Comparison of antecedent precipitation based rainfall-runoff models
Pankaj Upreti and C. S. P. Ojha

ABSTRACT

The Soil Conservation Service Curve Number (SCS-CN) method is one of the popular methods for calculating storm depth from a rainfall event. The previous research identified antecedent rainfall as a key element that controls the non-linear behaviour of the model. The original version indirectly uses five days antecedent rainfall to identify the land condition as dry, normal or wet. This leads to a sudden jump once the land condition changes. To obviate this, the present work intends to improve the performance of antecedent rainfall-based SCS-CN models. Two forms of SCS-CN model (M1 and M2), two recently developed P-P5 based models (M3 and M4), and an alternate approach of considering P5 in the SCS-CN model (M5 and M6), as proposed here, were investigated. Based on the evaluation of several error metrics, the new proposed model M6 has performed better than other models. The performance of this model is evaluated using rainfall-runoff events of 114 watersheds located in the USA. The median value of Nash-Sutcliffe Efficiency was found as 0.78 for the M6 model followed by M5 (0.75), M3 (0.73), M4 (0.72), M2 (0.63) and M1 (0.61) model.

Key words | antecedent runoff condition (ARC), maximum potential retention, optimization, SCS-CN method, surface runoff estimation, US watersheds

HIGHLIGHTS

- The study has been done on significant runoff producing events for which runoff coefficient is greater than 0.12.
- Research supports the superior performance of the proposed model in US watersheds.
- It acknowledges the applicability of five days antecedent rainfall (P5) on runoff prediction and shows improvement in model performance under all statistical indices.

GRAPHICAL ABSTRACT

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (http://creativecommons.org/licenses/by/4.0/).

doi: 10.2166/ws.2020.315
ABBREVIATIONS

SCS-CN  Soil Conservation Service Curve Number
AMC   antecedent moisture condition
ARC   antecedent runoff condition
CN    curve number
S     potential maximum retention
NEH-4 National Engineering Handbook-Section 4
I_a   initial abstraction
\(\lambda\) initial abstraction coefficient
USDA-ARS United States Department of Agriculture-Agricultural Research Service
RMSE  root mean square error
NSE   Nash-Sutcliffe Efficiency
PBIAS percentage bias
RGS   rank and grading system

INTRODUCTION

In surface water hydrology, the correct estimation of runoff is arguably the most important assignment for hydrologists and water scientists. This is useful in water supply, water allocation, hydrological analysis, watershed management, flood forecasting, flood protection work, integrated water management, control of non-point source pollution, etc. The runoff amount depends on rainfall intensity and its amount, wetness condition of the soil, watershed slope, various abstractions, land use, land cover, and many more factors. Hewlett et al. (1977) developed a rainfall-runoff relationship for a forest catchment and found negligible effects of rainfall intensity on peak discharge and runoff volume. Several studies have been conducted at event scale on various catchments of Europe to understand surface runoff generation process (Jordan 1994; Meyles et al. 2003; Latron et al. 2008). In case of events having both low-intensity rainfall and low-rainfall magnitude, the antecedent wetness state plays a major role in controlling runoff amount than rainfall intensity or its magnitude and a more precise and correct estimate can be achieved by using antecedent rainfall characteristics. If the joint dependence between rainfall event and antecedent precipitation is not taken into account properly, the runoff amount is consistently underestimated and when only one or two days’ antecedent rainfall is considered, the magnitude of design flood can be as much as 30% less than actual (Pathiraja et al. 2012). The impact of prior rainfall of 48 hrs to 120 hrs of a rainfall event is more significant in determining the resulting runoff compared to other factors such as average and maximum rainfall intensity, event magnitude, and rainfall duration.

The relationship of intensity of storm event with antecedent moisture condition has become an increasing research subject in the context of anthropogenic climate change. To understand the role of antecedent moisture in rainfall runoff modelling, a tank experiment has been conducted based on high resolution observation in Hohai University, China, and a non-linear relationship was observed between soil moisture index and total runoff (Song & Wang 2019). If a model is calibrated without considering the impact of prior rainfall on the land surface, there will be a high likelihood that calibrated parameters will not produce the correct runoff yield. The water content in the upper soil surface may be an important factor in the rainfall-runoff relationship. A relatively lower sensitivity of antecedent rainfall on surface runoff has been found, maybe, due to the relatively dry upper surface in semiarid small watersheds located in Southeastern Arizona in the USA, contrary to other reported results (Zhang et al. 2014). A soil moisture accounting procedure was proposed by Michel et al. (2003) but criticized by Sahu et al. (2007) for not circumventing an undesirable sudden jump. Verma et al. (2020) conceptualized a theory of activation soil moisture (ASM) by coupling the infiltration component with the Soil Moisture Accounting (SMA) concept. The rainfall intensity, state of antecedent moisture and process of surface runoff are the three main reasons which evolve spatial and temporal non-linearity and complicate the watershed response. Most of the research shows that the rainfall-to-runoff transformation process is non-linear and the prime factor of nonlinearity is the antecedent moisture condition.
(Radatz et al. 2013; Zhao et al. 2015). This antecedent moisture, along with soil characteristics, regulates the runoff process and affects the capability to store new water due to the occurrence of rainfall as well as the infiltration capacity of the soil (Merz & Blöschl 2009). It is a challenging task to evaluate the impact of antecedent rainfall on runoff at a watershed scale and it is required in the planning and management of a watershed.

There are distinct mathematical models available in hydrology with various merits, demerits and complications. The SCS-CN method is the simplest and universally accepted model for event-based rainfall-runoff modeling and integrated with various hydrological, water quality, or erosion estimation models. After a long experimental work, this method was developed for conditions prevailing in the USA. The model requires only maximum potential storage (S, mm) of the watershed in the form of a curve number (CN) to calculate runoff depth. Generally, soil type, land use and adopted practices are not much changed, but antecedent moisture condition status is changed frequently with the antecedent rainfall amount, which affects the runoff flow pattern. Antecedent moisture condition (AMC) classes were re-labelled as antecedent runoff condition (ARC) classes (NRCS 2004). The observation and monitoring of soil moisture are difficult; that is why antecedent precipitation, which can address initial soil moisture status by using five days of rainfall (Brocca et al. 2008), is in common use. This term is used as a predictor to decide the antecedent runoff condition, which is categorized in three levels i.e. ARC I (dry), ARC II (normal), and ARC III (wet). These levels form a discrete relation between antecedent rainfall and curve number and are responsible for an undesirable sudden jump in runoff estimation (Mishra et al. 2008). Generally, the CN value obtained from NEH-4 table or calculated from the P-Q dataset is CNII (normal) and can be converted into CNI (dry) or CNIII (wet) as per the antecedent rainfall amount. The CN model uses the antecedent five-day rainfall to categorize it into either dry, normal, or wet conditions to account for watershed initial losses (Sahu et al. 2007).

To obviate the error in predicting runoff calculations due to the sudden jump in curve number value, consideration of pre-storm rainfall is required in event-based runoff modelling, which minimizes the error and tries to correct the runoff value. This study has been done to evaluate the relative significance of antecedent precipitation (P5) on the calculated runoff amount. Very few studies have been done to investigate the effect of antecedent rainfall on runoff behaviour. This is assessed using six variants of models, which are introduced here.

**SCS-CN MODEL (M1 AND M2)**

The original SCS-CN equation (USDA 1985) calculates runoff depth directly using rainfall data. This universally accepted equation is well documented, easy to understand, and useful due to its simplicity. This water balance equation, based on two assumptions, is expressed, respectively, as follows:

\[
\frac{Q}{P-I_a} = \frac{F}{S} \quad (1)
\]

\[
I_a = \lambda S \quad (2)
\]

where \(P\) and \(Q\) are rainfall and runoff depth in mm, \(I_a\) is an initial abstraction, \(F\) is cumulative filtration which is equal to \(P-I_aQ\) and \(S\) is maximum potential retention in mm. After simplification of the above-stated assumptions, the expression is as follows:

\[
Q = \frac{(P-\lambda S)^2}{[P - (1-\lambda)S]} \quad \text{if } P > I_a \text{ or } \lambda S, \text{ otherwise } Q = 0 \quad (3)
\]

\(\lambda\) value can vary from 0 to 1 but assumes as 0.2, while \(S\) value in mm varies from 0 to 20. A dimensionless curve number (CN) for any watershed can be used to estimate \(S\) by using the following equation:

\[
S = \frac{25400}{\text{CN}} - 254 \quad (4)
\]

In addition, \(S\) can be directly obtained (\(\lambda = 0.2\)) using a gauged dataset of \(P\) and \(Q\) by solving Equation (3) with the quadratic equation as:

\[
S = 5[(P + 2Q) - (4Q^2 + 5PQ)^{0.5}] \quad (5)
\]

This Equation (5) produced a data-derived value of \(S\) (normal condition or \(S_2\)). Hawkins (1995) suggested a median CN value gives a better representation of the curve...
number ($\lambda = 0.2$) of any watershed using the $P$-$Q$ dataset. Two mathematical equations proposed by Mishra et al. (2008) can be used to convert $\text{CN}_{II}$ or $S_I$ to $\text{CN}_I$ ($S_I$) and $\text{CN}_{III}$ ($S_{III}$) for dry (ARC I) or wet conditions (ARC III), respectively. These are:

$$S_I = 2.2754 S_{II}$$  \hspace{1cm} (6)

$$S_{III} = 0.43 S_{II}$$  \hspace{1cm} (7)

The conversion of $S_{II}$ to $S_I$ or $S_{III}$ depends on the previous 5 days' rainfall. The value of $P_5 < 35.6$ mm, $35.6$ mm $\leq P_5 \leq 53.3$ mm, and $P_5 > 53.3$ mm assumes dry, normal, or wet conditions, respectively, for any storm event.

### AJMAL & KIM MODEL (M₃ AND M₄)

Ajmal & Kim (2015) proposed two new equations and investigated runoff prediction over 15 South Korean catchments. These two equations are as follows:

$$Q = \frac{P^2}{P + S} \frac{P + P_5}{S^2}$$  \hspace{1cm} (8)

$$Q = \frac{P^2}{P + S} - \frac{P_5}{S}$$  \hspace{1cm} (9)

It is to be noted that in both the above equations, Equations (8) and (9), $S$ is the only unknown parameter. These equations are unique in nature and also exclude $\lambda$. Their performance were found to be significantly better than the SCS-CN model for the studied catchments. Equations (8) and (9) directly used $P_5$ value instead to decide antecedent conditions as dry, normal, or wet before rainfall and to some extent were able to overcome the sudden jump in runoff computation. To check its applicability in other watersheds, similar equations are to be used in this study by utilizing the P-P$_5$ dataset of 114 US watersheds.

### PROPOSED MODEL (M₅ AND M₆)

The previous research suggested antecedent rainfall as a key component. The original model considers antecedent rainfall only to classify the land condition as dry, normal, or wet and ignored the exact amount of 5 days' prior rainfall ($P_5$) which creates an undesirable sudden jump in runoff computation. This can be explained by an example. If we assume a rainfall amount of 100 mm (which occurs in the growing season) over different land conditions with CN values as 60, 70, 80, and 90; and the antecedent five days rainfall variation from 1 to 100 mm. These CN values have been assumed, since for most of the watersheds its value falls in between 55 to 95 (Hawkins et al. 1985).

From Figure 1 (assuming $\lambda = 0.2$ and using Equation (3), it can be seen that the calculated values of runoff are 1.29 mm for ARC I ($P_5 < 35.6$ mm, $\text{CN} = 60$ or $S = 385.30$ mm), 18.57 mm for ARC II ($P_5 = 35.6$ mm to 53.3 mm, $\text{CN} = 60$ or $S = 169.33$ mm), and 46.13 mm for ARC III ($P_5 > 53.3$ mm, $\text{CN} = 60$ or $S = 72.81$ mm). It means if five days' prior rainfall value changes the antecedent rainfall condition from ARC I to ARC II, the runoff value suddenly jumps from 1.29 mm to 18.57 mm for 100 mm rainfall. Similarly, shifting the antecedent state from ARC II to ARC III, runoff jumps from 18.57 mm to 46.13 mm. Similar jumps are illustrated in Figure 1 at $\text{CN} = 70$, 80, and 90 for ARC I, ARC II and ARC III. This undesirable jump is due to the indirect use of $P_5$ and it reduces the model efficiency.

![Figure 1](http://iwaponline.com/ws/article-pdf/21/5/2122/920324/ws021052122.pdf)
In the proposed model, instead of only selecting antecedent rainfall conditions (ARC), $P_5$ is incorporated directly as a model component. This is done by replacing $S$ with $S_{P} = \frac{P + P_5}{P + P_5}$ and placing it in the original SCS-CN equation with the sole objective of improving runoff prediction. In this fashion, the replacement of $S$ will ensure the change in watershed characteristics ($S$) with different rainfall depth and $P_5$ value; and will avoid the chances of an unexpected jump in runoff calculation. The proposed model gives the following equation as:

$$Q = \frac{P - \lambda S \left( \frac{P}{P + P_5} \right)^2}{P + (1 - \lambda)S \left( \frac{P}{P + P_5} \right)}$$

(10)

After simplification, Equation (10) yields

$$Q = \frac{(P + P_5 - \lambda S)^2}{(P + P_5 + (1 - \lambda)S)} \cdot \frac{P}{(P + P_5)}$$

(11)

$\lambda = 0.2$ makes Equation (11) as:

$$Q = \frac{(P + P_5 - 0.2S)^2}{(P + P_5 + 0.8S)} \cdot \frac{P}{(P + P_5)}$$

(12)

This expression provides variation in the $S$ value and such replacement changes the runoff value only for those events for which $P_5$ is greater than zero. With increasing or decreasing $P_5$, the $S$ value changes significantly. If there is no capacity to store water in the soil, whole rain will convert into runoff i.e. $S \to 0$. Similarly, if the $S$ value tends to infinity ($CN \to 0$), all water goes for storage and there will be no runoff. Thus, these two boundary conditions are satisfied using this empirical model. For improving the model performance, instead of a fixed $\lambda$ value, it can also be obtained after optimization. The best $\lambda$ value obtained was zero in the tested watersheds, which leads to further simplification of Equation (11) as:

$$Q = \frac{P(P + P_5)}{(P + P_5 + S)}$$

(13)

This equation is a version of the SCS-CN equation with incorporating $P_5$ and represents a simplified form of model $M_6$. The different models using $P_5$ value either directly or indirectly and related equations are also summarized in Table 1.

### MATERIAL AND METHODS

#### Study area and data selection criteria

This study has been done over 114 US watersheds having areas varying from 0.17 ha to 30,351.45 ha. Data is taken

| S.No. | Model | Equation to be used and description of model | Remarks |
|-------|-------|---------------------------------------------|---------|
| 1.    | $M_1$ | According to the P-Q dataset, determine $S$ for individual storms using Equation (5). The median value of $S$ for the whole dataset was calculated, which represented watershed $S$ at normal condition. The runoff depth was calculated using Equation (3) at $\lambda = 0.2$. $S$ can be converted using Equation (6) or Equation (7) based on antecedent condition as normal, dry or wet. | SCS-CN model (USDA 1985) |
| 2.    | $M_2$ | $S$ value was optimized using Equation (3) at $\lambda = 0.2$, according to antecedent normal, dry, or wet condition which is decided based on $P_5$ value and using Equation (5), Equation (6), or Equation (7) respectively. | SCS-CN model (NRCS 2004) |
| 3.    | $M_3$ | Equation (8) was used which directly consider $P_5$ and optimized $S$ value | Ajmal model (Ajmal & Kim 2015) |
| 4.    | $M_4$ | Equation (9) was used which directly consider $P_5$ and optimized $S$ value | Ajmal model (Ajmal & Kim 2015) |
| 5.    | $M_5$ | Optimized $S$ value with $\lambda = 0.2$ using Equation (12) | Proposed model |
| 6.    | $M_6$ | Optimized $S$ value with varying $\lambda$ using Equation (11) | Proposed model |
from the United States Department of Agriculture-Agricultural Research Service (USDA-ARS) database which is a collection of storm depth (P mm), runoff depth (Q mm), and antecedent five days rainfall (P₅ mm) and generated from the breakpoint rainfall-runoff dataset. The information of watershed ID with its serial number, situated location, and states have been provided in Table 2. The average storm depth (P), average runoff depth (Q) and average antecedent rainfall value (P₅) in mm unit for different watersheds are illustrated in Figure 2(a). In addition, the drainage area of different watersheds (ha) in log scale and number of available and selected events for this study are presented in Figure 2(b).

Hawkins et al. (1985, 2008) suggested that only larger storms (P/S ≥ 0.46) should be used for better runoff prediction. This condition increases the chances of producing runoff by more than 90% and minimizes the biasing effect. Later, some other studies have been performed and support these criteria (Stewart et al. 2012; Ajmal & Kim 2015). In this study, the same criteria were used but in a different way. For doing this, the original equation of SCS-CN model can be reformulated into the following form as:

\[
Q = \frac{P}{S} - 0.2 \right)^2
\]

Here, P/S = 0.46 put into Equation (14), and finds Q/P as 0.12. It mean we can replace P/S ≥ 0.46 by Q/P ≥ 0.12. Thus, this study excluded lower runoff producing rainfall events (runoff coefficient value is less than 0.12) and sorted only those events for which C > 0.12. After adopting this criterion out of 28,849 events of 114 US watersheds, 11,784 events were selected for this study.

Parameter estimation

To obtain the best possible results with different models, optimization has been carried out by minimizing the sum of the square difference between observed and computed runoff employing Microsoft Excel (Solver) and using Equation (15). The main intention of optimization is to obtain a realistic and conceptually unique value of model parameter (Lal et al. 2015).

\[
\sum \frac{(Q_{oi} - Q_{ci})^2}{(15)} \Rightarrow Minimum
\]

Model M₁ used a fixed value of S (using Equation (3)) while the rest of the models obtained their S value through the optimization process. The initial estimate of S in the M₂ model was taken as 125 mm and allowed to vary in between 1 and 500, while in other models S was allowed to vary in the range of 1 to 1,000 with an initial estimate of 250 mm. Model M₆ optimized both the S and λ value. In the M₆ model, the initial estimate of λ was assumed as 0.05 and permitted to vary between 0 and 1. The statistical summary of S and λ value for different models are presented in Table 3.

Performance evaluation

The statistical indices-based assessment has been done to analyze the performance of different models. The root mean square error (RMSE), Nash-Sutcliffe Efficiency (NSE), percent bias (PBIAS), and n(t) criteria have been used on 114 US watersheds to evaluate the performance of different models. The mathematical equation of these criteria are respectively given below:

\[
RMSE = \left( \frac{1}{n} \sum_{i=1}^{n} (Q_{oi} - Q_{ci})^2 \right)^{1/2}
\]

\[
NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{oi} - Q_{ci})^2}{\sum_{i=1}^{n} (Q_{oi} - \bar{Q}_{oi})^2}
\]

\[
PBIAS = \frac{\sum_{i=1}^{n} (Q_{oi} - Q_{ci})}{\sum_{i=1}^{n} (Q_{oi})}
\]

\[
n(t) = \frac{SD_{OR}}{RMSE} - 1
\]

where Q_{oi}, Q_{ci} and SD_{OR} are observed runoff, computed runoff and variation in observed runoff given by standard deviation, respectively and i is an integer varying from 1 to N. The n(t) value depicts the number of times the cumulative variation in mean observation is more than the mean error.
Table 2 | Different watersheds ID’s with S.No., location, state and goodness of fit of different models based on NSE (Nash-Sutcliffe Efficiency) and RGS (Rank and grading system)

| S. No. | WS ID | Location | State   | M₁   | M₂   | M₃   | M₄   | M₅   | M₆   | Obtained score based on rank |
|--------|-------|----------|---------|------|------|------|------|------|------|-------------------------------|
| 1      | 9004  | Americus | Georgia | Neg  | 0.26 | 0.69 | 0.67 | 0.76 | 0.88 | 1 2 4 3 5 6                 |
| 2      | 13007 | Blacksburg | Virginia | Neg  | Neg  | 0.08 | 0.08 | Neg  | Neg  | 1 2 6 5 3 4                 |
| 3      | 13008 | Blacksburg | Virginia | Neg  | 0.62 | 0.89 | 0.89 | 0.79 | 0.92 | 1 2 5 4 3 6                 |
| 4      | 13009 | Blacksburg | Virginia | 0.42 | 0.44 | 0.67 | 0.67 | 0.53 | 0.65 | 1 2 6 5 3 4                 |
| 5      | 13010 | Blacksburg | Virginia | Neg  | Neg  | 0.57 | 0.56 | 0.21 | 0.59 | 1 2 5 4 3 6                 |
| 6      | 13012 | Blacksburg | Virginia | 0.13 | 0.13 | 0.58 | 0.57 | 0.41 | 0.61 | 1 2 5 4 3 6                 |
| 7      | 13014 | Blacksburg | Virginia | 0.83 | 0.87 | 0.95 | 0.95 | 0.92 | 0.94 | 1 2 6 5 3 4                 |
| 8      | 13015 | Blacksburg | Virginia | Neg  | Neg  | 0.89 | 0.89 | 0.66 | 0.90 | 1 2 5 4 3 6                 |
| 9      | 17001 | Edwardsville | Illinois | 0.75 | 0.75 | 0.79 | 0.78 | 0.80 | 0.82 | 1 2 4 3 5 6                 |
| 10     | 17002 | Edwardsville | Illinois | 0.72 | 0.72 | 0.77 | 0.76 | 0.79 | 0.80 | 1 2 4 3 5 6                 |
| 11     | 17003 | Edwardsville | Illinois | 0.72 | 0.72 | 0.72 | 0.71 | 0.78 | 0.80 | 2 4 3 1 5 6                 |
| 12     | 17004 | Edwardsville | Illinois | 0.70 | 0.70 | 0.81 | 0.80 | 0.80 | 0.84 | 1 2 5 3 4 6                 |
| 13     | 19001 | Lafayette | Indiana  | Neg  | Neg  | 0.07 | Neg  | 0.15 | 0.39 | 1 2 4 3 5 6                 |
| 14     | 19004 | Lafayette | Indiana  | 0.55 | 0.57 | 0.58 | 0.56 | 0.63 | 0.68 | 1 3 4 2 5 6                 |
| 15     | 19005 | Lafayette | Indiana  | 0.81 | 0.84 | 0.84 | 0.83 | 0.86 | 0.87 | 1 4 3 2 5 6                 |
| 16     | 19006 | Lafayette | Indiana  | 0.29 | 0.29 | 0.51 | 0.45 | 0.43 | 0.58 | 1 2 5 4 3 6                 |
| 17     | 19007 | Lafayette | Indiana  | 0.50 | 0.57 | 0.65 | 0.64 | 0.65 | 0.73 | 1 2 5 3 4 6                 |
| 18     | 19008 | Lafayette | Indiana  | 0.78 | 0.79 | 0.81 | 0.78 | 0.84 | 0.84 | 2 3 4 1 5 6                 |
| 19     | 19009 | Lafayette | Indiana  | 0.77 | 0.83 | 0.78 | 0.76 | 0.87 | 0.88 | 2 4 3 1 5 6                 |
| 20     | 19010 | Lafayette | Indiana  | 0.85 | 0.85 | 0.83 | 0.80 | 0.90 | 0.90 | 3 4 2 1 5 6                 |
| 21     | 19011 | Lafayette | Indiana  | 0.81 | 0.85 | 0.89 | 0.87 | 0.91 | 0.91 | 1 2 4 3 5 6                 |
| 22     | 22003 | Fourmile CK | Iowa  | 0.40 | 0.46 | 0.70 | 0.68 | 0.68 | 0.70 | 1 2 5 4 3 6                 |
| 23     | 22004 | Fourmile CK | Iowa  | 0.43 | 0.47 | 0.69 | 0.68 | 0.68 | 0.69 | 1 2 5 4 3 6                 |
| 24     | 25001 | Kingdom City | Missouri | 0.78 | 0.78 | 0.81 | 0.80 | 0.81 | 0.82 | 1 2 4 3 5 6                 |
| 25     | 26001 | Coshocton | Ohio     | 0.19 | 0.34 | 0.70 | 0.69 | 0.66 | 0.71 | 1 2 5 4 3 6                 |
| 26     | 26010 | Coshocton | Ohio     | 0.45 | 0.46 | 0.68 | 0.66 | 0.62 | 0.70 | 1 2 5 4 3 6                 |
| 27     | 26013 | Coshocton | Ohio     | Neg  | Neg  | 0.27 | 0.26 | 0.01 | 0.27 | 1 2 6 4 3 5                 |
| 28     | 26014 | Coshocton | Ohio     | 0.64 | 0.65 | 0.70 | 0.69 | 0.70 | 0.75 | 1 2 4 3 5 6                 |
| 29     | 26016 | Coshocton | Ohio     | 0.19 | 0.35 | 0.65 | 0.64 | 0.53 | 0.65 | 1 2 6 5 3 4                 |
| 30     | 26018 | Coshocton | Ohio     | 0.59 | 0.69 | 0.74 | 0.72 | 0.75 | 0.82 | 1 2 4 3 5 6                 |
| 31     | 26030 | Coshocton | Ohio     | 0.55 | 0.57 | 0.70 | 0.69 | 0.64 | 0.71 | 1 2 5 4 3 6                 |
| 32     | 26031 | Coshocton | Ohio     | Neg  | Neg  | 0.52 | 0.49 | 0.24 | 0.48 | 1 2 6 5 3 4                 |
| 33     | 26035 | Coshocton | Ohio     | 0.35 | 0.35 | 0.72 | 0.72 | 0.55 | 0.74 | 1 2 5 4 3 6                 |
| 34     | 26036 | Coshocton | Ohio     | 0.56 | 0.61 | 0.71 | 0.71 | 0.66 | 0.68 | 1 2 6 5 3 4                 |
| 35     | 26863 | Coshocton | Ohio     | 0.84 | 0.84 | 0.88 | 0.87 | 0.87 | 0.89 | 1 2 5 3 4 6                 |
| 36     | 33002 | Bentonville | Arkansas | Neg  | Neg  | 0.36 | 0.33 | Neg  | Neg  | 1 2 6 5 3 4                 |
| 37     | 33005 | Bentonville | Arkansas | 0.92 | 0.93 | 0.96 | 0.96 | 0.95 | 0.97 | 1 2 5 4 3 6                 |
| 38     | 33006 | Bentonville | Arkansas | 0.76 | 0.80 | 0.82 | 0.82 | 0.82 | 0.85 | 1 2 4 3 5 6                 |

(continued)
| S. No. | WS ID   | Location  | State     | M₁ | M₂ | M₃ | M₄ | M₅ | M₆ | Obtained score based on rank |
|-------|---------|-----------|-----------|----|----|----|----|----|----|-----------------------------|
| 39    | 34002   | Cherokee  | Oklahoma  | 0.68| 0.68| 0.70| 0.68| 0.73| 0.75| 1 2 4 3 5 6               |
| 40    | 34006   | Cherokee  | Oklahoma  | 0.48| 0.48| 0.59| 0.57| 0.60| 0.64| 1 2 4 3 5 6               |
| 41    | 34007   | Cherokee  | Oklahoma  | 0.55| 0.57| 0.61| 0.59| 0.66| 0.69| 1 2 4 3 5 6               |
| 42    | 34008   | Cherokee  | Oklahoma  | 0.50| 0.50| 0.58| 0.56| 0.61| 0.65| 1 2 4 3 5 6               |
| 43    | 35001   | Guthrie   | Oklahoma  | 0.66| 0.66| 0.78| 0.77| 0.78| 0.79| 1 2 5 3 4 6               |
| 44    | 35002   | Guthrie   | Oklahoma  | Neg | Neg | 0.76| 0.75| 0.55| 0.67| 1 2 6 5 3 4               |
| 45    | 35003   | Guthrie   | Oklahoma  | 0.68| 0.68| 0.79| 0.78| 0.80| 0.81| 1 2 4 3 5 6               |
| 46    | 35008   | Guthrie   | Oklahoma  | 0.19| 0.41| 0.67| 0.66| 0.67| 0.74| 1 2 4 3 5 6               |
| 47    | 35010   | Guthrie   | Oklahoma  | 0.30| 0.40| 0.66| 0.64| 0.68| 0.74| 1 2 4 3 5 6               |
| 48    | 35011   | Guthrie   | Oklahoma  | Neg | Neg | 0.76| 0.75| 0.55| 0.67| 1 2 5 4 3 6               |
| 49    | 37001   | Stillwater| Oklahoma  | 0.84| 0.88| 0.89| 0.88| 0.89| 0.89| 1 2 5 3 4 6               |
| 50    | 37002   | Stillwater| Oklahoma  | 0.72| 0.74| 0.77| 0.75| 0.78| 0.80| 1 2 4 3 5 6               |
| 51    | 42008   | Riesel    | Texas     | 0.68| 0.73| 0.69| 0.68| 0.75| 0.75| 2 4 3 1 5 6               |
| 52    | 42010   | Riesel    | Texas     | 0.70| 0.74| 0.81| 0.80| 0.80| 0.83| 1 2 5 4 3 6               |
| 53    | 42012   | Riesel    | Texas     | 0.64| 0.67| 0.73| 0.72| 0.73| 0.75| 1 2 4 3 5 6               |
| 54    | 42013   | Riesel    | Texas     | 0.27| 0.54| 0.71| 0.70| 0.74| 0.75| 1 2 4 3 5 6               |
| 55    | 42014   | Riesel    | Texas     | 0.55| 0.59| 0.71| 0.70| 0.74| 0.77| 1 2 4 3 5 6               |
| 56    | 42015   | Riesel    | Texas     | 0.66| 0.69| 0.77| 0.76| 0.76| 0.78| 1 2 5 3 4 6               |
| 57    | 42016   | Riesel    | Texas     | 0.63| 0.63| 0.69| 0.68| 0.72| 0.76| 1 2 4 3 5 6               |
| 58    | 42017   | Riesel    | Texas     | 0.72| 0.74| 0.78| 0.77| 0.79| 0.80| 1 2 4 3 5 6               |
| 59    | 42037   | Riesel    | Texas     | 0.80| 0.82| 0.83| 0.82| 0.87| 0.87| 1 3 4 2 5 6               |
| 60    | 42038   | Riesel    | Texas     | 0.75| 0.75| 0.71| 0.69| 0.78| 0.78| 3 4 2 1 5 6               |
| 61    | 42039   | Riesel    | Texas     | 0.75| 0.78| 0.75| 0.74| 0.83| 0.83| 3 4 2 1 5 6               |
| 62    | 42040   | Riesel    | Texas     | 0.77| 0.80| 0.77| 0.75| 0.85| 0.85| 2 4 3 1 5 6               |
| 63    | 44001   | Hastings  | Nebraska  | 0.61| 0.61| 0.74| 0.72| 0.74| 0.77| 1 2 5 3 4 6               |
| 64    | 44002   | Hastings  | Nebraska  | 0.71| 0.71| 0.79| 0.78| 0.83| 0.84| 1 2 4 3 5 6               |
| 65    | 44003   | Hastings  | Nebraska  | 0.73| 0.73| 0.76| 0.74| 0.80| 0.86| 1 2 4 3 5 6               |
| 66    | 44004   | Hastings  | Nebraska  | 0.67| 0.67| 0.79| 0.78| 0.79| 0.85| 1 2 5 3 4 6               |
| 67    | 44005   | Hastings  | Nebraska  | 0.58| 0.59| 0.62| 0.60| 0.66| 0.71| 1 2 4 3 5 6               |
| 68    | 44006   | Hastings  | Nebraska  | 0.57| 0.59| 0.50| 0.48| 0.60| 0.60| 3 4 2 1 5 6               |
| 69    | 44007   | Hastings  | Nebraska  | 0.83| 0.83| 0.83| 0.80| 0.85| 0.85| 3 4 2 1 5 6               |
| 70    | 44008   | Hastings  | Nebraska  | 0.81| 0.81| 0.85| 0.83| 0.85| 0.85| 1 2 4 3 5 6               |
| 71    | 44009   | Hastings  | Nebraska  | 0.81| 0.82| 0.87| 0.85| 0.87| 0.88| 1 2 4 3 5 6               |
| 72    | 44010   | Hastings  | Nebraska  | 0.77| 0.77| 0.81| 0.78| 0.84| 0.85| 1 2 4 3 5 6               |
| 73    | 44011   | Hastings  | Nebraska  | 0.72| 0.72| 0.75| 0.73| 0.78| 0.80| 1 2 4 3 5 6               |
| 74    | 44012   | Hastings  | Nebraska  | 0.75| 0.76| 0.82| 0.80| 0.81| 0.83| 1 2 5 3 4 6               |
| 75    | 44013   | Hastings  | Nebraska  | 0.59| 0.62| 0.75| 0.72| 0.76| 0.82| 1 2 4 3 5 6               |
| 76    | 44014   | Hastings  | Nebraska  | 0.56| 0.60| 0.65| 0.61| 0.71| 0.75| 1 2 4 3 5 6               |

(continued)
| S. No. | WS ID | Location    | State      | Model rank based on NSE | Obtained score based on rank |
|--------|-------|-------------|------------|-------------------------|-----------------------------|
|        |       |             |            | M1 | M2 | M3 | M4 | M5 | M6 | M1 | M2 | M3 | M4 | M5 | M6 |
| 77     | 44015 | Hastings    | Nebraska   | 0.72 | 0.72 | 0.80 | 0.78 | 0.81 | 0.82 | 1 | 2 | 4 | 3 | 5 | 6 |
| 78     | 44016 | Hastings    | Nebraska   | 0.48 | 0.50 | 0.63 | 0.61 | 0.63 | 0.67 | 1 | 2 | 5 | 3 | 4 | 6 |
| 79     | 44017 | Hastings    | Nebraska   | 0.66 | 0.68 | 0.78 | 0.76 | 0.83 | 0.85 | 1 | 2 | 4 | 3 | 5 | 6 |
| 80     | 44018 | Hastings    | Nebraska   | 0.66 | 0.68 | 0.79 | 0.77 | 0.83 | 0.85 | 1 | 2 | 4 | 3 | 5 | 6 |
| 81     | 44019 | Hastings    | Nebraska   | 0.52 | 0.55 | 0.70 | 0.67 | 0.71 | 0.76 | 1 | 2 | 4 | 3 | 5 | 6 |
| 82     | 44020 | Hastings    | Nebraska   | 0.72 | 0.72 | 0.79 | 0.76 | 0.81 | 0.83 | 1 | 2 | 4 | 3 | 5 | 6 |
| 83     | 44021 | Hastings    | Nebraska   | 0.68 | 0.69 | 0.78 | 0.75 | 0.80 | 0.81 | 1 | 2 | 4 | 3 | 5 | 6 |
| 84     | 44022 | Hastings    | Nebraska   | 0.31 | 0.34 | 0.70 | 0.70 | 0.60 | 0.67 | 1 | 2 | 6 | 5 | 3 | 4 |
| 85     | 44023 | Hastings    | Nebraska   | 0.75 | 0.75 | 0.81 | 0.79 | 0.82 | 0.83 | 1 | 2 | 4 | 3 | 5 | 6 |
| 86     | 44024 | Hastings    | Nebraska   | 0.05 | 0.23 | 0.42 | 0.38 | 0.46 | 0.56 | 1 | 2 | 4 | 3 | 5 | 6 |
| 87     | 44025 | Hastings    | Nebraska   | 0.64 | 0.66 | 0.74 | 0.72 | 0.76 | 0.78 | 1 | 2 | 4 | 3 | 5 | 6 |
| 88     | 44026 | Hastings    | Nebraska   | 0.63 | 0.63 | 0.78 | 0.76 | 0.79 | 0.80 | 1 | 2 | 4 | 3 | 5 | 6 |
| 89     | 44027 | Hastings    | Nebraska   | 0.53 | 0.56 | 0.69 | 0.66 | 0.74 | 0.76 | 1 | 2 | 4 | 3 | 5 | 6 |
| 90     | 44028 | Hastings    | Nebraska   | 0.66 | 0.66 | 0.78 | 0.76 | 0.79 | 0.80 | 1 | 2 | 4 | 3 | 5 | 6 |
| 91     | 45001 | Safford     | Arizona    | 0.06 | 0.16 | 0.43 | 0.40 | 0.43 | 0.52 | 1 | 2 | 4 | 3 | 5 | 6 |
| 92     | 45002 | Safford     | Arizona    | 0.77 | 0.79 | 0.82 | 0.81 | 0.78 | 0.80 | 1 | 3 | 6 | 5 | 2 | 4 |
| 93     | 47002 | Albuquerque| New Mexico | 0.25 | 0.28 | 0.50 | 0.47 | Neg | 0.48 | 2 | 3 | 6 | 4 | 1 | 5 |
| 94     | 47003 | Albuquerque| New Mexico | Neg  | Neg  | Neg  | Neg  | Neg  | Neg  | 2 | 3 | 5 | 4 | 1 | 6 |
| 95     | 61001 | Monticello  | Illinois   | Neg  | Neg  | 0.71 | 0.70 | 0.62 | 0.74 | 1 | 2 | 5 | 4 | 3 | 6 |
| 96     | 61002 | Monticello  | Illinois   | Neg  | Neg  | 0.67 | 0.66 | 0.53 | 0.67 | 1 | 2 | 5 | 4 | 3 | 6 |
| 97     | 61003 | Monticello  | Illinois   | Neg  | 0.42 | 0.66 | 0.63 | 0.69 | 0.75 | 1 | 2 | 4 | 3 | 5 | 6 |
| 98     | 61004 | Monticello  | Illinois   | Neg  | 0.22 | 0.52 | 0.49 | 0.44 | 0.61 | 1 | 2 | 5 | 4 | 3 | 6 |
| 99     | 62001 | Oxford      | Mississippi| 0.56 | 0.58 | 0.75 | 0.75 | 0.76 | 0.82 | 1 | 2 | 4 | 3 | 5 | 6 |
| 100    | 62002 | Oxford      | Mississippi| 0.81 | 0.82 | 0.82 | 0.81 | 0.85 | 0.85 | 2 | 4 | 3 | 1 | 5 | 6 |
| 101    | 62005 | Oxford      | Mississippi| 0.60 | 0.60 | 0.82 | 0.82 | 0.84 | 0.87 | 1 | 2 | 4 | 3 | 5 | 6 |
| 102    | 62007 | Oxford      | Mississippi| 0.71 | 0.77 | 0.85 | 0.85 | 0.83 | 0.85 | 1 | 2 | 6 | 4 | 3 | 5 |
| 103    | 62010 | Oxford      | Mississippi| 0.73 | 0.74 | 0.76 | 0.76 | 0.79 | 0.81 | 1 | 2 | 4 | 3 | 5 | 6 |
| 104    | 62011 | Oxford      | Mississippi| Neg  | 0.14 | 0.32 | 0.50 | 0.33 | 0.55 | 1 | 2 | 4 | 3 | 5 | 6 |
| 105    | 62012 | Oxford      | Mississippi| 0.24 | 0.27 | 0.50 | 0.49 | 0.46 | 0.55 | 1 | 2 | 5 | 4 | 3 | 6 |
| 106    | 62014 | Oxford      | Mississippi| 0.73 | 0.74 | 0.73 | 0.70 | 0.79 | 0.80 | 3 | 4 | 2 | 1 | 5 | 6 |
| 107    | 62018 | Oxford      | Mississippi| 0.52 | 0.63 | 0.79 | 0.79 | 0.74 | 0.79 | 1 | 2 | 6 | 5 | 3 | 4 |
| 108    | 63103 | Tombstone   | Arizona    | 0.65 | 0.91 | 0.95 | 0.95 | 0.89 | 0.92 | 1 | 3 | 6 | 5 | 2 | 4 |
| 109    | 63104 | Tombstone   | Arizona    | 0.78 | 0.83 | 0.88 | 0.87 | 0.83 | 0.86 | 1 | 2 | 6 | 5 | 3 | 4 |
| 110    | 63106 | Tombstone   | Arizona    | 0.47 | 0.55 | 0.72 | 0.70 | Neg | 0.63 | 2 | 3 | 6 | 5 | 1 | 4 |
| 111    | 63112 | Tombstone   | Arizona    | 0.63 | 0.64 | 0.63 | 0.57 | 0.75 | 0.77 | 3 | 4 | 2 | 1 | 5 | 6 |
| 112    | 76001 | Santa Rita  | Arizona    | 0.37 | 0.53 | 0.70 | 0.68 | 0.50 | 0.65 | 1 | 3 | 6 | 5 | 2 | 4 |
| 113    | 76002 | Santa Rita  | Arizona    | Neg  | 0.40 | 0.64 | 0.64 | Neg | 0.51 | 2 | 3 | 6 | 5 | 1 | 4 |
| 114    | 76003 | Santa Rita  | Arizona    | 0.39 | 0.42 | 0.59 | 0.57 | 0.48 | 0.60 | 1 | 2 | 5 | 4 | 3 | 6 |
The higher $n(t)$ value reflects the appropriateness of the model for efficient runoff computation.

To select the best model for a particular watershed, NSE based rank and grading system (RGS) was applied on different models and ranks (I to VI) were assigned according to their NSE value (Verma et al. 2018). Their awarded score was added to select the best model among all. The percentage improvement achieved by the best model over rest models can be addressed by $r^2$ criteria. The mathematical expression of $r^2$ is as follows:

$$r^2 = \frac{\left( NSE_b - NSE_c \right)}{1 - NSE_c}$$

(20)
Figure 3 | Variation in (a) Root Mean Square Error (RMSE, mm); (b) Nash-Sutcliffe Efficiency (NSE); (c) PBIAS (%) and (d) n(t) values with watershed serial no. using different models.
where NSE_b and NSE_r are the efficiencies of best model and referenced model. More than 10% indicates a significant improvement (Senbeta et al. 1999).

RESULTS AND DISCUSSION

The performance of all 114 US watersheds resulting from applications of each of the models has been compared using RMSE, NSE, PBIAS, n(t), rank and grading system, and by visual assessment. The performance of all models for individual watersheds was compared by using a scatter plot (Figure 3) and the collective performance of models can be seen in a Box and Whisker plot for all statistical indices (Figure 4). The best model suggestion was based on total score obtained using rank and grading system (RGS) for all 114 US watersheds. The value of \( S \) was optimized for all six models which are presented in Table 3. The mean and median value of \( S \) was found to be higher for the M6 model and lowest for the M1 model. The higher \( S \) value also increases the standard deviation (SD) and standard error (SE) value of the M6 model.

The RMSE values for all models are presented in Figure 3(a). The lower the RMSE, the better the performance of the model, and vice versa. It can be seen that the existing SCS-CN model shows a worse performance than the other models. The median value of RMSE for M1, M2, M3, M4, M5, and M6 models were found to be 7.54, 7.23, 5.70, 5.88, 5.85 and 5.32 mm, respectively, which is lowest for the M6 model. Its mean value was also lowest (5.53 mm) for the M6 model. When we compared all models based on RMSE value, out of 114 watersheds the M6 model performs best with minimum RMSE values in 95 watersheds. Next is the model M3, which had the lowest RMSE values in the remaining 19 watersheds. From the RMSE value, it can be inferred that the M6 model performs well followed by M5, M4, M2, and M1. The higher RMSE values exhibit the worst performance and are found mostly in the M1 and M2 models. Figure 4(a) exhibits the overall RMSE performance of all models by using a Box and Whisker plot. Noteworthy, the
M₃ and M₄ models follow the same trend and the RMSE value of the M₃ model is better than the M₄ model.

The NSE value indicates the model efficiency and a high value means a better model. The NSE value was found to be better in the M₆ model for most of the watersheds (Figure 5(b)). NSE values fall in a good range (0.80 ≤ NSE ≤ 0.90) in 41 watersheds followed by 30, 25, 19, 15, and 11 for M₅, M₃, M₄, M₂, and M₁, respectively. The cumulative median value for all watersheds was found to be highest for the M₆ model as 0.78 followed by M₅ (0.75) > M₃ (0.73) > M₄ (0.72) > M₂ (0.63) > M₁ (0.61). The mean value was very low, as 0.62 for the M₅ model, since some of the watersheds’ NSE values were found to be very low. In some cases it was negative, which indicates model prediction was worse than the mean observed value. From Figure 4(b), it is evident that model M₆ performed superiorly, with higher NSE than other models and model M₃ and M₄ depict nearly the same performance.

PBIAS quantifies a model tendency either to overestimate or underestimate. A PBIAS value of zero indicates perfect fit, its negative value indicates overestimation and vice versa. Models M₃ and M₄ underestimated (positive PBIAS) the runoff in all 114 watersheds and the mean PBIAS value was also as high as 14.13% and 17.12% respectively compared to the other models. Models M₁, M₂, and M₅ underestimated the runoff in 80, 107, and 101 watersheds and overestimated (negative PBIAS) in 34, 7, and 13 watersheds respectively. The mean and median PBIAS were both lowest and nearer to zero for the M₆ model with 4.77% and 2.62% respectively. The PBIAS results indicated that the M₆ model performance was very good in 91 watersheds and unsatisfactory in 4 watersheds only. By using the M₆ model, most of the watersheds fall either in the very good or good range (Figure 5(c)). The PBIAS statistical index prefers the M₆ model because it gives a more consistent and better PBIAS value (Figure 4(c)). The overall statistics of RMSE, NSE and PBIAS values for all models are presented in Table 4. The overall SD and SE values of RMSE, NSE, and PBIAS for 114 watersheds were found to be less for the M₆ model. For the M₃ model, SD and SE values are quite high because in some watersheds the performance of the model was very poor, which increases dispersion from its mean value, lowers the mean and maximizes their range.

Like the previous three indices, the n(t) value was also found to be best in most of the watersheds using the M₆ model.
model (Figure 3(d)). Similar to the NSE, the cumulative mean of the \(n(t)\) value was found to be high for the M6 model at 1.19, followed by 1.04 for model M3. It was lowest for the M1 model at just 0.58 followed by the M2 model at 0.70. Table 5 summarises the guidelines for classifying the model performances according to their range as unsatisfactory, satisfactory, good and very good. This table suggests the usefulness and better performance of the M6 model compared to other models. Model M6 found exemplary performance in maximum cases, while poor performance was found comparatively in fewer watersheds.

The superiority of the M6 model over the rest of the models was judged by making a cumulative frequency distribution curve for percentage improvement \(r^2\) criteria (Figure 5). The M6 model performed better than the M1, M2, and M5 models for all watersheds while for the M3 and M4 models, only 17 and 14\% watersheds respectively performed better than M6. To visually assess the performance

| Performance Index | Range               | Rating       | M1 | M2 | M3 | M4 | M5 | M6 |
|-------------------|---------------------|--------------|----|----|----|----|----|----|
| No. of watersheds with ‘−’ve NSE | NSE < 0            | Unsatisfactory | 18 | 12 | 2  | 3  | 7  | 3  |
| NSE performance criteria set by Ritter & Muñoz-Carpena (2013) | NSE < 0.65        | Unsatisfactory | 65 | 60 | 27 | 31 | 34 | 24 |
|                   | 0.65 ≤ NSE < 0.80  | Satisfactory  | 37 | 37 | 59 | 61 | 46 | 42 |
|                   | 0.80 ≤ NSE < 0.90  | Good         | 11 | 15 | 25 | 19 | 30 | 41 |
|                   | NSE ≥ 0.90         | Very good    | 1  | 2  | 3  | 3  | 4  | 7  |
| NSE Performance criteria set by Moriasi et al. (2007) | NSE ≤ 0.50        | Unsatisfactory | 42 | 37 | 11 | 15 | 19 | 8  |
|                   | 0.50 < NSE ≤ 0.65  | Satisfactory  | 23 | 23 | 16 | 16 | 15 | 16 |
|                   | 0.65 < NSE ≤ 0.75  | Good         | 27 | 29 | 35 | 35 | 24 | 23 |
|                   | NSE ≥ 0.75         | Very good    | 22 | 25 | 52 | 48 | 56 | 67 |
| PBIAS performance criteria set by Moriasi et al. (2007) | PBIAS ≥ 25        | Unsatisfactory | 25 | 13 | 16 | 18 | 12 | 4  |
|                   | 15 ≤ PBIAS < 25    | Satisfactory  | 20 | 28 | 23 | 44 | 16 | 9  |
|                   | 10 ≤ PBIAS < 15    | Good         | 17 | 19 | 36 | 32 | 13 | 10 |
|                   | PBIAS < 10         | Very good    | 52 | 54 | 39 | 20 | 73 | 91 |
| n(t) performance criteria set by Ritter & Muñoz-Carpena (2015) | n(t) < 0.7        | Unsatisfactory | 64 | 61 | 27 | 30 | 34 | 24 |
|                   | 0.7 ≤ n(t) < 1.2   | Satisfactory  | 38 | 36 | 55 | 59 | 40 | 36 |
|                   | 1.2 ≤ n(t) < 2.2   | Good         | 11 | 15 | 29 | 22 | 36 | 47 |
|                   | n(t) > 2.2         | Very good    | 1  | 2  | 3  | 3  | 4  | 7  |

Figure 5 | Cumulative frequency distribution for percentage improvement of M6 model over other models using \(r^2\) criteria.
of different models a scatter plot (Figure 6) has been drawn between observed and computed runoff for WS ID- 9004, and 33005. The visual assessment indicates almost equal performance of M6 and M5 models for WS ID 9004 and much better performance of the M6 model than the rest of the models for WS ID 33005.

A NSE-based rank and grading based system (RGS) was adopted to select the preference of the best model. A rank was assigned to each model for the individual watershed. A high NSE value has been given to the best rank as 1 and credit 6 point score in its account. From Table 2, for WS ID 9004, the NSE value was highest for the M6 model (Rank I, Score 6) followed by M5 (Rank II, Score 5), M4 (Rank III, Score 4), M3 (Rank IV, Score 3), M2 (Rank V, Score 2), and M1 (Rank VI, Score 1) as 0.88, 0.76, 0.67, 0.69, 0.26 and a negative NSE respectively. Model M6 gained 6, 5, 4, 3, 2, and 1 score in 95, 3, 16, 0, 0, and 0 watersheds respectively. The cumulative sum of the score was highest for the M6 model at 649 (6 × 95 + 5 × 3 + 4 × 16 + 3 × 0 + 2 × 0 + 1 × 0 = 649) followed by 504 for M3, 471 for M5, 368 for M4, 264 for M2 and 138 for the M1 model (Figure 7). Therefore, on the basis of RGS, the M6 model can be also rated as the best model. After the M6 model, the next better performing models were found to be M3, M5, M4, M2, and M1 respectively.

The results indicate that the indirect approach to categorize runoff conditions on the basis of antecedent five days rainfall as dry, normal, or wet does not reflect the best performing potential. Better is to incorporate P5 directly in the runoff model and this certainly helps in improved model performance. Using trial and error methods, Ajmal and Kim proposed two models for South Korean catchments that directly consider the P5 value in model formulation. Both model performances were found to be better than the SCS-CN model and increase the model efficiency of US watersheds. In this study, the SCS-CN model was modified by incorporating P5 value and provides a more rational basis to M5 and M6 models. Despite being empirical in nature, it is needless to reiterate that the new model proposed in this work shows the promise of better performance using several error metrics.

**CONCLUSION**

Based on this study, the following can be inferred:

1. The proposed study obviates the problem of the sudden jump and improves the performance of the model. The proposed model changes the maximum potential retention value (S, mm) due to the antecedent 5 days’ rainfall values.
2. All statistical criteria were found to be better for the proposed model with less RMSE, high NSE, better PBIAS, high \( n(t) \) value, and better overall rank and grading based score.

3. Between M5 and M6 models, M5 performance was poor due to the fixed \( \lambda \) value. The M5 model indicates that a fixed \( \lambda \) value of 0.2 does not fit well and some other value should be used. Model M6 includes variation in \( \lambda \) value and it increases the efficiency of the model. For 97 watersheds, the \( \lambda \) value was found to be zero. The median value of parameter \( \lambda \) was found to also be zero. Therefore, model M6 can be used with \( \lambda \) value as zero (Equation (11)) simplifying the M5 model.

**ACKNOWLEDGEMENT**

A special thanks to Prof. R.H. Hawkins, Emeritus Professor, University of Arizona for providing rainfall-runoff dataset of US watersheds and Prof. C.S.P. Ojha for supervising and giving useful suggestions to complete this research work.

**DATA AVAILABILITY STATEMENT**

All relevant data are included in the paper or its Supplementary Information.

**REFERENCES**

Ajmal, M. & Kim, T. W. 2015 Quantifying excess stormwater using SCS-CN-based rainfall runoff models and different curve number determination methods. *Journal of Irrigation and Drainage Engineering* 141 (3), 04014058.

Brocca, L., Melone, F. & Moramcarco, T. 2008 On the estimation of antecedent wetness conditions in rainfall–runoff modelling. *Hydrological Processes* 22 (5), 629–642.

Hawkins, R. H. 1993 Asymptotic determination of runoff curve numbers from data. *Journal of Irrigation and Drainage Engineering* 119 (2), 334–345.

Hawkins, R. H., Hjelmfelt Jr., A. T. & Zevenbergen, A. W. 1985 Runoff probability, storm depth, and curve numbers. *Journal of Irrigation and Drainage Engineering* 111 (4), 330–340.

Hawkins, R. H., Ward, T. J., Woodward, D. E. & Van Mullem, J. A. 2008 Curve Number Hydrology: State of the Practice. American Society of Civil Engineers, Reston, VA, 106pp.

Hewlett, J. D., Fortson, J. C. & Cunningham, G. B. 1977 The effect of rainfall intensity on storm flow and peak discharge from forest land. *Water Resources Research* 13 (2), 259–266.

Jordan, J. P. 1994 Spatial and temporal variability of stormflow generation processes on a Swiss catchment. *Journal of Hydrology* 153 (1), 357–382.

Lal, M., Mishra, S. K. & Pandey, A. 2015 Physical verification of the effect of land features and antecedent moisture on runoff curve number. *Catena* 135, 318–327.

Latron, J., Soler, M., Llorens, P. & Gallart, F. 2008 Spatial and temporal variability of the hydrological response in a small Mediterranean research catchment (Vallecibre, Eastern Pyrenees). *Hydrological Processes* 22 (6), 775–787.

Merz, R. & Bloschl, G. 2009 A regional analysis of event runoff coefficients with respect to climate and catchment characteristics in Austria. *Water Resources Research* 45 (1), W01405.

Meyles, E., Williams, A., Ternan, L. & Dowd, J. 2003 Runoff generation in relation to soil moisture patterns in a small Dartmoor catchment, Southwest England. *Hydrological Processes* 17 (2), 251–264.

Michel, C., Andréassian, V. & Perrin, C. 2005 Soil conservation service curve number method: how to mend a wrong soil moisture accounting procedure? *Water Resources Research* 41 (2), W02011.

Mishra, S. K., Jain, M. K., Suresh Babu, P., Venugopal, K. & Kaliappan, S. 2008 Comparison of AMC-dependent CN-conversion formulae. *Water Resources Management* 22 (10), 1409–1420.

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

NRCS 2004 Chapter 10 Estimation of Direct Runoff From Storm Rainfall. In: Part 630 Hydrology National Engineering Handbook. Natural Resource Conservation Service, U.S.A., Washington, DC.

Pathiraja, S., Westra, S. & Sharma, A. 2012 Why continuous simulation? The role of antecedent moisture in design flood estimation. *Water Resources Research* 48, 6.

Radatz, T. F., Thompson, A. M. & Madison, F. W. 2013 Soil moisture and rainfall intensity thresholds for runoff generation in southwestern Wisconsin agricultural watersheds. *Hydrological Processes* 27 (25), 3521–3534.

Ritter, A. & Muñoz-Carpena, R. 2013 Performance evaluation of hydrological models: statistical significance for reducing subjectivity in goodness-of-fit assessments. *Journal of Hydrology* 480, 33–45.

Sahu, R. K., Mishra, S. K., Eldho, T. I. & Jain, M. K. 2007 An advanced soil moisture accounting procedure for SCS curve number method. *Hydrological Processes* 21 (21), 2872–2881.

Senbeta, D. A., Shamseldin, A. Y. & O’Connor, K. M. 1999 Modification of the probability-distributed interacting storage capacity model. *Journal of Hydrology* 224 (3–4), 149–168.
Song, S. & Wang, W. 2019 Impacts of antecedent soil moisture on the rainfall-runoff transformation process based on high-resolution observations in soil tank experiments. Water 11 (2), 296.

Stewart, D., Canfield, E. & Hawkins, R. 2012 Curve number determination methods and uncertainty in hydrologic soil groups from semiarid watershed data. Journal of Hydrologic Engineering 17, 1180–1187.

USDA 1985 National Engineering Handbook, Supplement A, Section 4. US Department of Agriculture, Washington, DC.

Verma, S., Singh, P. K., Mishra, S. K., Jain, S. K., Berndtsson, R., Singh, A. & Verma, R. K. 2018 Simplified SMA-inspired 1-parameter SCS-CN model for runoff estimation. Arabian Journal of Geosciences 11 (15), 420.

Verma, S., Singh, P. K., Mishra, S. K., Singh, V. P., Singh, V. & Singh, A. 2020 Activation soil moisture accounting (ASMA) for runoff estimation using soil conservation service curve number (SCS-CN) method. Journal of Hydrology 589, 125114.

Zhang, Y., Wei, H. & Nearing, M. A. 2011 Effects of antecedent soil moisture on runoff modeling in small semiarid watersheds of southeastern Arizona. Hydrology and Earth System Sciences 15 (10), 3171–3179.

Zhao, N., Yu, F., Li, C., Zhang, L., Liu, J., Wenbin, M. & Wang, H. 2015 Soil moisture dynamics and effects on runoff generation at small hillslope scale. Journal of Hydrologic Engineering 20 (7), 05014024.

First received 31 August 2020; accepted in revised form 30 October 2020. Available online 11 November 2020