

On the I_a – S relation of the SCS-CN method

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Abstract The initial abstraction (I_a) versus maximum potential retention (S) relation in the Soil Conservation Service Curve Number (SCS-CN) methodology was revisited, and a new non-linear relation incorporating storm rainfall (P) and S was proposed and tested on a large set of storm rainfall-runoff events derived from the water database of United States Department of Agriculture-Agriculture Research Service (USDA-ARS). Employing root mean square error (RMSE), the performance of both the existing and proposed models was evaluated using the complete database, and for model calibration and validation, data were split into two groups: based on ordered rainfall (P -based) and runoff (Q -based). A specific formulation of the proposed model $I_a = \lambda S(P/(P + S))^\alpha$ with $\lambda = 0.3$ and $\alpha = 1.5$ was found to generally perform better than the existing $I_a = 0.2S$, and therefore was recommended for field applications. When evaluated using the observed I_a data, the proposed version performed significantly better than the existing one.

Keywords Agriculture Research Service; curve number; initial abstraction; rainfall-runoff modelling; SCS-CN method

Introduction

The US Soil Conservation Service-Curve Number (SCS-CN) method (Soil Conservation Service 1956, 1964, 1969, 1971, 1972, 1985, 1993) (also known as the Natural Resource Conservation Service Curve Number (NRCS-CN) method) is one of the most popular methods for computing the volume and peak quantiles of direct surface runoff from rainfall quantiles (McCuen 1982; Hjelmfelt 1991; Ponce and Hawkins 1996; Mishra and Singh 2003). Since the method works with mean and it does not account for storm duration (Ponce and Hawkins 1996), the method is poorly suited for use in estimating runoff volumes for actual events. However, based on a tremendous amount of experimental work, it has been widely used in the United States and across the world and has more recently been integrated into several rainfall-runoff models, supporting its robustness and popularity (Michel *et al.* 2005). Mishra and Singh (2003) provided the current state of the art of the SCS-CN methodology, its enhanced analytical treatment, and applications to areas other than the originally intended use.

This SCS-CN method is based on the water balance equation and two fundamental hypotheses which can be expressed, respectively, as

$$P = I_a + F + Q \quad (1)$$

$$\frac{Q}{P - I_a} = \frac{F}{S} \quad (2)$$

$$I_a = \lambda S \quad (3)$$

where P = total rainfall, I_a = initial abstraction, F = cumulative infiltration, Q = direct surface runoff, S = potential maximum retention ($0, \infty$), and λ = initial abstraction

coefficient. Combination of Equations (1) and (2) leads to the popular form of the SCS-CN method:

$$Q = \frac{(P - I_a)^2}{P - I_a + S} \quad (4)$$

Equation (4) is valid for $P \geq I_a$, otherwise, $Q = 0$. Parameter S in Equation (4) is expressed as

$$S = \frac{25400}{CN} - 254 \quad (5)$$

where S is in mm and CN is a non-dimensional quantity varying in the range (0, 100).

Since its inception, the above method has been in question for its dealing with various aspects, such as the antecedent moisture condition (AMC), initial abstraction ratio (called “Lambda” (λ)), applicability to watersheds’ size and type, etc. Out of these, the standard assumption of $\lambda = 0.2$ in Equation (3) has been frequently questioned for its validity and applicability (Hawkins *et al.* 2002), invoking a critical examination of the I_a – S relationship for pragmatic applications. Thus, the objective of this paper is (a) to provide a critical review of the I_a – S relationship and propose an improvement incorporating P as well as S ; and (b) to compare the performance of the formulated model and its versions on a large set of observed rainfall-runoff data, split as well as complete data sets, and the observed I_a data set.

The I_a – S relationship: an overview

An elementary expression for the transformation of rainfall into runoff is $Q = P - L$, where Q is the runoff, P is the rainfall, and L is the hydrologic abstraction, which is difficult to quantify in nature (Ponce and Hawkins 1996). This abstraction includes interception, storage, surface storage, evaporation from water bodies such as ponds, lakes, etc., infiltration, and evapotranspiration from all types of vegetation. The initial abstraction (I_a) accounts for depression (surface) storage, interception, and infiltration, occurring before runoff begins. The interception and depression storage values vary widely with types of vegetative cover, wind, area of depression and depth, etc., which are difficult to quantify accurately. Hjelmfelt (1991) pointed out that many storm and landscape factors interact to define the initial abstraction.

The initial abstraction was not a part of the SCS-CN model in its initial formulation (Plummer and Woodward 2002), but as development continued, it was included as a fixed ratio of I_a to S (Equation (3)). This relationship was justified on the basis of measurements in watersheds (of less than 10 acres) despite a considerable scatter in the resulting I_a – S plot (SCS 1985). NEH-4 (SCS 1985) reported 50% of data points to lie within $0.095 \leq \lambda \leq 0.38$, leading to a standard value of $\lambda = 0.2$ (Ponce and Hawkins 1996). Because of this large variability, the $I_a = 0.2S$ relation has been focus of discussion and modification since its inception. For example, based on their field data, the Central Unit for Soil Conservation (1972) recommended a λ value of 0.3 for all regions of India, except for the black cotton region for which it is 0.1 under AMC II (normal) and III (wet) conditions. Aron *et al.* (1977) suggested $\lambda \leq 0.1$ and Golding (1979) provided curve number dependent λ values for urban watersheds: $\lambda = 0.075$ for $CN \leq 70$, $\lambda = 0.1$ for $70 < CN \leq 80$, and $\lambda = 0.15$ for $80 < CN \leq 90$. Springer *et al.* (1980) found $\lambda = 0.2$ not to be appropriate for both arid and humid watersheds and cautioned against its use for other watersheds. In his mathematical treatment, Chen (1981) physically signified λ as a square root ratio of initial (f_o) and final infiltration rates (f_∞), and varied it from 0 to 1. His I_a – S analysis was however based on ‘ S

including I_a . Since S does not include I_a , the US National Engineering Handbook was corrected accordingly (Van Mullem *et al.* 2002).

Cazier and Hawkins (1984) found $\lambda = 0.0$ to fit best to their data set and, as an alternative, Bosznay (1989) suggested to treat I_a as a random variable. According to Ponce and Hawkins (1996), the fixing of λ at 0.2 is tantamount to regionalization based on geologic and climatic settings. Plummer and Woodward (2002) described the origin of I_a/S and explained its development between $I_a = 0$ and $I_a = 0.2S$, a result of the cooperative effort of the US Forest Service (FS), ARS, and NRCS.

Based on their mathematical analysis, Mishra and Singh (1999a, b) found λ to vary from 0 to ∞ . While explaining the SCS-CN's proportionality concept (Equation (2)) using the volumetric concept of soil–water–air, Mishra and Singh (2003) described λ as the degree of atmospheric saturation. They also provided a complete SCS-CN-based initial abstraction model incorporating all its segments described above. For infiltration only, $\lambda = f_o t_p / S$ or αt_p , where f_o is the initial infiltration rate, t_p is the time to ponding, and α is the infiltration decay parameter analogous to the Horton (1938) infiltration decay parameter.

Among others (for example, Woodward *et al.* 2002; Bonta 1997), Hawkins *et al.* (2002) examined the data-supported values of the I_a/S ratio and suggested accommodations for updating its role employing two techniques, event analysis and model fitting, to determine I_a/S from field data. They used only “large” storms to avoid the biasing effects of small storms towards high CNs . They employed both “natural” and “ordered” data sets to establish a relation between $S_{0.05}$ and $S_{0.20}$ and then convert CNs based on $\lambda = 0.2$ to those based on $\lambda = 0.05$. Here, the subscript 0.05 and 0.2 of S represent λ values. Since λ varied from storm to storm or watershed to watershed, $\lambda = 0.05$ fitted better than $\lambda = 0.2$, which was found to be unusually high. However, the values of median λ varied from 0.0005 to 0.4910, with a median of 0.0476 for the data sets in event analysis. In model fitting, it varied from 0–0.996, with a median of 0 for “natural” data sets, and 0–0.9793 with a median of 0.0618 for “ordered” data sets. $\lambda = 0.05$ was found to significantly affect the low P/S situations, and subsequently, hydrograph structures defined by time and peak values (especially at lower CNs).

It is interesting to note that (from the NRCS website): “. . .each relationship of I_a to S requires a unique set of runoff curve numbers. Simple revision of the relationship of I_a to S to something other than $I_a = 0.2S$ requires more than a simple change of the runoff equation. There is no linear relationship between the runoff curve numbers for the two I_a conditions. It also requires a new set of runoff curve numbers developed from analysis of small watershed data. . .”. Thus, it is probably not justifiable to tweak this relationship as part of the development of a design hydrograph for a site with no calibration data available. If the existing relationship is played with, the standard CN values are no longer valid (Rallison and Miller 1981). Here, it is noted that I_a values were originally derived from rainfall-runoff plots considering I_a as the rain that fell prior to the beginning of direct runoff (SCS 1985). The sources of error associated with these estimates and listed in NEH-4 include the likelihood of some abstracted rainfall to have eventually appeared at the outlet. For example, it is likely that some of this rainfall might have contributed to quick response in tile-drained watersheds (Walker *et al.* 1998). It was for this reason that Rallison (1980) did not recommend its further refinement.

Proposed I_a – S relation and model formulation

It is clear from the above that the selection of a proper λ value or an I_a – S relationship is crucial to accurate estimation of direct runoff from the SCS-CN method. From Equation (3), since I_a is related to S linearly, λ take values in the range $(0, \infty)$, for S values range $(0, \infty)$, consistent with the Mishra and Singh (1999a, 2003) description. Thus, among others, it is also the assumption of linearity in the I_a – S relation which precludes the existing SCS-CN

methodology from being perfectly predictive of direct runoff volume. From the mathematical treatment of Mishra and Singh (1999a) and Mishra et al. (2003), it can be seen that λ varies with $C (= Q/P)$ and the ratio I_a/P . Since C directly reflects the variation of CN (or S) (the larger the CN , the larger C , and vice versa), λ is implicitly correlated with S and P , rather than S alone. Furthermore, being a regional and climatic parameter, $\lambda = 0.2$ is not appropriate for the watersheds other than those used in its derivation. Since precipitation (P) in a way accounts for such climatic/meteorological characteristics of a watershed, the proposed I_a - S relation incorporates it as follows:

$$I_a = \lambda S \left(\frac{P}{P+S} \right)^\alpha \quad (6)$$

where α = a coefficient. Since Equation (6) reduces to Equation (3) for $\lambda = 0.2$ and $\alpha = 0$, the former becomes a generalized form of the latter. Equation (6), when coupled with the water balance equation (Equation (1)) and proportionality hypothesis (Equation (2)), leads to a modified version of the existing SCS-CN methodology.

For testing, Table 1 shows six variants of SCS-CN-inspired models formulated using Equations (3) and (6). In this table, CN is taken as a varying parameter, consistent with the works of Hjelmfelt et al. (1981) and Hjelmfelt (1991) suggesting CN as a random variable. Model M1 represents the existing SCS-CN method with $I_a = \lambda S$ (Equation (3)) relationship and λ is allowed to vary. In Model M2, $\lambda = 0.2$. Models M4 and M5 are particular forms derived from Model M3 utilizing the proposed I_a - S relationship. Models M4 and M5 with different, but fixed, values of “ λ ” and “ α ” derived by trial and error. Model M6 also represents Equation (3) with $\lambda = 0.05$ (Hawkins et al. 2002).

To determine model parameters, the Marquardt (1963) algorithm of constrained least squares approach was employed using the objective function

$$\sum_{i=1}^N (Q - \hat{Q})_i^2 \Rightarrow \text{Minimum} \quad (7)$$

where N is the total number of rainfall-runoff events for a catchment, i is an integer varying from 1 to N , Q is the observed runoff from the data set, and \hat{Q} is the model computed runoff.

For model performance evaluation, the root mean square error (RMSE) was considered. It is expressed as

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Q - \hat{Q})_i^2} \quad (8)$$

where $RMSE$ is an index of the variance between computed and observed runoff values (Madsen et al. 2002; Itenfsu et al. 2003; Moradkhani et al. 2004).

Table 1 Various model formulations considered for the analysis

Model	Parameters			Remarks
	α	λ	CN	
M1	0	Varying		
M2	0	0.2		Existing I_a - S relation; Equation (3)
M3	Varying	Varying	Varying	
M4	1.5	Varying		Modified I_a - S relation; Equation (6)
M5	1.5	0.3		
M6	0	0.05		Hawkins et al. (2002) I_a - S relation; Equation (3)

Model calibration and validation

Data

For model testing, the data were derived from the US Department of Agriculture-Agricultural Research Service (USDA-ARS) Water Database, a collection of rainfall and stream flow data derived from agricultural watersheds of the United States. This database is available on WWW at URL: <http://www.ars.usda.gov/arsdb.html> and <http://hydrolab.arsusda.gov/arswater.html>. There are currently about 16 600 station years of data stored in the database. The existing raingauge networks range from one station per watershed to over 200 stations. However, only 1 raingauge for each watershed was considered in this study, and data for 22 392 storm events from 84 watersheds varying from 0.17–72 ha were used.

The available dataset for each watershed was split into two groups such that the length of data in both calibration and validation was nearly the same and each dataset belonged to the same population. The data were split following two schemes: based on observed precipitation (P) values (P -based), which is an implicit descriptor of meteorological characteristics and widely used in P - Q ordering (Hawkins *et al.* 2002), and based on the observed runoff (Q) (Q -based), an actual descriptor of the runoff-producing feature of watershed. To that end, the data were first sorted based on P (or Q) in descending order, and then alternate rainfall-runoff values were selected and put in two groups, one for calibration and the other for validation, for each watershed.

Parameter estimation

Employing the above Marquardt algorithm, model parameters were estimated utilizing the dataset marked for calibration. Here, the model parameters are treated to be independent of each other, which is a limitation of the study. For all the models studied, the parameter CN was varied in the range (1, 100) with initial value of 80. In Model M1, the value of λ was varied in the range (0, 1) with an initial value equal to 0.05. The values of λ and α in Model M3 ranged from (0, 50) and (-10, 10), respectively, with their initial value as 1.0. $\alpha = 1.5$ in Models M4 and M5 and $\alpha = 0.3$ in Model M5 are specific cases of Model M3. Model M6 with $\alpha = 0$ and $\lambda = 0.05$ represents the Hawkins *et al.* (2002) model. Table 2 summarizes the resulting parameter values in calibration. In this table, as an example, the optimized parameter CN for Model M1 ranged from 58.67 to 91.43 with mean = 81.19, median = 82.73, standard deviation = 6.95, and negative skewness = 1.25. Likewise, the variation of other model parameters can be explained. The following text presents the model calibration and validation using the above P - and Q -based datasets and compares the model performance based on RMSE.

“P-based” dataset. The overall comparative performance of a model is judged based on the mean RMSE value resulting from a model application to all watersheds as well as ranked RMSE values for individual watersheds. Figure 1 depicts the scatter of RMSE values resulting from the application of all six models to the “ P -based” calibration dataset. The resulting average RMSE values of Models M1 to M6 are 4.94, 5.18, 4.80, 4.91, 5.01, and 5.04 mm, respectively. Obviously, the proposed model M3 performs the best of all other model variants. Based on these RMSE values, the decreasing order of performance of all the models can be given as follows:

$$M3 > M4 > M1 > M5 > M6 > M2.$$

Here, the left-hand side model works better than the adjacent right-hand side model.

For quantitative evaluation, the models were ranked (or graded) based on RMSE statistics derived from the data of each watershed. To this end, ranks of 1 to 6 were assigned to the lowest

Table 2 Summary of the optimized parameters of various models in calibration of “P-based” as well as “Q-based” datasets

Dataset	Statistics	M1		M2	M3			M4		M5	M6
		λ	CN	CN	λ	α	CN	λ	CN	CN	CN
“P-based”	Min	0.00	58.67	21.72	0.00	-10.00	45.90	0.13	52.58	29.20	31.81
	Max	1.00	91.43	94.38	50.00	10.00	99.03	5.19	96.96	90.19	88.61
	Mean	0.08	81.19	69.97	14.14	3.89	85.04	1.01	82.80	72.84	73.09
	Median	0.00	82.73	74.08	3.51	2.90	88.16	0.83	84.22	77.49	75.85
	STDV	0.19	6.95	15.98	19.78	3.19	11.32	0.86	9.16	14.00	10.92
	Skewness	3.46	-1.25	-1.18	1.23	-0.24	-0.93	1.83	-0.77	-1.42	-1.40
“Q-based”	Min	0.00	8.47	60.20	0.00	-10.00	35.79	0.00	46.58	23.61	42.20
	Max	0.79	91.73	92.27	50.00	10.00	99.13	3.23	96.47	90.35	89.09
	Mean	0.06	71.57	81.82	10.34	3.50	85.17	0.99	83.52	74.23	74.17
	Median	0.01	74.84	82.90	3.21	2.89	91.07	0.95	86.98	77.40	75.52
	STDV	0.14	14.46	6.30	16.28	3.00	13.81	0.69	10.02	12.81	9.78
		Skewness	3.63	-1.76	-1.24	1.95	-0.40	-1.47	0.69	-1.37	-1.63

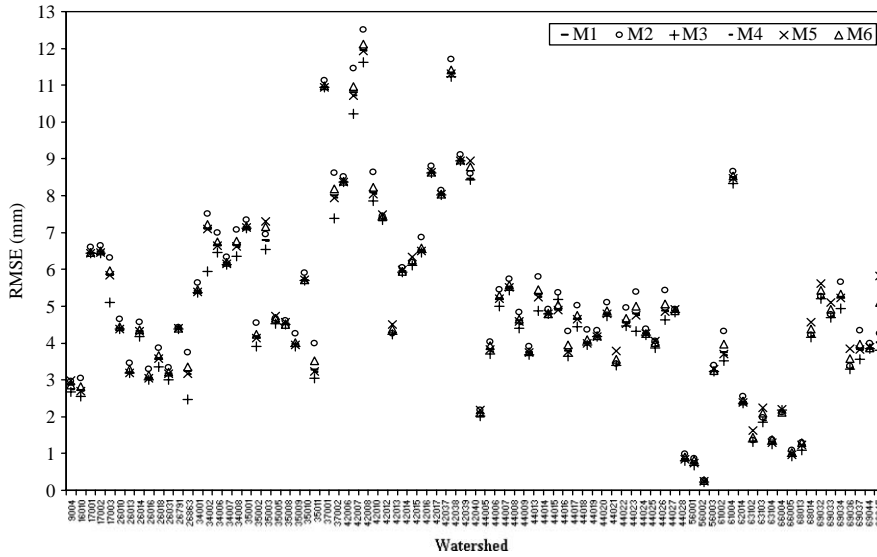


Figure 1 Statistical comparison of models based on RMSE criteria for “P-based” dataset of calibration

to highest (ascending order) *RMSE* values, and corresponding marks of 6 to 1 were given to each watershed. As an example, a model showing the minimum *RMSE* for a watershed was ranked 1, scoring 6 marks. Figure 2 shows the ranking of models for all 84 watersheds.

Based on the above scores secured by each model in its application to the data of each watershed, the total percent scores and corresponding overall ranking were determined, as shown in Table 3. Apparently, the proposed model M3 performs the best based on *RMSE* scoring, and the existing Model M2 the poorest. Based on overall ranking, the decreasing order of performance of the models is as follows:

$$M3 > M4 > M1 > M5 > M6 > M2.$$

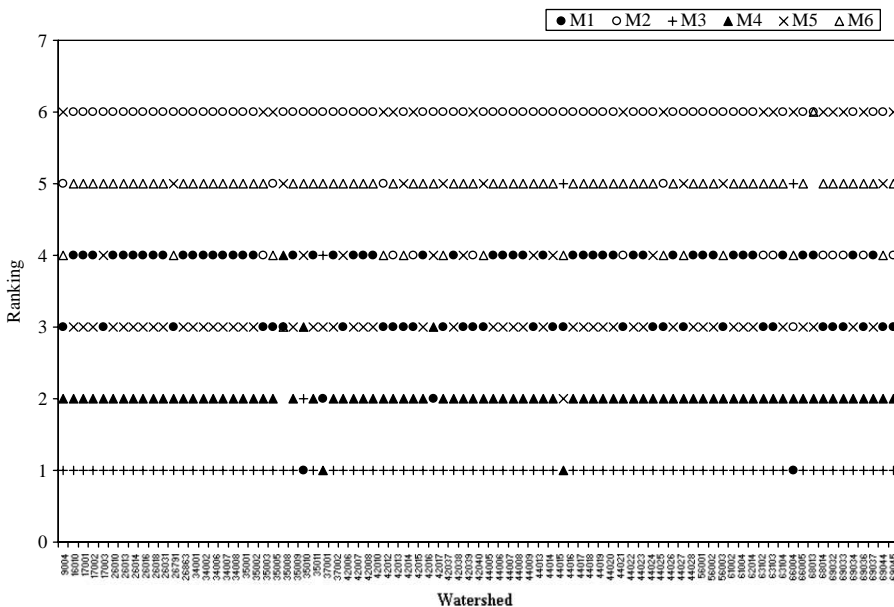


Figure 2 Models ranking based on RMSE for “P-based” dataset of calibration

Table 3 Percent scores and overall ranking for calibration on both data sets based on RMSE

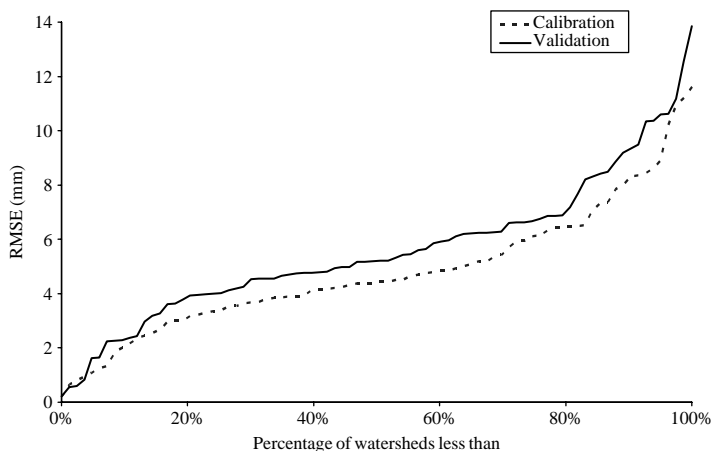
Data set	Calibration	M1	M2	M3	M4	M5	M6
"P-based"	%score (ranking)	58.13 (iii)	22.82 (vi)	97.62 (i)	82.94 (ii)	51.98 (iv)	36.11 (v)
"Q-based"	%score (ranking)	62.1 (iii)	23.61 (vi)	97.82 (i)	79.96 (ii)	46.63 (iv)	39.29 (v)

This is similar to the performance of models based on "mean" *RMSE* criteria. As above, the proposed Model M3 (three-parameter model) performs the best in calibration, with high scores (>95%) in *RMSE*-based evaluation of all models. It is noted that the two-parameter Model M4, which is a particular form of M3, performs better than the existing two-parameter Model M1 (score > 80%). In one parameter category, Model M5 performs better than M6 and M2, with score > 50%. As expected from Hawkins *et al.* (2002) analysis, Model M6 ($\lambda = 0.05$) performs better than Model M2 ($\lambda = 0.2$). Here, as expected, the performance deteriorates with reduction in the number of parameters.

For testing, the validation dataset was utilized to compute *RMSE* for all the models. A comparative performance of M3 (three-parameter model) and M5 (one-parameter model) in calibration and validation is presented in Figures 3 and 4, respectively. Figure 3 shows that, for Model M3, 90% watersheds have *RMSE* values less than 8.3 mm in calibration, whereas these are less than 9.3 mm in validation, and 50% watersheds have *RMSE* less than 4.4 mm and 5.2 mm in calibration and validation, respectively. Since the validation results are generally poorer than the calibration results, the closeness of these *RMSE* values (from calibration and validation) indicates, in relative terms, a satisfactory model performance. A similar inference can be drawn from Figure 4. Such an assertion is, however, further checked on a sample (*Q*-based) dataset derived differently.

"*Q*-based" dataset. Figure 5 shows the *RMSE* values derived using a *Q*-based dataset in calibration. The resulting mean *RMSE* values of Model M1 to M6 are 5.11, 5.30, 5.02, 5.08, 5.16, and 5.17 mm, respectively. Thus, the decreasing order of model performance is the same as for the above "*P*-based" dataset. As seen from Table 3 showing the results of ranking and scoring, as above, Model M3 performs the best, and M2 the poorest. Models M4, M1, M5, and M6 are ranked as 2nd, 3rd, 4th, and 5th, respectively, similar to "*P*-based" analysis.

Figures 6 and 7 show the *RMSE* values in calibration and validation, respectively, of Models M3 and M5. Here, it is noted that these models perform almost equivalently in

**Figure 3** Calibration and validation *RMSE* comparison of Model M3 for "*P*-based" dataset

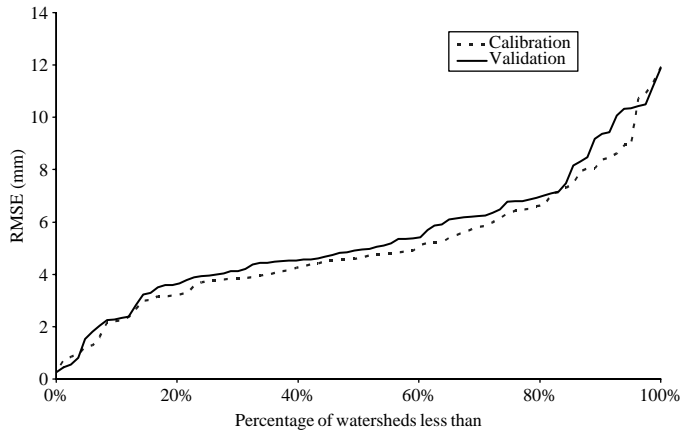


Figure 4 Calibration and validation *RMSE* comparison of Model M5 for “*P*-based” dataset

calibration and validation, in contrast to that in “*P*-based” analysis. Figure 6 shows nearly 90% and 50% of watersheds to yield *RMSE* values less than 8.4 mm and 4.5 mm, respectively, in calibration of Model M3, while their respective values are 8.3 mm and 4.9 mm in its validation. Figure 7 also leads to similar results. Thus, the greater closeness (than that in *P*-based grouping) of these values reasonably affirms not only a more satisfactory model performance but also indicates *Q*-based data grouping to be more appropriate for model testing than is the *P*-based data grouping. For relative evaluation of model performance on a larger dataset, the same analysis was repeated with a full dataset (only calibration), in what follows.

Performance evaluation on full dataset

Table 4 summarizes the results on a full dataset and Figure 8 compares all the models using *RMSE* values. Based on the mean *RMSE* values of Model M1 to M6, which are 5.10, 5.31, 5.02, 5.09, 5.13, and 5.16 mm, respectively, the models can be ranked as follows:

$$M3 > M4 > M1 > M5 > M6 > M2.$$

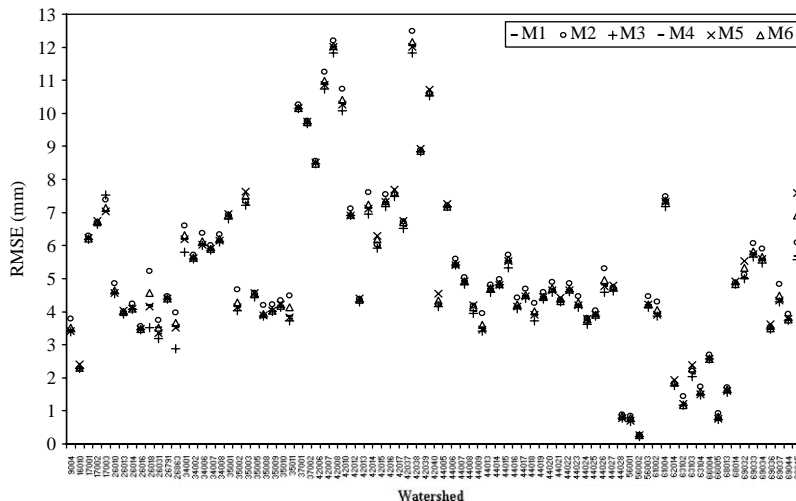


Figure 5 Statistical comparison of models based on *RMSE* criteria for “*Q*-based” dataset of calibration

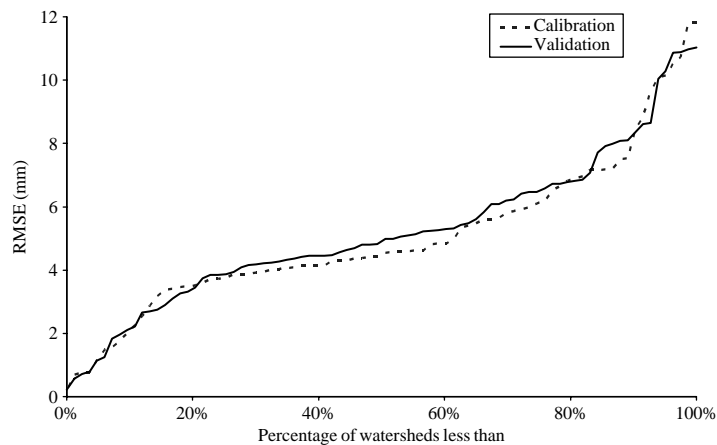


Figure 6 Calibration and validation *RMSE* comparison of Model M3 for “Q-based” dataset

It is generally consistent with the above analysis results derived from split data. The results of model ranking based on their scores (Table 5) indicate Model M3 to perform the best, and M2 the poorest. Models M4, M1, M5, and M6 rank as second to fifth, respectively.

Figure 9 compares the observed runoff values with the ones computed using Models M1 through M6 for watershed-26018. Model M2 (existing I_a-S relation with $\lambda = 0.2$) can be seen to perform most poorly, producing “zero” runoff for most low rainfall-runoff events, in contrast to other models. Model M1 shows greater scatter than does Model M3 (with the proposed I_a-S relationship) and M4, indicating the three-parameter model M3 to perform better than Model M4. In the two-parameter category, Model M4 (a particular form of M3) performs the best, and it is M5 which performs the best in the one-parameter category. The last being a one-parameter model, consistent with the existing SCS-CN model, it can be recommended for field use. Here, it is in order to evaluate these models using the observed initial abstraction (I_a) data.

Evaluation based on observed I_a data

Hawkins *et al.* (2002) examined the λ variation on a large set of data and recommended $\lambda = 0.05$ (Model M6) against the existing $\lambda = 0.2$ (Model M2). Notably, the I_a-S relationship was considered the same as Equation (3). I_a values were calculated by summing

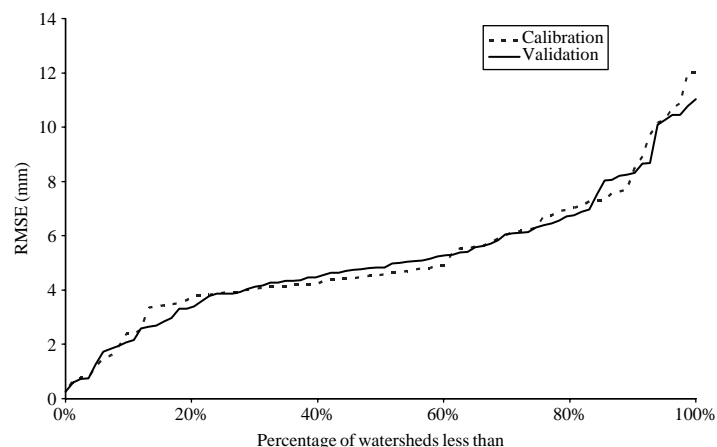


Figure 7 Calibration and validation *RMSE* comparison of Model M5 for “Q-based” dataset

Table 4 Summary of the optimized parameters on full data set of various models

Statistics	M1		M2	M3			M4		M5	M6
	λ	CN		CN	λ	α	CN	λ		
Min	0.00	13.04	61.56	0.00	-1.98	40.12	0.00	54.70	29.23	45.73
Max	1.00	89.97	92.08	50.00	10.00	98.97	2.28	95.95	90.17	88.96
Mean	0.04	69.79	81.57	11.06	3.71	82.44	0.79	81.58	73.40	73.74
Median	0.00	73.50	82.22	2.76	2.67	84.44	0.72	82.34	77.41	75.78
STDV	0.13	14.28	6.13	17.02	3.43	13.01	0.60	8.71	12.95	9.37
Skewness	5.62	-1.59	-1.01	1.62	0.74	-1.14	0.61	-0.83	-1.41	-0.95

up the rainfall depth of an event to the point where direct runoff hydrograph began, as shown in Figure 10 (Hawkins *et al.* 2002). From these values, S values were computed from Equation (4). Consistent with the analysis of Hawkins *et al.* (2002), only those watersheds containing more than 20 events of $P-I_a \geq 25.4$ mm (= 1 inch) and $S \geq 0$ were selected. Only 61 out of 84 watersheds satisfied this criterion. In contrast to the “median” λ value, the optimized λ value was considered as the representative value for a watershed. Analogous to the above (Equation (7)), the sum of squares of the difference between observed and computed values of I_a was minimized in optimization. The results are presented in Table 6. For Model M1, the resulting standard deviation from the data of 132 ARS watersheds is 0.08 (Hawkins *et al.* 2002), and it is 0.04 for 61 of these watersheds, approximately half of the former.

Considering the same *RMSE* as a goodness-of-fit criterion (Table 7), the models can be ranked as follows:

M3 > M4 > M5 > M1 > M6 > M2.

Consistent with the results of split and full datasets, Model M2 performed most poorly, because of a very high λ (= 0.2) value, in conformity with the inference of Hawkins *et al.* (2002). Table 8 showing the percentage of overall scores and *RMSE*-based model ranks indicate Model M3 to perform the best, and M2 the poorest. Models M4, M5, M1, and M6 rank second to fifth, respectively. Here, it is important to note that M6 proposed by Hawkins *et al.* (with $\lambda = 0.05$) performs poorer than all the other models, except M2.

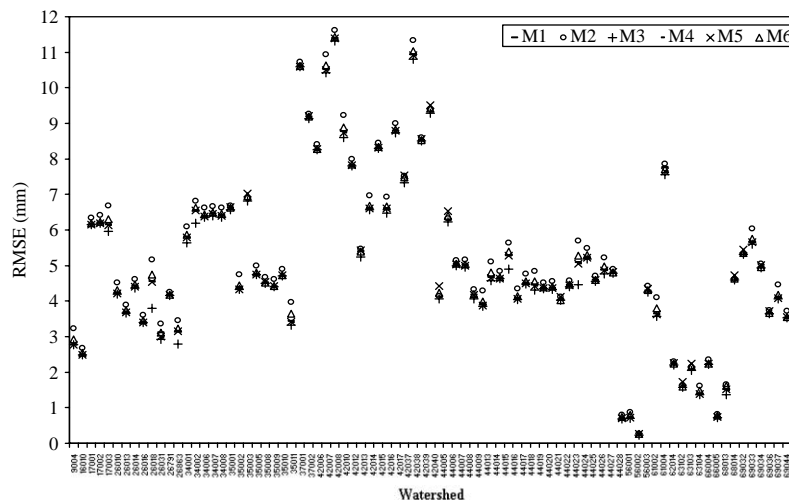
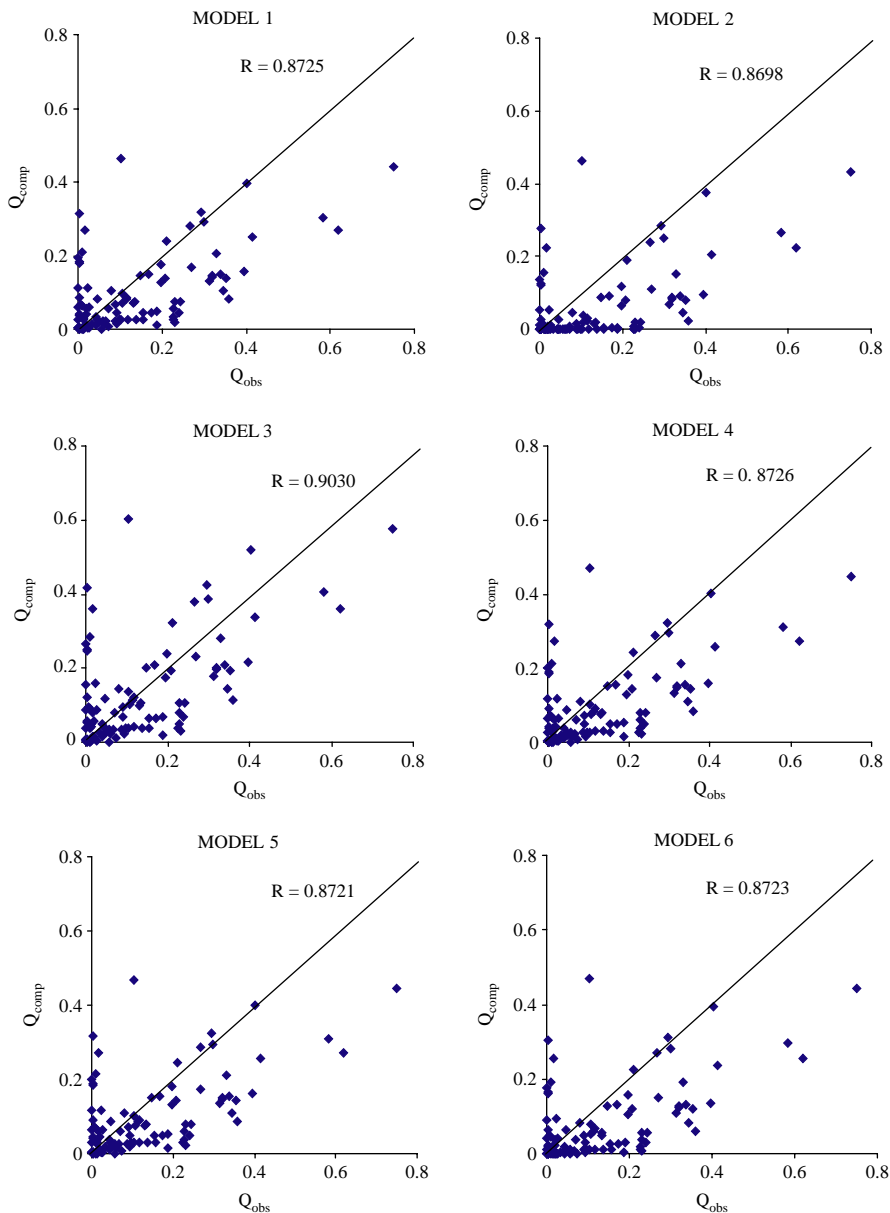
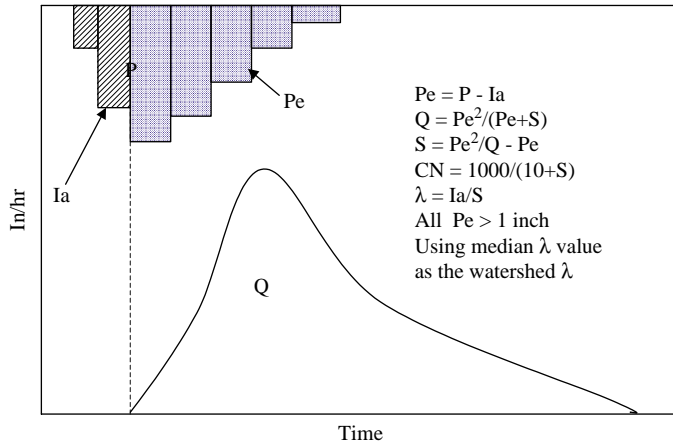
**Figure 8** *RMSE* comparison of models for full dataset

Table 5 Per cent scores and overall rankings for full data set based on RMSE criteria

Models	M1	M2	M3	M4	M5	M6
%score	58.13	20.24	100	78.97	54.37	38.1
Overall ranking	III	VI	I	II	IV	V

Thus, it is evident from the above analysis that the proposed I_a-S relationship (Equation (6)) performs significantly better than all the other models. It, however, requires the determination of 3 parameters (CN , λ , and α) for application. On the other hand, Model M5, a one-parameter model, fairly close to Model M3 in performance, is noteworthy and can be

**Figure 9** Scatter plot for WS 26018 for models M1, M2, M3, M4, M5, and M6



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Figure 10 Event analysis method (Hawkins et al. 2002)

Table 6 Summary of the optimized parameters of models based on Hawkins et al. (2002) methodology

Statistics	M1	M3		M4
	λ	λ	α	λ
Min	0.00	0.09	0.82	0.00
Max	0.21	5.40	7.20	1.08
Mean	0.02	0.63	1.66	0.43
Median	0.01	0.33	1.26	0.35
STDV	0.04	0.83	1.09	0.29
Skewness	3.00	3.90	3.06	0.72

Table 7 Statistical summary of models based on RMSE criteria for Hawkins et al. (2002) methodology

Models	Min	Max	Mean	Median	STDV	Skewness
M1	3.0148	19.89	9.45	8.21	3.76	0.84
M2	7.0723	11904.08	545.41	99.19	1666.97	5.71
M3	2.5999	13.28	6.63	6.21	2.57	0.60
M4	2.6977	16.76	7.47	7.23	2.99	0.87
M5	3.0164	17.84	7.78	6.72	3.54	0.87
M6	5.0346	2975.24	137.13	23.18	416.18	5.72

Table 8 Percentage of scores and overall rankings for Hawkins et al. (2002) methodology

Models	M1	M2	M3	M4	M5	M6
%score	51.64	17.76	100	74.32	73.77	32.51
Overall ranking	IV	VI	I	II	III	V

recommended for field applications. In the two-parameter model category, Model M4 (with varying λ and $\alpha = 1.5$) is somewhat better than M1.

Conclusions

The following conclusions can be derived from the study:

1. The proposed three-parameter Model M3 containing the proposed I_a-S relationship performed the best of all the other five variants considered in the study, including the existing I_a-S relationship in Models M1 and M2.
2. Model M3 performed better on “ Q -based” datasets than on “ P -based” datasets in both calibration and validation, the best on a full dataset as well as on the data utilizing observed initial abstraction. On the other hand, the existing SCS-CN method with $\lambda = 0.2$ (Model M2) generally performed significantly poorer than all other models.
3. Based on the relative performance on different data sets, Models M5 (with $\lambda = 0.3$ and $\alpha = 1.5$) and M4 (with $\alpha = 1.5$) in the one- and two-parameter categories, respectively, can be recommended for field use.

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