly proportional to potential maximum retention S i.e., $I_a \neq 0.2S$) as reported by USDA and was also affected with residue cover. Similar conclusions were reported by other investigators (Mishra et al. 2004, 2006; Jain et al. 2006).
5. The CN equations were modified to account for moisture condition and residue cover. This can allow for more accurate estimates of surface runoff.

Scale is an important factor to consider when characterizing heterogeneity of landscape attributes and surface runoff. A single CN value may not represent the watershed characteristics because of the expected variability in soil texture, average slope, moisture condition, land use, and cover. However, within the field scale, the variability in these factors may be small, and thus a single *CN* value may represent the field. Under this condition, the *CN* values obtained from an experimental plot may represent the *CN* value of a tested field. However, this requires that the experimental plot has similar characteristics as the field in terms of soil texture, average slope, moisture condition, land use, and cover. At the development stages of an experimental test-bed matrix, the locations of the plots within the fields can be obtained from digital elevation and soil maps (e.g., Iowa Soil Properties and Interpretations Database (ISPAID) and Soil Survey Geographic (SSURGO)) and with the assistant of the local NRCS officers. However, the selected locations must be verified later via surveying and core sampling. The data obtained from different fields within a watershed can be integrated together to obtain a representative *CN* value reflecting the watershed characteristics. However, the validity of the proposed approach should be examined at instrumented watersheds with long-term records.

In conclusion, this study is limited by its application to the investigated fields in Iowa and other fields that may have similar conditions. The use of benchmark soils for this study makes the results transferable to many other fields in the state. However, it would be advisable to repeat this study at different counties or even in other parts of the county.

Acknowledgements This study was funded by the United States Department of Agriculture—Natural Resources Conservation Service (NRCS) Iowa offices and The University of Iowa. The authors would like to thank especially Laurel Foreman (hydrologist—Iowa NRCS), Claudia Scheer (National Hydraulic Engineer—Arizona NRCS), Mike Sucik (Soil Scientist—Iowa NRCS), and Mark Jensen (State Conservation Engineer) for their support and guidance during the study. Also, the discussions with Prof. Richard (Pete) Hawkins (University of Arizona) and Donald Woodward (Hydraulic Engineer, NRCS) are greatly appreciated.

References

Arnold JG, Williams JR, Nicks AD, Summons NB (1990) SWRRB—A basin scale simulation model for soil and water resources management. Texas A&M University Press, College Station

Auerswald K, Haider J (1996) Runoff curve numbers for small grain under German cropping conditions. J Environ Manag 47:223–228. doi:10.1006/jema.1996.0048

Bales J, Betson RP (1981) The curve number as a hydrologic index. In: Singh VP (ed) Rainfall runoff relationship. Water Resources, Littleton, pp 371–386

Beven K (1983) Surface water hydrology-runoff generation and basin structure. Rev Geophys 21(3):721–730. doi:10.1029/RG021i003p00721

Bhuyan SJ, Mankin KR, Koelliker JK (2003) Watershed-scale AMC selection for hydrologic modeling. Trans ASAE 46:237–244

Bondelid TR, McCuen RH, Jackson TJ (1982) Sensitivity of SCS models to curve number variation. Water Resour Bull 18:111–116

Brezonik PL, Bierman VJ, Alexander R, Anderson J, Barko J, Dortch M, Hatch L, Hitchcock GL, Keeney D, Mulla D, Smith V, Walker C, Whitledge T, Wiseman WJ (1999) Effects of reducing nutrient loads to surface waters within the Mississippi River Basin and the Gulf of Mexico: topic 4 report for the integrated assessment on hypoxia in the Gulf of Mexico. In: NOAA Coastal Ocean Program. Decision Analysis Series, no 18. National Oceanic and Atmospheric Admnistration Coastal Ocean Office, Silver Spring, pp 113

Draper N, Smith H (1998) Applied regression analysis, 3rd edn. Wiley, New York

Frasson RPM (2007) Observational studies of rainfall interception by corn. Master thesis, Department of Civil and Environmental Engineering, The University of Iowa

Graf WL (1988) Fluvial processes in dryland rivers. Springer, New York

Hawkins RH (1975) The importance of accurate curve numbers in the estimation of storm runoff. Water Resour Bull 11:887–891

Hawkins RH (1978) Runoff curve numbers with varying site moisture. J Irrig Drain Eng 104(4): 389–398

Hawkins RH (1981) Interpretation of source-area variability in rainfall–runoff relationships. In: Singh VP (ed) Rainfall runoff relationship. Water Resources, Littleton, pp 303–324

Hawkins RH (1993) Asymptotic determination of runoff curve numbers from data. J Irrig Drain Eng 119(2):334–345. doi:10.1061/(ASCE)0733-9437(1993)119:2(334)

Hjelmfelt AT (1991) Investigation of curve number procedure. J Hydraul Eng 117(6):725–737. doi:10.1061/(ASCE)0733-9429(1991)117:6(725)

Hjelmfelt AT, Kramer LA, Burwell RE (1982) Curve numbers as random variables. In: Proceedings of the international symposium on rainfall–runoff modeling. Water Resources, Littleton, pp 365–373

Jain MK, Mishra SK, Babu PS, Venugopal K, Singh VP (2006) Enhanced runoff curve number model incorporating storm duration and a nonlinear Ia-S relation. J Hydrol Eng 11(6):631–635. doi:10.1061/(ASCE)1084-0699(2006)11:6(631)

Knisel WG (ed) (1980) CREAMS: a field-scale model for chemical, runoff and erosion from agricultural management systems. Conservation Research Report, No 26. USDA, Washington, DC

Linsley RK, Kohler MA, Paulhus JL (1986) Hydrology for engineers, 3rd edn. McGraw-Hill, New York

Littleboy M, Silburn DM, Freebairn DM, Woodruff D, Hammer UL, Leslie JK (1992) Impact of soil erosion on production in cropping land systems: 1. Development and validation of a simulation model. Aust J Soil Res 30:757–774. doi:10.1071/SR9920757

Marshall JS, Palmer WK (1948) The distribution of raindrops with size. J Meteorol 5:165–166

McCuen RH (2002) Approach to confidence interval estimation for curve numbers. J Hydrol Eng 7(1):43–48. doi:10.1061/(ASCE)1084-0699(2002)7:1(43)

McCuen RH (2003) Hydrologic analysis and design, 3rd edn. Prentice Hall, Englewood Cliffs

Mishra SK, Jain MK, Singh VP (2004) Evaluation of SCS-CN-based model incorporating antecedent moisture. Water Resour Manag 18(6):567–589. doi:10.1007/s11269-004-8765-1

Mishra SK, Jain MK, Bhunya PK, Singh VP (2005) Field applicability of the SCS-CN-based Mishra-Singh general model and its variant. Water Resour Manag 19(1):37–62. doi:10.1007/s11269-005-1076-3

Mishra SK, Sahu RK, Eldho TI, Jain MK (2006) An improved Ia-S relation incorporating antecedent moisture in SCS-CN methodology. Water Resour Manag 20:643–660. doi:10.1007/s11269-005-9000-4

Mishra SK, Singh VP (1999) Another look at SCS-CN method. J Hydrol Eng 4(3):257–264. doi:10.1061/(ASCE)1084-0699(1999)4:3(257)

Mishra SK, Singh VP (2003) Soil conservation service curve number (SCS-CN) methodology. Kluwer Academic, Dordrecht

Nearing MA, Liu BY, Risse LM, Zhang XC (1996) Curve numbers and Green-Ampt effective hydraulic conductivities. Water Resour Bull 32(1):125–136

Norton LD (2006) A linear variable intensity rainfall simulator for erosion studies. In: Wanielista M, Smoot J (eds) Proc. of 2nd bieannial stormwater management research symp., May 4–5, 2006. Univ. of Central Florida, Orlando, pp 93–103

Papanicolaou AN, Abaci O (2008) Upland erosion modeling in a semi-humid environment via the water erosion prediction project model. J of Irrigation and Drainage Engineering, Ms. No. IRENG-07-5256R1, p 127

Papanicolaou AN, Elhakeem M, Krallis G, Prakash S, Edinger J (2008) Sediment transport modeling review—current and future developments. J Hydraul Eng 134(1):1–14. doi:10.1061/(ASCE)0733-9429(2008)134:1(1)

Ponce VM (1989) Engineering hydrology, principles and practices. Prentice Hall, Englewood Cliffs

Ponce VM, Hawkins RH (1996) Runoff curve number: Has it reached maturity? J Hydrol Eng 1(1):11–19. doi:10.1061/(ASCE)1084-0699(1996)1:1(11)

Rallison RE (1980) Origin and evolution of the SCS runoff equation. In: Proceedings of symposium on watershed management. ASCE, New York, pp 912–924

Rallison RE, Miller N (1981) Past, present, and future SCS runoff procedure. In: Singh VP (ed) Rainfall runoff relationship. Water Resources, Littleton, pp 353–364

Ravisangar V, Dennett KE, Sturm TW, Amirtharajah A (2001) Effect of sediment pH on resuspension of kaolinite sediments. J Environ Eng 127(6):531–538. doi:10.1061/(ASCE)0733-9372(2001)127:6(531)

Rawls WJ, Onstad CA (1978) Residue and tillage effects on SCS runoff curve number. In: American society of agricultural engineers for winter meeting. Chicago, 18–20 December 1978, p 18

Rawls WJ, Onstad CA, Richardson HH (1980) Residue and tillage effects on SCS runoff curve numbers. Trans Am Soc Agric Eng 23:357–361

Risse LM, Nearing MA, Savabi MR (1994) Determining the green-ampt effective hydraulic conductivity from rainfall–runoff data for the WEPP model. Trans Am Soc Agric Eng 37(2):411–418

Schneider LE, McCuen RH (2005) Statistical guidelines for curve number generation. J Irrig Drain Eng 131(3):282–290. doi:10.1061/(ASCE)0733-9437(2005)131:3(282)

Shahin M, van Orschot HL, Delange SJ (1993) Statistical analysis in water resources engineering. A. A. Balkema, Rotterdam

Sharpley AN, Williams JR (1990) EPIC—Erosion/productivity impact calculator: 1. model documentation. USDA-technical bulletin, No 1768. US Government Printing Office, Washington, DC

Silveira L, Charbonnier F, Genta JL (2000) The antecedent soil moisture condition of the curve number procedure. Hydrol Sci 45(1):3–12

SUDAS (2004) Statewide Urban design and specifications, Iowa statewide urban design standards manual. Chapter 3: stormwater management and drainage, Central Iowa Metropolitan Areas and Municipalities

USDA (1986) Urban hydrology for small watersheds. Technical release, no 55 (TR-55). Soil Conservation Service, Washington, DC

USDA (1993) Soil survey manual. Handbook 18. Soil Conservation Service, Washington, DC

Wehmeyer LL (2006) Evaluation of design flood frequency methods for Iowa stream. M.Sc. Thesis, Department of Civil and Environmental Engineering, The University of Iowa, Iowa, USA

Williams JR, Nicks AD, Arnold JG (1985) Simulator for water resources in rural basins. J Hydraul Eng 111:970–986

Young RA, Onstad CA, Bosch DD, Anderson WP (1987) AGNPS, agricultural non-point source pollution model—a watershed analysis tool. USDA Conserv Res Rep 35:1–80

Young RA, Onstad CA, Bosch DD, Anderson WP (1989) AGNPS: a non-point source pollution model for evaluating agricultural watersheds. J Soil Water Conserv 44(2):168–173

Young RA, Onstad CA, Bosch DD, Anderson WP (1994) Agricultural non-point source pollution model. Version 4.03, AGNPS User's Guide. North Central Soil Conservation Research Laboratory, Morris, Minnesota

Yu B (1998) Theoretical justification of SCS method for runoff estimation. J Irrig Drain Eng 124(6):306–310. doi:10.1061/(ASCE)0733-9437(1998)124:6(306)