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Research papers

Activation soil moisture accounting (ASMA) for runoff estimation using soil conservation service curve number (SCS-CN) method

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ABSTRACT

In this study, the concept of activation soil moisture (ASM) has been conceptualised by coupling the Soil Moisture Accounting (SMA) concept with the static infiltration component (Fc) for simulating rainfall-runoff process. The ASM has been defined as the height of soil moisture barrier (or the amount of soil moisture deficit), which must be fulfilled before runoff can start. Most of the SCS-CN inspired methods, including the original one do not consider ASM in their formulation to simulate rainfall-runoff process. To account for ASM, here, we develop an activation soil moisture accounting (ASMA) based method (ASMA-SCS-CN) by coupling the SMA concept of Michel-Vazken-Perrin (MVP) method with the static infiltration (Fc) based Mishra-Singh (MS) method, which presents a fuller picture of SMA system. The performance of the ASMA-SCS-CN method is compared with the original SCS-CN method, MS method and MVP method by applying a large dataset of 56,343 storm events from 164 small to large watersheds in the United States using goodness-of-fit statistics in terms of Nash-Sutcliffe efficiency (NSE), the root mean square error (RMSE), normalized RMSE (nRMSE), percent bias (PBIAS), mean absolute error (MAE), standard error (SE) and RMSE-observations standard deviation ratio (RSR). The ASMA-SCS-CN method has the highest median value of NSE (0.71; varying from 0.11 to 0.97) with inter-quartile range (IQR) as (0.62–0.80) followed by MVP with NSE (0.67; varying from 0.10 to 0.0.96) and IQR as (0.57–0.74), MS with NSE (0.61; varying from 0.02 to 0.97) and IQR range as (0.46–0.72), and SCS-CN with NSE (0.58; varying from 0,01 to 0.92) and IQR as (0.44–0.69). The ASMA-SCS-CN method is found to have lowest mean and median values of RMSE, nRMSE, MAE, SE and RSR than the MVP, MS and SCS-CN method. The PBIAS values of the ASMA-SCS-CN and MVP methods are lower than that of MS and SCS-CN method. In addition, the performance of all four methods is further evaluated based on the watershed characteristics such as landuse, soil type, drainage area, and mean rainfall and the results show that in all cases the ASMA-SCS-CN method performs much better than the rest of the methods. Overall, the improved performance of ASMA-SCS-CN can be attributed to the inclusion of SMA along with the static infiltration component for representing the complete picture of SMA system in modelling rainfall-runoff process.

1. Introduction

Estimation of direct surface runoff resulting from a storm rainfall event is needed for myriad applications, including planning watershed conservation and management practices, measures for mitigation of drought and flood hazards, stream flow prediction, reservoir operation, and irrigation scheduling. Various methods available for estimation of direct surface runoff have limited applicability in data scarce watersheds due to large input data requirement, uncertainty in specifying the parameters values, and the difference between the spatial scales of the application, i.e., a catchment versus a field (Gupta et al., 2019a,b; Sahu et al., 2010; Shi et al., 2009). The Soil Conservation Service Curve Number (SCS-CN) method, developed by the United States Department of Agriculture (USDA), (SCS, 1956) is one of the most commonly applied methods in practical hydrology for computing the direct surface runoff amount from a storm event (Mishra and Singh, 1999; Singh et al., 2010; Durán-Barroso et al., 2019; Walega et al., 2017; Walega et al, 2015; Wang, 2018; Baiamonte, 2019; and Zhang et al, 2019). The method is well suited for estimating surface runoff from small agricultural watersheds (gauged/ungauged) and establishes CN values

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(descriptive of runoff potential of watershed) under various hydrologic soil groups, landuse/landcover, and antecedent moisture conditions (AMCs) with acceptable accuracy (Berthet et al., 2009; Chung et al., 2010; Wałęga and Rutkowska, 2015; Bartlett et al., 2016; Walegaa and Salatab, 2019; Hawkins et al., 2019). As a result, the method is widely preferred by the hydrologists, engineers and watershed managers as an independent simple watershed model (Ponce and Hawkins, 1996; Garen and Moore, 2005; Singh et al., 2010; Hawkins, 2014; Bartlett et al., 2016), as well as the runoff estimating component in many complex process based model for water availability, soil erosion, flood control, and water quality such as Storm Water Management Model (SWMM) (Metcalf and Eddy, 1971); Hydrologic Engineering Center-1 (HEC-1) (HEC, 1981); Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) (Smith and Williams, 1980), Agricultural Non-Point Source (AGNPS) (Young et al., 1989a,b) and Soil and Water Assessment Tool (SWAT) (Neitsch et al., 2002) to name a few of them. Singh and Goyal (2017) incorporated the modified CN relationships (Mishra et al., 2008) in to SWAT model to reduce the model uncertainty in simulated and projected streamflows in a Himalayan catchment. More recently, Zhang et al. (2019) incorporated rainfall intensity depended CN (ICN) relationships in the SWAT model (SWAT-ICN) to improve the rainfall-runoff simulation process.

However, the original SCS-CN method has some limitations and misinterpretations (Garen and Moore, 2005; Ponce and Hawkins, 1996; Grimaldi et al., 2013a,b; Hawkins, 2014; Bartlett et al., 2016; and Ogden et al., 2017). It has an unstable theoretical and structural foundation to flexibly incorporate AMC conditions, unaccounted static infiltration, rainfall intensity and storm duration, and fixing of initial abstraction coefficient (λ) (Ponce and Hawkins, 1996; De Michele and Salvadori, 2002; Mishra et al., 2003a; Michel et al., 2005; Jain et al., 2006; Shi et al., 2009; Soulis et al., 2009; and Bartlett et al., 2016; Santikari and Murdoch, 2018; Baiamonte, 2019). Notably, the AMCs only explains a portion of the inter-event variation of the CN parameter (Ogden et al., 2017; Hjelmfelt, 1991). For any change in AMC (say from AMC_I to AMC_{III}) on a given catchment, a sudden jump in the CN value (i.e. from CN I to CN III) invariably occurs, and this variability is discontinuous in nature, which ultimately results in a quantum jump in computed runoff (McCuen, 1989, 2002; Mishra et al., 2003a,b; Singh et al., 2013; Singh et al., 2015). Ahmadisharaf et al. (2018) found that the swing between the AMC classes and rainfall patterns has a greater impact on the runoff generating mechanisms in the watershed than the variation in rainfall depth.

Many investigators argue that the initial soil moisture condition of the watershed is the most important factor to determine the predictive outcome of an event (Williams and LaSeur, 1976; Brocca et al., 2009a,b; De Michele and Salvadori, 2002; Mishra and Singh, 2004a,b; Sahu et al., 2010; Bonaccorso et al., 2017; Michel et al., 2005). Worth mentioning, that the initial soil moisture conditions represent a major parameter in the surface runoff generation (Bonaccorso et al., 2017). Ahmadisharaf et al. (2018) mentioned that the SCS-CN method does not directly use the actual antecedent moisture in the computations and rather classifies AMC into three discrete classes. The soil moisture accounting (SMA) procedure was developed by Michel et al. (2005) to rectify the classical problem of sudden jump in SCS-CN method. The SMA procedure developed by Michel et al. (2005) (hereafter Michel-Vazken-Perrin, MVP, method) is based on the notion that "higher the moisture store level, higher the fraction of rainfall that is converted into runoff. If the moisture storage level is full, all the rainfall will become runoff. Kannan et al. (2007) found that the combination of SMA procedure with the SCS-CN method is necessary for predicting runoff from rainfall realistically due to the CN variation from storm to storm. Beck et al. (2009) stated that soil moisture is a key factor in determining the partitioning of rainfall into runoff and infiltration and the soil moisture proxies are calculated to account for a catchment's wetness status prior to the rainfall event in the hope to improve stream flow prediction. Camici et al. (2011) stated that a SMA procedure has to incorporate all the above-mentioned conditions and termed the soil moisture conditions before the storm event as "design soil moisture". Rajib and Merwade (2016) observed that the CN method suffers from several structural inconsistencies and lack of theoretical foundation, which need to be addressed to enable improved SMA system in in the model and developed SWAT –SMA model for improved streamflow predictions. Ogden et al. (2017) suggested that a new runoff prediction model shall have valid theoretical underpinnings with needed model capabilities and verifiable outperform existing models to solve specific problem, e.g., water management, erosion sedimentation, etc. Recently, Cho and Engel (2019) developed a long-term hydrologic simulation model by coupling the original SCS-CN method and revised SMA procedure.

To overcome the structural and hydrological inconsistency associated and to account for the SMA procedure in the original SCS-CN method, the basic proportionality concept [$C = S_r$ concept] (Gupta et al., 2019a,b; Mishra and Singh, 2003a,b; Singh et al., 2015) has been modified accordingly and advanced versions of the SCS-CN method have also been developed by various researchers worldwide (e.g., Mishra et al., 2004; Ajmal et al., 2015; Gupta et al., 2019a,b; Kannan et al., 2008; Sahu et al., 2007; Michel et al., 2005; Singh et al., 2015). Mishra and Singh (2003a,b) proposed a revised SCS-CN based (hereafter Mishra-Singh, MS, method) by incorporating the static infiltration component (F_c) in the basic proportionality concept, however, the method does not consider the SMA procedure in its formulation. MVP method (Michel et al., 2005) incorporated the SMA procedure in the SCS-CN method and developed renewed and improved version of SCS-CN method. The MVP method conceptualizes the SMA procedure based on threshold soil moisture (S_a) as the soil moisture barrier which has to be overcome before runoff to start, however, if we critically examine the MVP method, it can be diagnosed that it does ignores the static infiltration component of infiltration, which also plays an important role in assessing the SMA system (Mishra and Singh, 2003a,b). Interestingly, Mishra and Singh (2003a,b) highlighted that the original SCS-CN method also does not include the static component of infiltration rather considers only the dynamic (capillary) portion of the infiltration and hence it underestimates infiltration. Therefore, there exists a scope for further development of an improved SCS-CN method based on the coupling of the concept of SMA procedure (MVP method) and static infiltration (MS method) for a complete assessment of SMA system and has been termed here as the activation soil moisture accounting (ASMA) system for improving the overall rainfall-runoff modelling process.

Keeping in view of the above, this study has twofold objectives as: (i) to develop a ASMA based SCS-CN (ASMA-SCS-CN) method by coupling the SMA concept of MVP method with Fc of MS method to present a complete assessment of SMA system; and (ii) to compare the performance of the ASMA-SCS-CN method with the original SCS-CN method, MVP method, and MS method and by applying a large dataset of 56,343 storm events from 164 small to large watersheds in the United States. This paper has been organised as follows: Section 1 introduces the rationale behind the development of the proposed ASMA-SCS-CN method, explores the concepts which can be coupled with the SCS-CN method for this purpose and outlines the objectives of the study. Section 2 deals with the study area and data used and presents a broad overview of the data used in this study. Section 3 briefly discusses the original SCS-CN method, Mishra-Singh (MS) method (SCS-CN method coupled with static infiltration component), Michel-Vazken-Perrin (MVP) method (SCS-CN method coupled with SMA procedure) and develops the ASMA-SCS-CN method by coupling the SMA procedure with the MS method to present a fuller picture of SMA system in modelling rainfall-runoff process. Section 3 also deals with the application of all the four methods, i.e., original SCS-CN method, MS method, MVP method and ASMA-SCS-CN method using storm event data of 164 watersheds. This sections also discusses the parameter estimation technique and different formulations used for this purpose. This section discusses six different performance evaluation indices as Nash-Sutcliffe efficiency (NSE), the

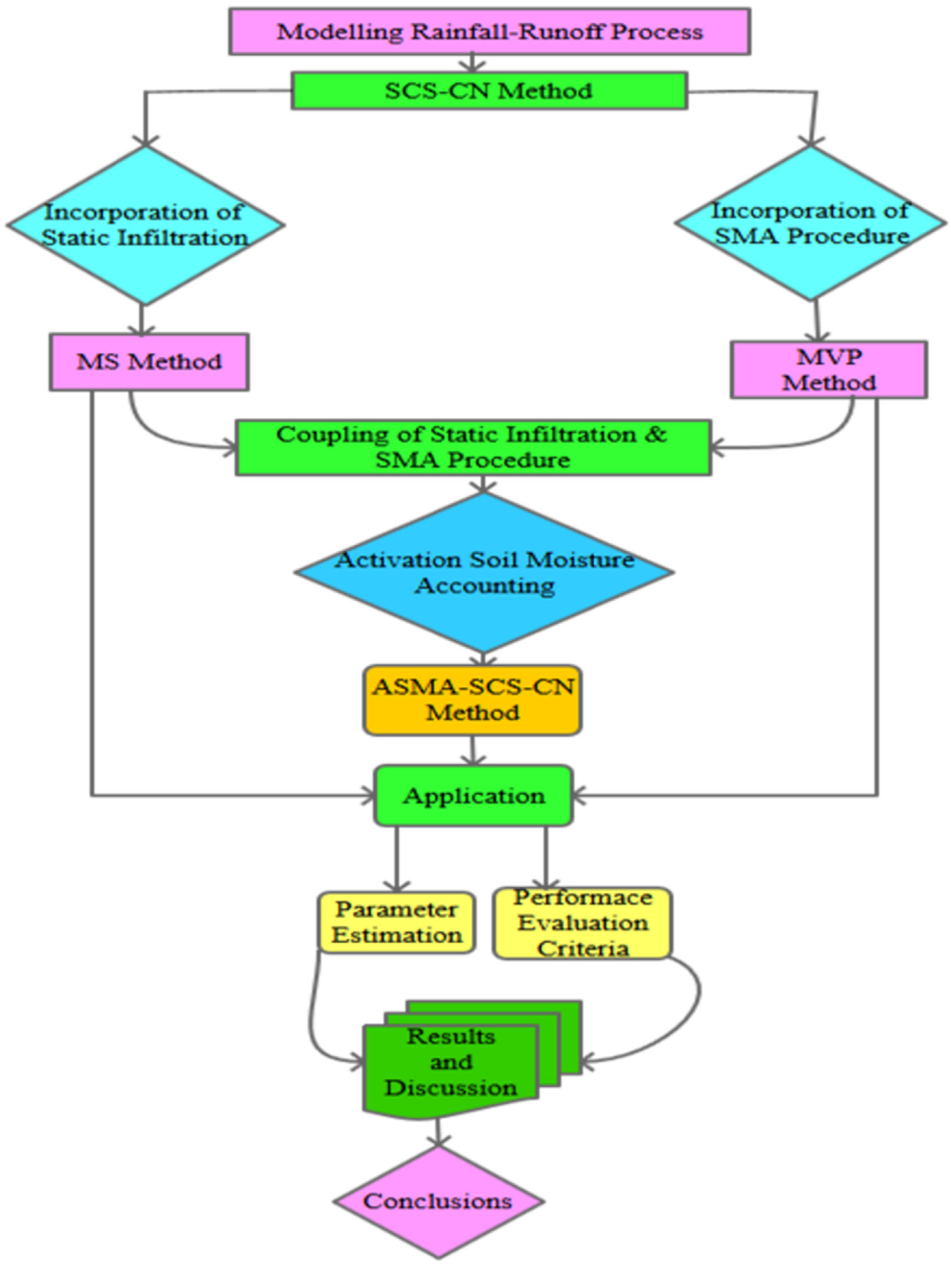

Fig. 1. Workflow of the Methodology.

root mean square error (RMSE), normalized RMSE (nRMSE), percent bias (PBIAS), mean absolute error (MAE), standard error (SE), RMSE-observations standard deviation ratio (RSR) and reason for their candidature in performance evolution. Section 4 deals with the results and discussion of the study. It discusses the parameters variability, in-depth analysis on the comparative performance evaluation of the four methods using six performance indices, factors affecting model uncertainty, rationale behind the improved performance of the ASMA-SCS-CN method as compared to the SCS-CN, MS, MVP methods, performance evaluation of these methods based on watershed characteristics such as land use, soil type, landuse and soil type combination, and drainage area. Finally, Section 5 deals with the important conclusions drawn from the study. A workflow of the methodology is also given in Fig. 1 to have an overall structural organization of the paper.

2. Study area and data used

To test the activation soil moisture concept in the SCS-CN method, the present study utilizes the rainfall-runoff datasets of 164 watersheds with areas varying from 0.2 to 17,353 ha from different regions of USA (Fig. 2). These watersheds have different landuse (pasture, mixed, cultivated) and soil type (silty, sandy, clayey). Data for a total of 56,343 storm events from these watersheds has been used in this study. The number of events ranged from 8 to 1924 for different watersheds. These rainfall-runoff datasets were derived from USDA Agricultural Research Service (USDA-ARS) Water Database, which is a collection of rainfall and stream flow data from small agricultural watersheds of the United States. The database is available on http://www.ars.usda.gov/arsdb.html.The existing rain gauge networks range from one station to over 200 stations per watershed. The period of record for individual watersheds vary from 1 to 50 years. Some watersheds have been in continuous observation since the mid 1930′s. USDA also maintains various types of ancillary data, such as air temperature, land management practices, topography, and soil types along with rainfall and streamflow data.

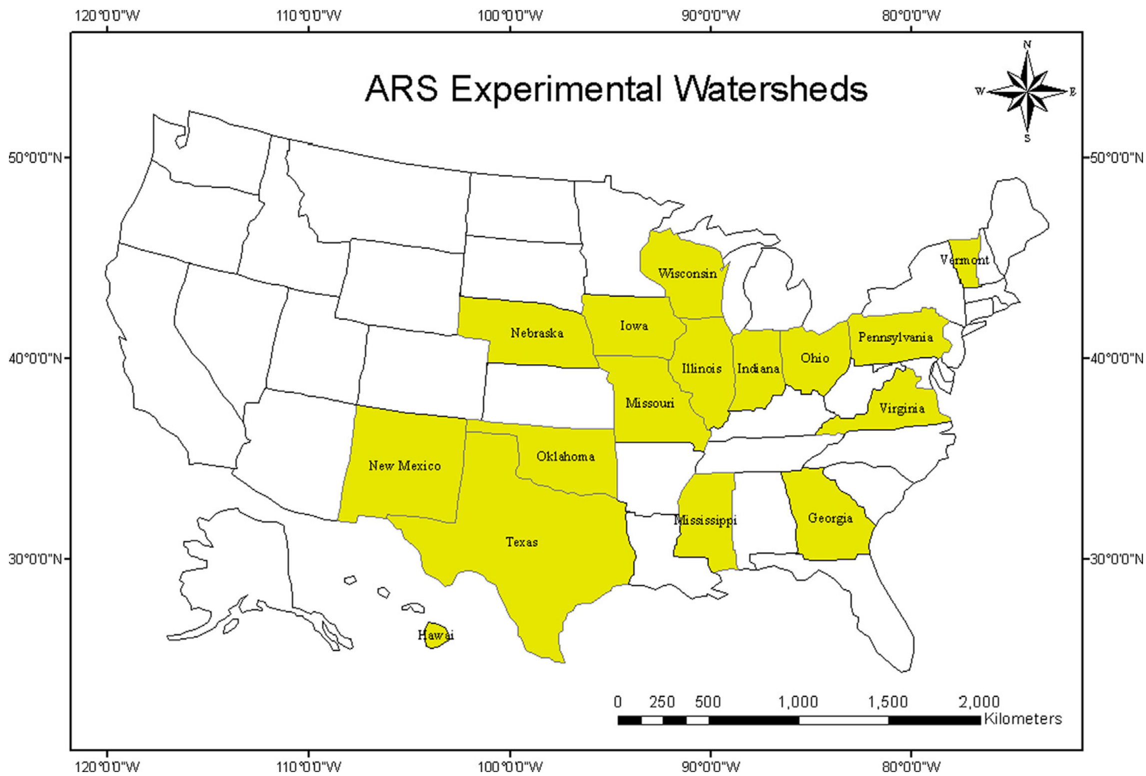

Fig. 2. Location of USDA ARS experimental watersheds.

3. Methodology

3.1. Original soil conservation service curve number method

A brief structural and conceptual background of the original soil conservation service curve number (SCS-CN) method is given here as follows. The method is based on the water balance equation along with two fundamental relationships. The *first relationship* equates the ratio of actual amount of direct surface runoff (Q) to the total rainfall (P) (or maximum potential surface runoff) to the ratio of actual infiltration (F) to the amount of the potential maximum retention (S) (Mishra and Singh, 2003a,b; Singh et al., 2010). The *second relationship* relates the initial abstraction (I_a) to S and also described as potential post initial abstraction retention (McCuen, 2002) as:

(a) Water balance equation

$$P = Ia + F + Q \tag{1}$$

(b) Basic proportional equality (First hypothesis)

$$\frac{Q}{P - Ia} = \frac{F}{S} \tag{2}$$

(c) I_a-S relationship (Second hypothesis)

$$Ia = \lambda S \tag{3}$$

The values of P, Q, and S are in depth dimensions, while the initial abstraction coefficient (λ) is dimensionless. The basic proportional equality (Eq. (2)) is also known as C = Sr concept; where C = [Q/(P-Ia)] and Sr = F/S (Jain et al., 2006; Mishra and Singh, 2002, 2003a,b; Sahu et al., 2010; Santikari and Murdoch, 2018; Singh et al., 2010, 2015).

Combination of Eqs. (1) and (2) leads to the basic equation of the original SCS-CN as:

$$Q = \frac{(P - Ia)^2}{P - Ia + S} \text{ if } P > I_a, \quad Q = 0, \text{ otherwise} \tag{4}$$

For λ = 0.2, the coupling of Eqs. (3) and (4) results in:

$$Q = \frac{(P - 0.2S)^2}{P + 0.8S} \tag{5}$$

Equation (5) is the popular form of the original SCS-CN method having only one parameter S. The parameter S of the SCS-CN method depends on soil type, land use, hydrologic condition, and AMC. The parameter S is mapped onto a dimensionless curve number CN, varying in a range 0 ≤ CN ≤ 100, as:

$$S = \frac{25400}{CN} - 254 \tag{6}$$

where S has the unit in mm.

3.2. Mishra-Singh method

For inclusion of the cumulative static portion of infiltration (F_c) in the original SCS-CN method, Mishra and Singh (2003a,b) modified the proportionality concept [C = S_r, concept] as:

$$\frac{Q}{P - I_a - F_c} = \frac{F_d}{S} \tag{7a}$$

The water balance equation can be written as:

$$P = I_a + F_d + F_c + Q \tag{7b}$$

where F_d and F_c are the cumulative dynamic (capillary) and static (gravitational) infiltration, respectively. The coupling of Eqs. (7a&b) yields the expression of Q as:

$$Q = \frac{(P - I_a - F_c)^2}{(P - I_a - F_c + S)}; \quad \text{for } P \geqslant (I_a + F_c), \ \ 0 \text{ otherwise} \tag{8}$$

For λ = 0.2, Eq. (8) can be written as:

$$Q = \frac{(P - 0.2S - F_c)^2}{(P + 0.8S - F_c)}; \quad \text{for } P \geqslant (0.2S + F_c), \ 0 \text{ otherwise} \tag{9}$$

where

$$F_c = f_c T \tag{10}$$

where f_c is the minimum infiltration rate (mm/h) and T is the rainfall duration (h). The Mishra-Singh method has been denoted as MS method in the forthcoming sections.

3.3. Michel-Vazken-Perrin method

Michel et al. (2005) incorporated the SMA procedure in the SCS-CN method and developed a renewed version of SCS-CN method, expressed as.:

$$\text{If } V_0 \leqslant (S_a - P), \text{ then } Q = 0 \tag{11}$$

If $(S_a - P) < V_0 < S_a$, then,

$$Q = \frac{(P + S_a - V_0)^2}{(P + V_0 - S_a + S)} \tag{12}$$

If $S_a \leq V_0 \leq (S_a + S)$, then,

$$Q = P\left[1 - \frac{(S + S_a - V_0)^2}{S^2 + (S + S_a - V_0)P}\right] \tag{13}$$

where V_0 = initial soil moisture, i.e. the soil moisture before the storm event; S_a = threshold soil moisture = $(V_0 + I_a)$; and I_a = Initial abstractions. The values of S_a and V_0 are given in depth dimensions. The Michel-Vazken-Perrin Method has been referred to as MVP method in the forthcoming sections.

3.4. Development of activation soil moisture accounting (ASMA) based SCS-CN method

For the development of the activation soil moisture accounting (ASMA) based SCS-CN (ASMA-SCS-CN) method, Eq. (8) was selected as the base equation which is valid for the accumulated rainfall (P) and accumulated runoff (Q) for any storm event and considers the static infiltration in its formulation. However, it can be shown that Eq. (8) is hydrologically unstable as it does not yield Q = 0 for P < $(I_a + F_c)$. Now, assuming that V is the soil moisture store at any time t during a storm event, P is the accumulated rainfall up to the time t and Q is the corresponding runoff. The water balance equation can be written as:

$$V = V_0 + P - Q \tag{14}$$

Substituting the value of Q from Eq. (8) in Eq. (14) we get,

$$V = V_0 + P - \left[\frac{(P - I_a - F_c)^2}{(P - I_a - F_c + S)}\right] \tag{15}$$

The runoff rate (q = dQ/dt) can be obtained by taking the derivative of Eq. (8) as:

$$q = \frac{(P - I_a - F_c)(P - I_a - F_c + 2S)}{(P - I_a - F_c + S)^2} p \text{ if } P > (I_a + F_c) \tag{16}$$

where p is the rainfall intensity (rate) and is equal to (dP/dt).

Now, deriving the value of P from Eq. (15) and putting into Eq. (16) results into:

$$q = \frac{[V - (V_0 + I_a + F_c)][2S - V + (V_0 + I_a + F_c)]}{S^2} p \text{ if } V > (V_0 + I_a + F_c) \tag{17}$$

$q = 0$, otherwise

The detailed derivations are given in Appendix A.

Now, if we critically look at Eq. (17), then the numerator has $(I_a + F_c)$ in addition to the initial soil moisture V_0. Notably, the V_0 represents the state of the system (Mishra and Singh, 2003a,b; Michel et al., 2005). This $(I_a + F_c)$ acts as the as the activation soil moisture (V_{ASM}) and term $(V_0 + I_a + F_c)$ is taken as the *revised threshold soil moisture* $(V_{et}) = (V_0 + V_{ASM})$. Graphically, this has been shown in Fig. 3. Eq. (17) shows that if the amount of moisture is less than the V_{et}, then there will be no runoff and hence for runoff generation, the moisture store has to be more than the V_{et}. Therefore, the complete SMA system should consider the *revised threshold soil moisture* (V_{et}) and the concept of threshold soil moisture (S_a) is just the part of the complete SMA system.

On replacing $(I_a + V_0 + F_c)$ with V_{et}, Eq. (17) leads to

$$q = \left(\frac{V - V_{et}}{S}\right)\left[2 - \left(\frac{V - V_{et}}{S}\right)\right] p \text{ if } V > V_{et}, \tag{18}$$

$q = 0$, otherwise

Taking the derivative of Eq. (14) can be expressed as:

$$\frac{dV}{dt} = p - q \tag{19}$$

Now, coupling the expressions for V_{ASM} and V_{et} in Eq. (8) (MS method) (the base method incorporating the F_c) yields:

$$Q = \frac{(P + V_0 - V_{et})^2}{(P + V_0 - V_{et} + S)} \text{if } (P + V_0) > V_{et}, \tag{20}$$

$Q = 0$, otherwise

If the soil is fully saturated before the start of storm event, i.e., $V_0 = (V_{et} + S)$, then Q should be equal to P from Eq. (20). However, putting $V_0 = (V_{et} + S)$, in Eq. (20) yields a value of Q greater than P which is not possible in reality as:

$$Q = P + \frac{S^2}{(P + 2S)} \tag{21}$$

Therefore, the MS method (Eq. (20)) is hydrologically not sound and needs some conceptual and structural modifications. Notably, the MS method does not consider the SMA procedure in its formulation.

Therefore, a hydrologically sound and structurally stable formulation can be obtained by recalculating the formula for the total amount of rainfall and runoff (P and Q) by integrating the Eq. (19) and using the value of q from Eq. (18) as:

$$Q = P\left[1 - \frac{(S + V_{et} - V_0)^2}{(S^2 + (S + V_{et} - V_0)P)}\right] \tag{22}$$

The detailed derivations are given in Appendix B.

Eq. (22) shows that if $V_0 = (V_{et} + S)$, then Q = P, and this is consistent both mathematically and hydrologically. Similarly, for the intermediate and lowest conditions, i.e., (i) for $V_0 < V_{et}$, but $(P + V_0) > V_{et}$ i.e. $(V_{et} - P) < V_0 < V_{et}$, the generated runoff (Q) can be computed using Eq. (20), and (ii) for $V_0 < (V_{et} - P)$, i.e., rainfall P is not large enough to overcome the initial moisture deficit of the soil moisture store, then Q = 0.

These conditions are summarised as follows:

$$\text{If } V_0 < (V_{et} - P), \text{ then, } Q = 0 \tag{23}$$

If $(V_{et} - P) < V_0 < V_{et}$, then,

$$Q = \frac{(P + V_0 - V_{et})^2}{(P + V_0 - V_{et} + S)} \tag{24}$$

If $V_{et} \leqslant V_0 \leqslant (V_{et} + S)$, then,

$$Q = P\left[1 - \frac{(S + V_{et} - V_0)^2}{(S^2 + (S + V_{et} - V_0)P)}\right] \tag{25}$$

Eqs. (23)–(25) represent the ASMA-SCS-CN method. The proposed approach is more logical, and hydrologically more stable and complete than the other methods under study. A summary of all the four CN based methods is given in Table 1.

3.5. Applications of the methods

All the four methods i.e., the Original SCS-CN method (Eq. (6)) (SCS-CN), Mishra-Singh method (Eq. (8)) (MS), Michel-Vazken-Perrin method (Eqs. (11)–(13)) (MVP), and the ASMA-SCS-CN method (Eqs.

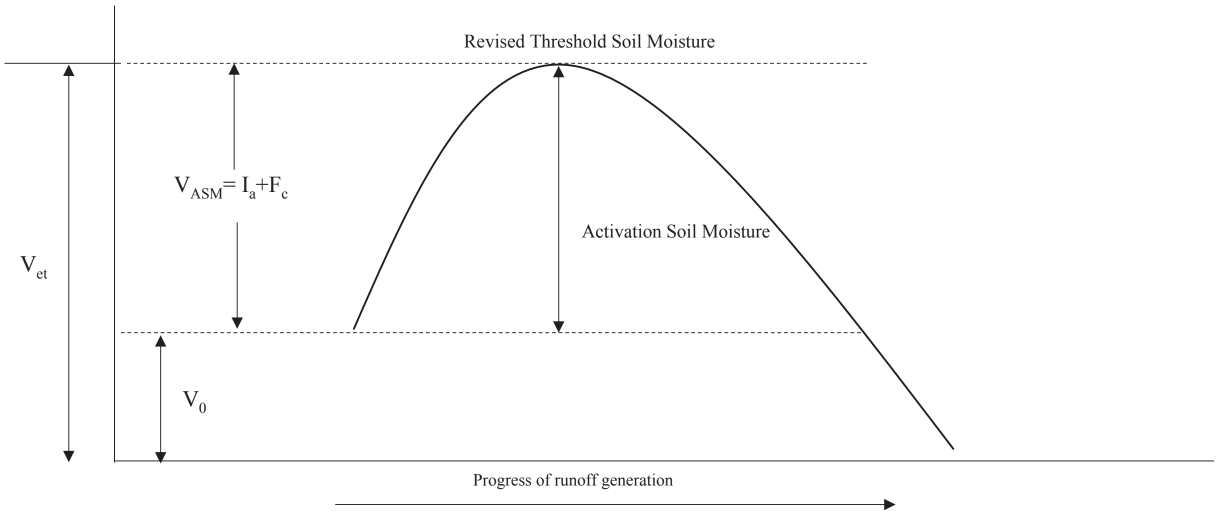

Fig. 3. Similarity between threshold energy and activation energy versus threshold soil moisture and activation soil moisture [V_0 – Initial soil moisture, V_{ASM} – Activation soil moisture, V_{et} – Threshold soil moisture].

Table 1
Mathematical representation all the four methods: SCS-CN, MS, MVP and ASMS-SCS-CN.

Sl. No.	Method Name	Case	Method Formulation
1	SCS-CN	$P \geq I_a$,	$Q = \frac{(P-I_a)^2}{P-I_a+S}$
		$P < I_a$	$Q = 0$
2	MS	$P \geq (I_a + F_c)$	$Q = \frac{(P-I_a-F_c)^2}{(P-I_a-F_c+S)}$
		$P < (I_a + F_c)$	$Q = 0$
3	MVP	$V_0 \leq (S_a–P)$	$Q = 0$
		$(S_a–P) < V_0 < S_a$	$Q = \frac{(P+S_a-V_0)^2}{(P+V_0-S_a+S)}$
		$S_a \leq V_0 \leq (S_a + S)$	$Q = P\left[1 - \frac{(S+S_a-V_0)^2}{S^2+(S+S_a-V_0)P}\right]$
4	ASMA-SCS-CN	$V_0 < (V_{et} - P)$	$Q = 0$
		$(V_{et} - P) < V_0 < V_{et}$,	$Q = \frac{(P+V_0-V_{et})^2}{(P+V_0-V_{et}+S)}$
		$V_{et} \leqslant V_0 \leqslant (V_{et} + S)$	$Q = P\left[1 - \frac{(S+V_{et}-V_0)^2}{(S^2+(S+V_{et}-V_0)P)}\right]$

(23)–(25)) (Table 1) were applied to the large US rainfall-runoff datasets (164 watersheds with 56,343 storm events) to test the comparative performance of these methods.

3.5.1. Parameter estimation

To estimate the different parameters of all the four methods, i.e., the original SCS-CN method (SCS-CN), Mishra-Singh method (MS), Michel-Vazken-Perrin Method (MVP), and the proposed ASMA-SCS-CN method, simplified expressions were used in this study as suggested by Mishra et al. (2006b), and Singh et al. (2015), expressed here:

$$V_0 = \alpha\sqrt{P_5 S} \tag{26}$$

$$S_a = \beta S \tag{27}$$

$$F_c = f_c T \tag{28}$$

where, P_5 is the antecedent rainfall amount (mm), f_c is the minimum infiltration rate (mm/h), T is the rainfall duration (h), and α, β are coefficients.

The Marquardt (1963) algorithm of constrained least squares (MCLS) was used for optimizing the parameters of all the four methods, i.e., SCS-CN, MS, MVP and ASMA-SCS-CN. The Marquardt provided an elegant and improved version of the non-linear optimization method originally proposed by Levenberg (1944). The method primarily provides a smooth variation between the two extremes of the Inverse-Hessian method and the steepest descent method. The latter is used when the trial solution is far from the minimum and it tends continuously towards the former as the minimum is approached. This Levenberg–Marquardt method is also known as Marquardt method, which works well in practice and has become the standard of non-linear least squares routines (Mishra and Singh, 2003a).

In application to the SCS-CN method, the initial estimate of CN was taken as 50 and was allowed to vary in the range of 0 to 100. For all the methods except SCS-CN, the initial estimate of parameter S was taken as 125 mm and was assumed to vary in the range of 0 to 2500 mm. For MVP method, the V_0 and S_a parameters were allowed to vary in the range of 0 to 500 mm with its initial estimate of 100 mm. For the proposed ASMA-SCS-CN method, an initial estimate of both the parameters α and β was taken as 0.01 and was allowed to vary in the range of 0.00 and 2.00 and 0.00 to 1.00, respectively. Parameter f_c was allowed to vary in the range of 0.00 and 25.00 with an initial estimate 1.00. The V_{et} was estimated as the sum of S_a and F_c, i.e., ($S_a + F_c$).

3.5.2. Performance evaluation of methods

The process of performance evaluation of models is of primary importance, not only in their development and calibration process, but also when communicating the results to other researchers and to the stakeholder (Schaefli and Gupta, 2007). For evaluating the performance of all the four methods having different parameters, seven indices of agreement between observed and computed runoff values are used in this study. These performance indices are Nash-Sutcliffe efficiency (NSE), the root mean square error (RMSE), normalized RMSE (nRMSE), percent bias (PBIAS), mean absolute error (MAE), standard error (SE) and RMSE-observations standard deviation ratio (RSR) as discussed here. Mathematically, these indices are expressed as:

$$NSE = \left[1 - \frac{\sum_{i=1}^{N}(Q_{obs} - Q_{comp})_i^2}{\sum_{i=1}^{N}(Q_{obs} - \bar{Q}_{obs})_i^2}\right] \tag{29}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_{obs} - Q_{comp})_i^2} \tag{30}$$

nRMSE =

$$\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_{obs}-Q_{comp})_i^2}}{\bar{Q}_{obs}} \quad (31)$$

$$PBIAS = \left[\frac{\sum_{i=1}^{N}(Q_{obs}-Q_{comp})_i}{\sum_{i=1}^{N}(Q_{obs})_i}\right] * 100 \quad (32)$$

$$MAE = \frac{1}{N}\sum_{i-1}^{N}|Q_{obs}-Q_{comp}|_i \quad (33)$$

$$SE = \frac{1}{(N-m+1)}\sqrt{\sum_{i=1}^{N}(Q_{obs}-Q_{comp})_i^2} \quad (34)$$

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{N}(Q_{obs}-Q_{comp})_i^2}}{\sqrt{\sum_{i=1}^{N}(Q_{obs}-\bar{Q}_{obs})_i^2}} \quad (35)$$

where, Q_{obs} is the observed runoff, Q_{comp} is the computed runoff, $\bar{Q}_{obs}$ is the mean of observed runoff values in a watershed, N is the total number of rainfall-runoff events, m the number of model parameters and i is an integer varying from 1 to N.

The NSE compares the variance of the errors against the observations (how well the plot of observations versus simulations fit the 1:1 line (Ahmadisharaf et al., 2019). The NSE ranges between $-\infty$ and 1.0 (1 inclusive), with NSE = 1 being the optimal value. The values between 0.0 and 1.0 are generally viewed as acceptable levels of performance (Moriasi et al., 2007). A value of zero indicates that the observed mean is as good a predictor as the model, while negative values indicate that the observed mean is a better predictor than the model (Ahmadisharaf et al., 2019; Moriasi et al., 2007; Wilcox et al., 1990; Coffey et al., 2004a,b). McCuen et al. (2006) stated that NSE is a very good criterion for assessing comparative performance of hydrologic models.

According to Legates and McCabe (1999), the NSE is sensitive to the differences in the observed and model simulated means and variance and can be thought of as an improvement over the coefficient of determination (R^2) widely used for evaluating the goodness-of-fit of hydrologic and hydro-climatic models. The NSE cannot also help identify the bias and is sensitive to extreme values (Criss and Winston, 2008; Larabi et al., 2018), and if the goal is to quantify the bias, the PBIAS, can be used (Krause et al., 2005; Moriasi et al., 2015; Alamdari et al. 2017; Alamdari and Sample 2019). According to Pérez-Sánchez et al. (2019), however, NSE cannot help identify model bias (Moriasi et al., 2015), and it should be complemented by other measures, such as PBIAS, in order to consider how well the model simulates the average magnitudes for the outputs and to identify the average model simulation bias (over-prediction versus under-prediction). Therefore, PBIAS has been used in this study to identify the average model simulation bias by all the four methods.

Similarly, Normalized root mean square error (nRMSE) is an another most widely used statistical indicator for model performance evaluation (Santhi et al., 2001; Van Liew et al., 2003, Mishra et al., 2006a). The nRMSE standardizes the RMSE values into a common and comparable scale (Ranatunga et al., 2017). The RMSE and MAE can be used to determine confidence intervals in model predictions, and it is possible to incorporate measurement uncertainty (Harmel and Smith, 2007; Harmel et al., 2010; Moriai et al., 2015). The RMSE-observations standard deviation ratio (RSR) (Chu and Shirmohammadi, 2004; Moriasi et al., 2007; Vazquez-Amábile and Engel, 2005) standardizes RMSE using the observations standard deviation, and it combines both an error index and the additional information recommended by Legates and McCabe (1999). RSR incorporates the benefits of error index statistics and includes a scaling/normalization factor, so the resulting statistics and reported values can apply to various output responses. The lower RSR, the lower the RMSE, and the better the model simulation performance. RSR is a relatively new statistical performance measure has not been widely used in the H/WQ modelling literature (Moriasi et al., 2015).

Moriasi et al. (2007) established a performance criterion for model's evaluation where NSE $<$ 0.50 (unsatisfactory), 0.50 $<$ NSE $\leq$ 0.65 (satisfactory), 0.65 $<$ NSE $\leq$ 0.75 (good), and 0.75 $<$ NSE $\leq$ 1.00 (very good). According to Ritter and Muñoz-Carpena (2013), a model is judged to be 'very good' if NSE $\geq$ 0.90, 'good' if 0.90 $>$ NSE $\geq$ 0.80, 'acceptable' if 0.80 $>$ NSE $\geq$ 0.65 and 'unsatisfactory' if 0.65 $>$ NSE. The value of RMSE equal to 0 shows a perfect agreement between observed and estimated values. The lower the RMSE, the better is the model's performance and vice versa. The PBIAS measures model's tendency to underestimate or overestimate values. Negative (positive) value of PBIAS indicates model overestimation (underestimation) whereas a value of zero shows perfect fit (Moriasi et al., 2007). For the hydrologic models, performance was indicated as 'unsatisfactory' if PBIAS $> \pm$ 25%, 'fair' if $\pm$ 15% $\leq$ PBIAS $\leq \pm$ 25%, 'good' if $\pm$ 10% $\leq$ PBIAS $< \pm$ 15% and 'very good' if PBIAS $< \pm$ 10% (Durbude et al., 2011; Moriasi et al., 2007). The nRMSE and RSR estimate show how important these are errors relative to the magnitude of the observations (Ahmadisharaf et al., 2019). According to Moriasi et al. (2007), the model performance is rated as 'very good', if 0.00 $<$ RSR $\leq$ 0.50; 'good' if 0.50 $<$ RSR $\leq$ 0.60; 'satisfactory, if 0.60 $<$ RSR $\leq$ 0.70, and unsatisfactory, if RSR greater than 0.70. The standard error (SE) of all the four methods has also been evaluated to evaluate the methods' performance. Higher the SE, poorer is the model performance and vice versa. A value of SE equal to zero exhibits a perfect fit. SE has the advantages of having the same units as the variable and accounts for the methods' degree of freedom in case of comparing the methods having different number of parameters, which is generally the case in most of the applications.

The hydrological models are subjected to the uncertainty (Ahmadisharaf et al., 2018). The uncertainty in hydrological modeling arises from input datasets (Shrestha et al., 2009; Montanari et al., 2009), observed flow, choice of hydrological model, model structure and parameters, accounting of relevant physical processes in the watershed, choice of goodness-of-fit measures, and calibration/validation period (Krzysztofowicz and Kelly, 2000; Krzysztofowicz and Herr, 2001; Montanari and Brath, 2004; Liu and Gupta, 2007; McMillan et al., 2010; 2011; 2012; Renard et al. 2010, Ahmadisharaf et al., 2018), and also the experience of the modeler in manual calibration (Orth et al., 2015; Martina and Todini, 2008). The parameter uncertainty estimation is one of the major challenges in hydrological modeling and it reflects the inability to specify exact values of model parameters (Renard et al., 2010) and it may stem from errors in input data and observations used for model conditioning. Navratil et al. (2011) also discussed various sources of uncertainty associated with the observations such as (i) choice of suitable instrument; (ii) data acquisition strategy; (iii) field sampling procedures for water and sediment sampling; (iv) laboratory procedures; and (v) discharge and water level measurement, among many others.

4. Results and discussions

4.1. Parameter estimation

As discussed in Section 3.5.1, the optimized parameters values of all the four methods, i.e., SCS-CN, MS, MVP and ASMA-SCS-CN for 164 USDA study watersheds are given in Appendix I. The statistical range of all the parameters for four methods is also given in Table 2. It can be

Table 2
Range of parameters obtained after application of SCS-CN, MS, MVP and ASMA-SCS-CN methods to 164 US watersheds.

Method	Parameter	Mean	Median	Min.	Max.	Lower Bound	Upper Bound
SCS-CN	CN	82.0	87.7	30.8	96.3	79.9	84.2
MS	fc	1.0	0.5	0.0	6.8	0.8	1.2
	S	46.2	33.5	3.2	327.5	39.0	53.0
MVP	V0	153.0	106.0	0.0	500.0	136.9	169.2
	Sa	150.0	100.9	1.6	500.0	132.8	167.2
	S	227.6	123.5	0.1	2451.6	176.9	278.3
ASMA-SCS-CN	α	0.3	0.2	0.0	1.3	0.2	0.3
	β	0.1	0.1	0.0	1.0	0.1	0.1
	fc	0.5	0.0	0.0	7.0	0.3	0.7
	S	232.8	126.4	24.8	2500.0	172.0	293.6

seen from Table 2 that the average value of parameter '*CN*' for the SCS-CN method is 82.03 with min. and max. values as 30.80 and 96.30, respectively. Table 2 also show that the min. infiltration rate (f_c) for ASMA-SCS-CN method is lower (0.52) than that of MS method (0.99). The average values of parameters α and β are found to be 0.24 and 0.12, with min. to max. values as 0.01 to 1.30 and 0.00 to 7.00, respectively. Singh et al. (2015) also reported the average values of α and β as 0.220 and 0.118, while applying their modified SMA based MSCS-CN (MMSCS-CN) method to 35 USDA watersheds dataset. The average values of parameter 'S' for ASMA-SCS-CN, MVP and MS method are found to be 232.80 mm and 227.61 mm and 46.24 mm, respectively while applying to 164 USDA study watersheds.

4.2. Comparative performance evaluation of the methods

The performance of all the four methods is evaluated on the basis of their (i) (visual) closeness of the observed and computed runoff and (ii) goodness of fit (GOF) in terms of NSE, RMSE, nRMSE, MAE, SE, PBIAS, and RSR as discussed in Section 3.5.2. Worth highlighting that any method having greater NSE and lesser RMSE, nRMSE, MAE, SE RSR. As well as PBIAS (either positive or negative) than the other methods can be ranked as superior and vice versa. For visual comparison, Fig. 4a-h show the comparison between the observed and computed runoff by all the four methods for 8 different watersheds. In general, it can be observed from these figures that the ASMA-SCS-CN method resembles a better agreement with the observed runoff and are closest to the 1:1 line than the other methods. Fig. 4a-h also show that the R^2 value of the AMA-SCS-CN is higher than the rest of the three methods, i.e., SCS-CN, MS, and MVP. Another visual comparison (event-wise) is also shown in Fig. 5a–d. It is evident from these figures that the ASMASCS-CN method has better agreement between the observed and computed runoff than the SCS-CN, MS, MVP methods. There is a larger mismatch between the observed and computed runoff for most of the events (underestimation) in case of MS and SCS-CN method than the MVP and ASMA-SCS-CN method. The improved performance of the ASMA-SCS-CN method may be due attributed to inclusion of SMA and Fc in its model structure and overall in the rainfall-runoff process. Similar results are found for most of the watersheds not shown here.

As discussed above, the GOF statistics is evaluated in terms of NSE, and error indices as RMSE, nRMSE, MAE, SE, PBIAS, and RSR and the results are given in Appendix IIa&b for all the 164 watersheds. The mean value of NSE for ASMA-SCS-CN is found to be highest (0.696) followed by MVP (0.643), MS (0.571), and SCS-CN (0.53), respectively while application to all the 164 watersheds. Similar results can also be drawn from Fig. 6a, which shows the plot of NSE values for all the for methods on 164 watersheds (Annexure II a&b).

It can be seen from Fig. 6(a) that the ASMA-SCS-CN method has higher NSE as compared to the other methods, i.e. MVP, MS and SCS-CN. for most of the watersheds. The improved performance of ASMA-SCS-CN can be attributed to the inclusion of SMA along with the static infiltration component for representing the complete picture of SMA system in modelling rainfall-runoff process. The range of variation of NSE values for all the four methods is also shown using Box-whisker plots as shown in Fig. 6b. It can be observed from Fig. 5(b) that the ASMA-SCS-CN method has the highest median value of NSE (0.71; varying from 0.11 to 0.97) with inter-quartile range (IQR) as (0.62–0.80) followed by MVP with NSE (0.67; varying from 0.10 to 0.0.96) and IQR as (0.57–0.74), MS with NSE (0.61; varying from 0.02 to 0.97) and IQR range as (0.46–0.72), and SCS-CN with NSE (0.58; varying from 0,01 to 0.92) and IQR as (0.44–0.69).

The NSE performance rating as per the criteria given by Moriasi et al. (2007) is also given in Table 3a. The ASMA-SCS-CN method performs very good on 87 watersheds, good on 63, satisfactory on 23 and unsatisfactory on 15 watersheds. The MVP method is found to perform very good on 63 watersheds, good on 73 watersheds, satisfactory on 31 watersheds and unsatisfactory on 23 watersheds. The MS method performs very good on 52 watersheds, good on 55 watersheds, satisfactory on 30 watersheds and unsatisfactory on 47 watersheds. The SCS-CN method performs very good on the least no. of watersheds, i.e., 35, good on 55 watersheds, satisfactory on 38 watersheds and performs unsatisfactory on the larger number of the watersheds, i.e., 56. Therefore, on the basis of Moriasi et al. (2007) NSE performance rating, the order of performance is ASMA-SCS-CN > MVP > MS > SCS-CN method and the improved performance is attributed to the inclusion of Fc in the SMA procedure resulting into the improved representation of the rainfall-runoff process.

Similarly, Table 3b shows the performance rating based on the criteria given by Ritter and Muñoz-Carpena (2013). The results show that the SCS-CN, MS, MVP, and ASMA-SCS-CN perform *very good* on 1, 6, 1, and 10 watersheds, *good* on 6, 9, 13, and 30 watersheds, and *acceptable* on 45, 49, 76, and 68 watersheds respectively. The RMC performance rating also show the improved performance of the ASMA-SCS-CN method than the MVP, MS and SCS-CN method. Fig. 6(c) also shows the NSE variation with watershed area for all the four methods. Here, it is found that the method ASMA-SCS-CN performs better than the other methods for small as well as large watersheds. The NSE values at 50%; 75%; and 90% probability of exceedance (Fig. 6d) resulting from the application of all the four methods on 164 watersheds are found to be 0.56, 0.60, 0.66, 0.70; 0.66, 0.71, 0.73, 0.77; and 0.72 0.76, 0.77, 0.82, respectively for SCS-CN, MS, MVP, and ASMA-SCS-CN methods. Fig. 5d shows that the ASMA-SCS-CN method has the highest values of NSE corresponding for all the three probability of exceedance during application to 164 watersheds.

The performance of all the four methods is further evaluated based on RMSE as shown in Fig. 7(a)&(b) and Appendix IIa for all the 164 watersheds. Fig. 7(a) and Appendix IIa show the RMSE variation for 164 watersheds. It is evident from Fig. 7(a) and Appendix IIa that the ASMA-SCS-CN method has lower RMSE as compared to MVP, MS and SCS-CN method. Fig. 7(b) shows the box-whisker plots of RMSE values obtained by applying all the four methods to 164 watersheds. Fig. 7(b) shows that the ASMA-SCS-CN method has lower median value (4.03 mm) and inter-quartile range (3.07–5.97 mm) compared to other methods, i.e., MVP (median value: 4.56 mm and IQR: 3.29–6.33 mm); MS (median value: 4.61 mm and IQR: 3.57–6.70 mm); and SCS-CN (median value: 5.04 mm and IQR: 3.92–7.14 mm). The mean values of the RMSE are found to be 4.653 mm, 5.058, 5.415 and 5.643, respectively for ASMA-SCS-CN, MVS, MS and SCS-CN method. Therefore, based on RMSE criteria, the ASMA-SCS-CN is found to perform best followed by MVP, MS and SCS-CN methods. Using the RMSE statistics, the performance of all the four methods based on the different watershed characteristics is also discussed in the forthcoming section.

The nRMSE statistics is also evaluated to assess the comparative performance of all the four methods as shown in Fig. 8a&b and Appendix IIb. Fig. 8a shows the variation of nRMSE for all the four methods on 164 watersheds. It can be seen from Fig. 8a that the ASMA-SCS-CN method has lower values of nRMSE as compared to the MVP,

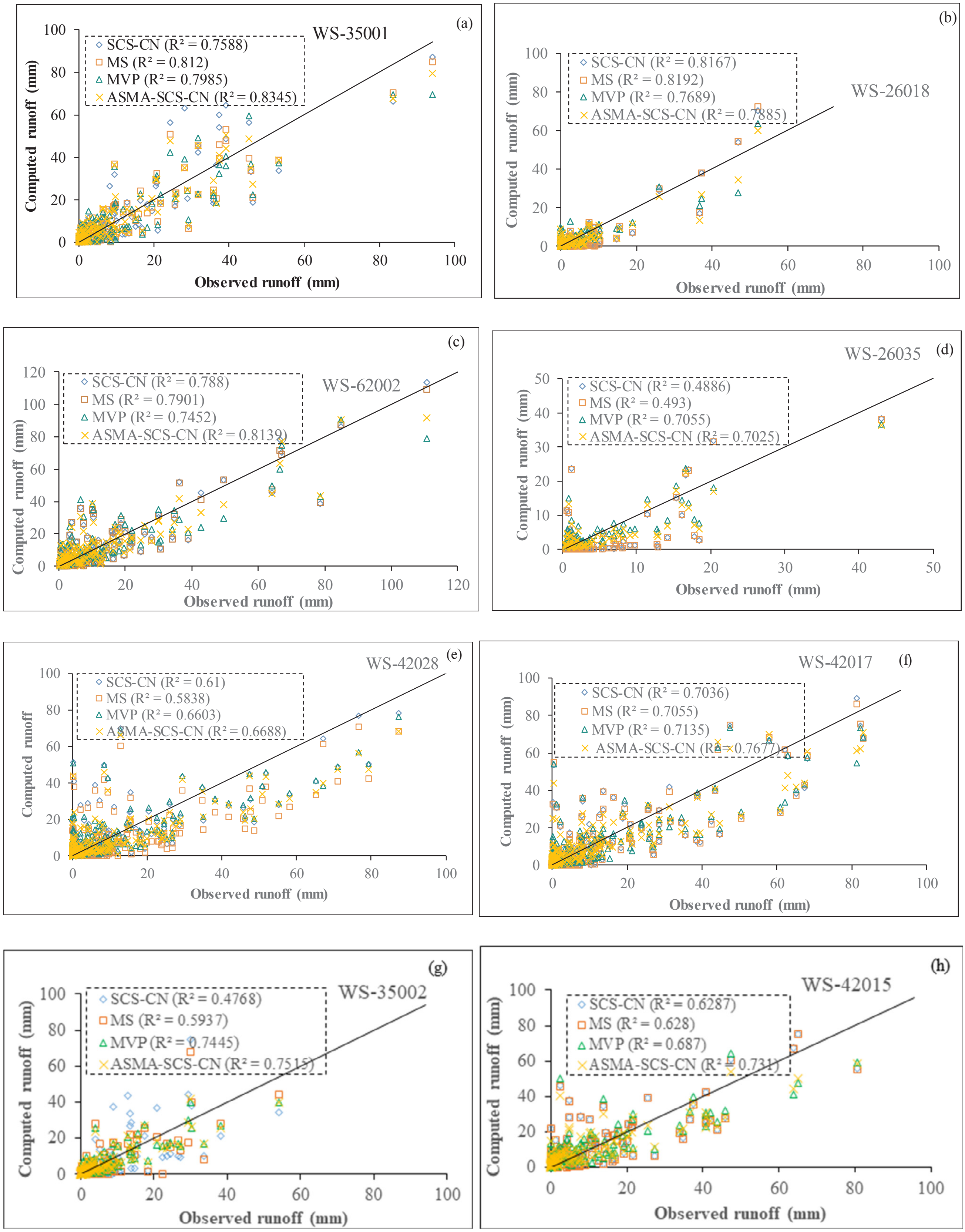

Fig. 4. a-h: Visual comparison between the observed and computed runoff by all the four methods for eight different watersheds, i.e., WS-35001, 35002, 26018, 62002, 26035, 4205, 42028, and 42017.

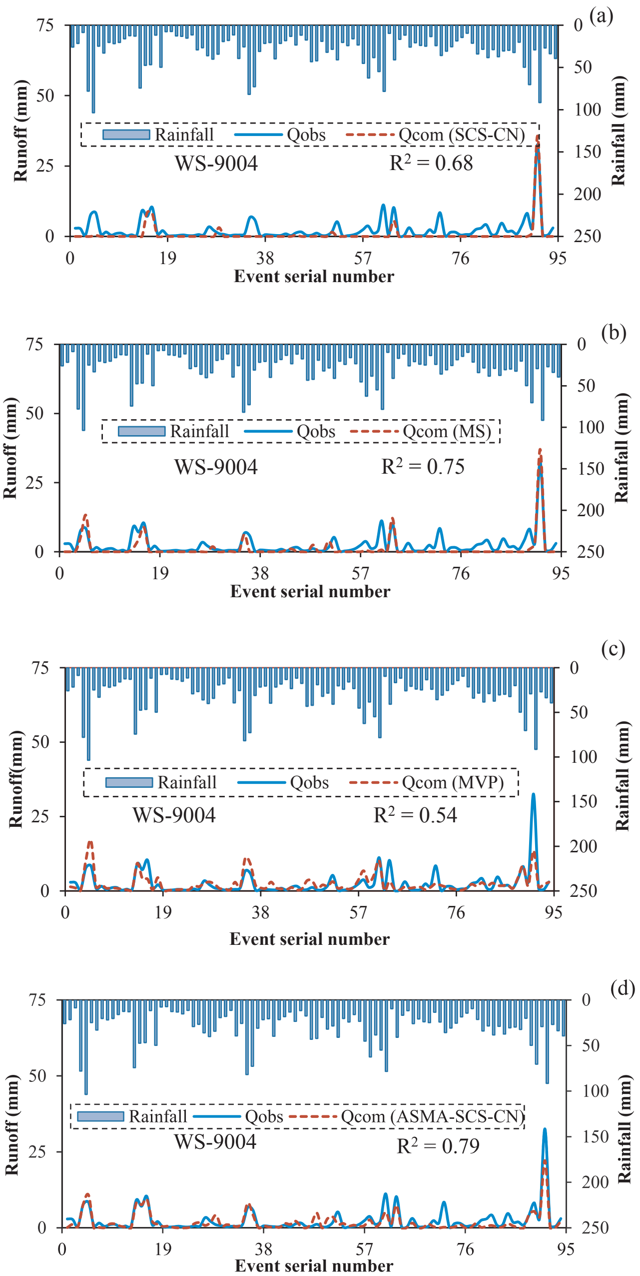

Fig. 5. a-d: Visual comparison (event wise) between the observed and computed runoff by (a) SCS-CN method; (b) MS method; (c) MVP method; and (d) ASMA-SCS-CN method for WS-42015 watershed.

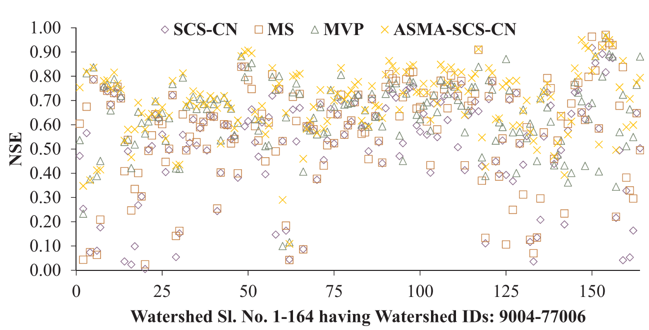

Fig. 6a. Variation of NSE for all the four methods on 164 watersheds (Watershed Sl. No. 1–164 having Watershed IDs from 9004 to 77006). Sl. No. is the numbering of 164 watersheds (1 to 164) having different watershed Ids starting from 9004 to 77,006 as given in Annexure 1a&b.

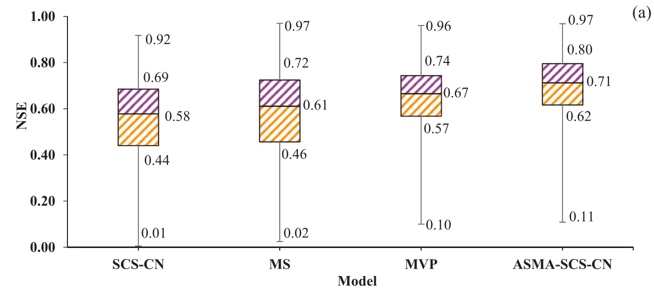

Fig. 6b. Box-whisker plots of NSE variability for all the four methods. The height of the box portion is given by the interquartile range (IQR, 25th to 75th percentile) of the performance metrics NSE.

Table 3a
NSE goodness-of-fit criteria evaluation using Moriasi et al. (2007) rating.

Performance Rating	NSE Range	SCS-CN	MS	MVP	ASMA-SCS-CN
Very good	0.75 < NSE ≤ 1.0	35	52	63	87
Good	0.65 < NSE ≤ 0.75	55	55	73	63
Satisfactory	0.50 < NSE ≤ 0.65	38	30	31	23
Unsatisfactory	NSE ≤ 0.5	56	47	23	15

Table 3b
NSE goodness-of-fit criteria evaluation using Ritter and Munoz-Carpena (RMC) (2013) rating.

Performance Rating	NSE Range	SCS-CN	MS	MVP	ASMA-SCS-CN
Very good	NSE ≥ 0.90	1	6	1	10
Good	0.80 ≤ NSE < 0.90	6	9	13	30
Satisfactory	0.65 ≤ NSE < 0.80	45	49	76	68
Unsatisfactory	NSE < 0.65	112	100	74	56

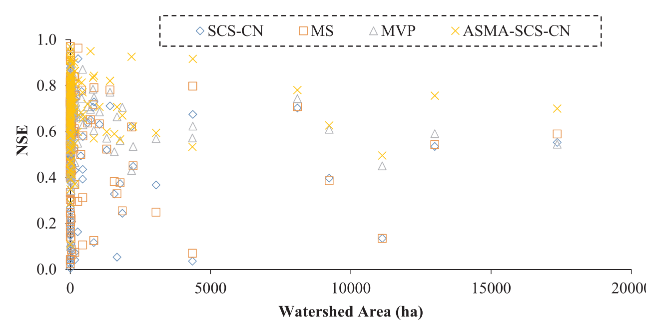

Fig. 6c. Graph between watershed area and NSE for all the four methods.

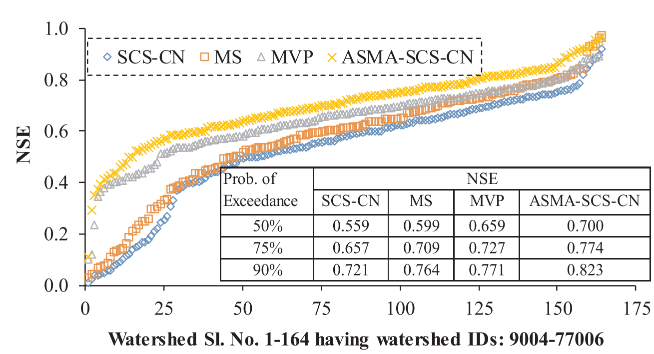

Fig. 6d. Probability of exceedance of NSE values resulting from application of four methods on 164 watersheds. Watershed Sl. No. is the numbering of 164 watersheds (1 to 164) having different watershed Ids starting from 9004 to 77,006 as given in Annexure II a&b.

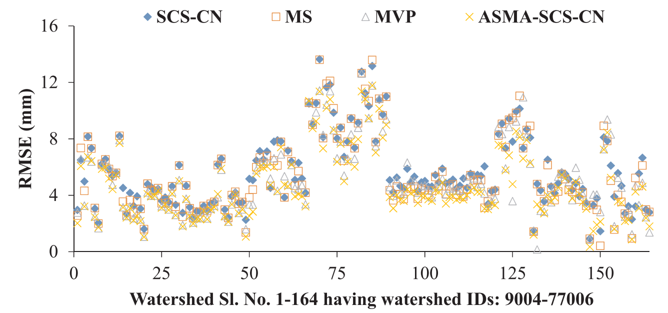

Fig. 7a. Variation of RMSE for all the four methods on 164 watersheds. Watershed Sl. No. is the numbering of 164 watersheds (1 to 164) having different watershed Ids starting from 9004 to 77,006 as given in Annexure II a&b.

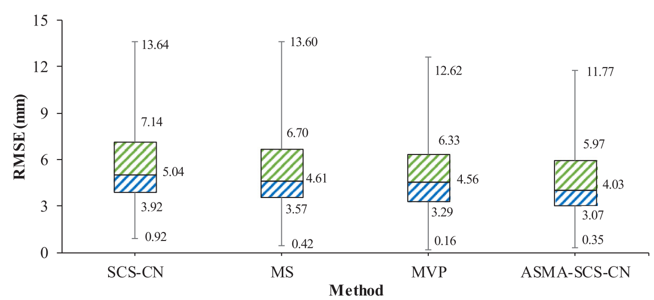

Fig. 7b. Box-whisker plots of RMSE values for all the four methods. The whiskers represent the minimum and maximum RMSE values. The height of the box portion is given by the interquartile range (IQR, 25th to 75th percentile) of the performance metrics RMSE.

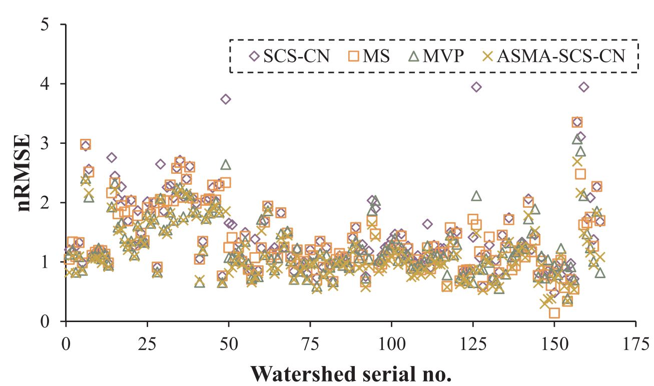

Fig. 8a. Variation of nRMSE for all the four methods on 164 watersheds (Watershed Sl. No. 1–164 having Watershed IDs from 9004 to 77006).

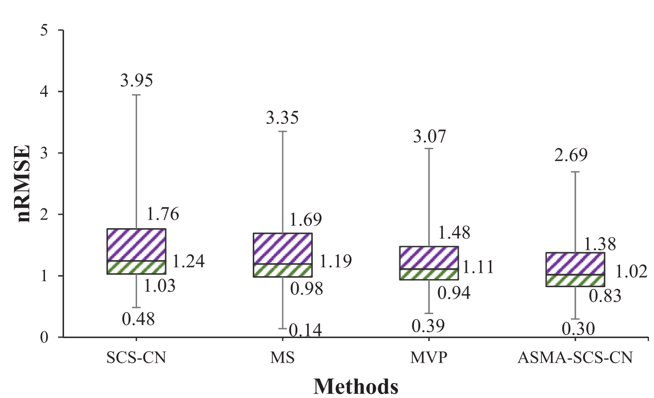

Fig. 8b. Box-whisker plots of nRMSE values for all the four methods. The whiskers represent the minimum and maximum nRMSE values. The height of the box portion is given by the interquartile range (IQR, 25th to 75th percentile) of the performance metrics nRMSE.

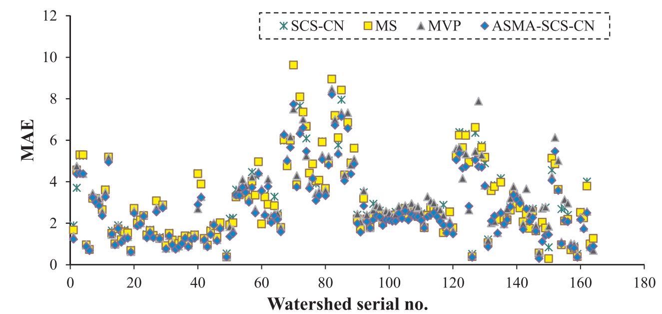

Fig. 9a. Variation of MAE for all the four methods on 164 watersheds (Watershed Sl. No. 1–164 having Watershed IDs from 9004 to 77006).

MS and SCS-CN method. The median nRMSE and IQR for ASMA-SCS-CN method is found to be lowest (IQR = 0.83–1.38 and median nRMSE = 1.02) followed by MVP (IQR = 0.94–1.48 and median nRMSE = 1.11), MS (IQR = 0.98–1.69 and median nRMSE = 1.19) and SCS-CN method (IQR = 1.03–1.76 and median nRMSE = 1.24) (Fig. 8b). According to Stow et al. (2003), smaller the values of RMSE and nRMSE, the greater is the agreement between the simulations and observations. Therefore, based on nRMSE criteria, the ASMA-SCS-CN performs best followed by MVP, MS and SCS-CN methods. Based on RMSE and nRMSE, it may also be stated that the ASMA-SCS-CN method has lower uncertainty as compared to the SCS-CN, MS and MVP method.

The Goodness-of-fit statistics is also evaluated in terms of MAE (Eq. (33)) for all the four methods as shown in Fig. 9a&b and Appendix IIb. Detailed MAE statistics is also given Appendix IIb. Fig. 9a shows the general variability of MAE statistics for all the 164 watersheds, which shows that ASMA-SCS-CN method has lowest values of MAE for most of the watersheds as compared to the SCS-CN, MS, MVP methods. The mean values of MAE for ASMA-SCS-CN, MVP, MS and SCS-CN method are found to be 2.66 mm, 2.93 mm, 2.99 mm and 3.07, respectively. The box-whisker plots (Fig. 9b) shows that the ASMA-SCS-CN method has lower variability outside the upper and lower quartiles and median MAE than the rest of the three methods. Overall, MAE statistics shows that the ASMA-SCS-CN method has improved performance than the SCS-CN, MS, and MVP methods. The MAE results also show that as the area of the watershed increases, the ASMA-SCS-CN method has much lower MAE as compared to the rest of the three methods. The SE results for all the four methods are also shown in Figs. 10a and 10b. The SE results show that the ASMA-SCS-CN method has lowest mean value of SE (0.661 mm) followed by MVP method (0.664 mm), MS (0.733) and SCS-CN (0.777 mm) for all the 164 watersheds. Fig. 10a shows the SE variability for 164 watersheds and Fig. 10b shows the box-whisker plots for all the four methods. These Figures also show that the difference between the SE values of ASMA-SCS-CN and MVP method is very less as compared to the MS and SCS-CN method. However, the SE results also show that as the watershed area increases the ASMA-SCS-CN method

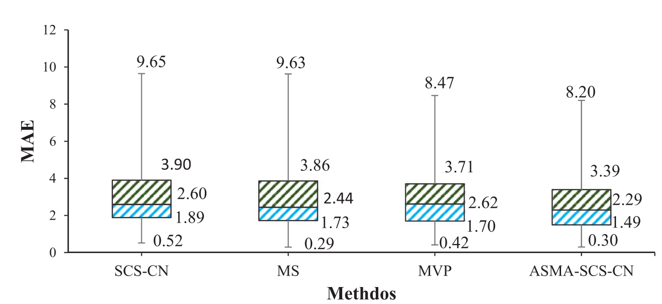

Fig. 9b. Box-whisker plots of MAE values for all the four methods. The whiskers represent the minimum and maximum MAE values. The height of the box portion is given by the interquartile range (IQR, 25th to 75th percentile) of the performance metrics MAE.

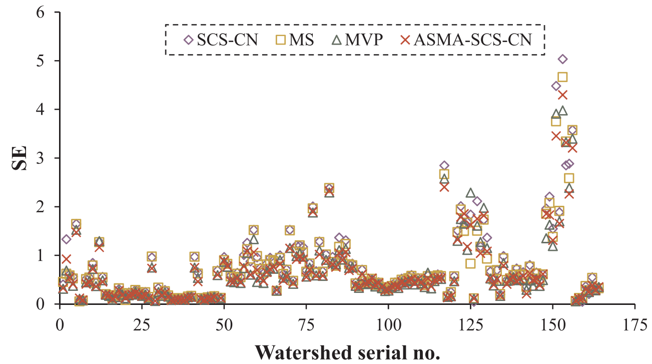

Fig. 10a. Variation of SE for all the four methods on 164 watersheds (Watershed Sl. No. 1–164 having Watershed IDs from 9004 to 77006).

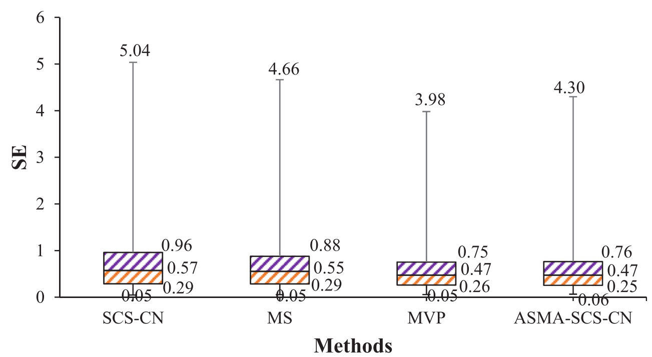

Fig. 10b. Box-whisker plots of SE values for all the four methods. The whiskers represent the minimum and maximum MAE values. The height of the box portion is given by the interquartile range (IQR, 25th to 75th percentile) of the performance metrics SE.

has much lower values of SE as compared to the SCS-CN, MS, and MVP method. Based on the MAE and SE statistics, it can be stated that the ASMA-SCS-CN method has lower uncertainty as compared to the rest of the three methods.

As discussed above, the performance of all the four methods is further evaluated using PBIAS statistics for all the 164 watersheds. The results are given in Appendix IIa and Figs. 11a and 11b. It is observed from these figures that both the ASMA-SCS-CN and MVP methods have lower PBIAS (either positive or negative) than the MS and SCS-CN methods for all the 164 watersheds. The box-whisker plots (Fig. 11b) depicts the data distribution through their quartiles, which shows that ASMA-SCS-CN method has lower variability outside the upper and lower quartiles than the MVP method and lower median RMSE than the MS and SCS-CN methods. Further, the results also show that MVP method has quite lower median PBIAS than the rest of the three methods and notably the difference between median PBIAS values of

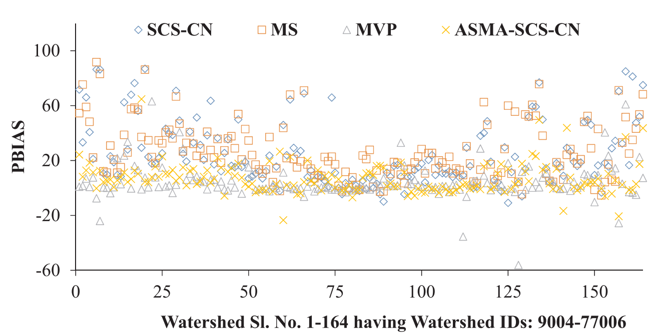

Fig. 11a. Variation of PBIAS for all the four methods on 164 watersheds (Watershed Sl. No. 1–164 having Watershed IDs from 9004 to 77006).

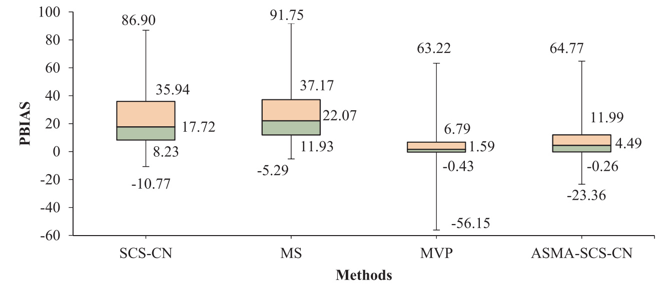

Fig. 11b. Box-whisker plots of PBIAS values for all the four methods. The whiskers represent the minimum and maximum RMSE values. The height of the box portion is given by the interquartile range (IQR, 25th to 75th percentile) of the performance metrics RMSE.

ASMA-SCS-CN and MVP is very small as compared to the MS and SCS-CN methods. This also indicates that the ASMA-SCS-CN method has lower uncertainty as compared to the other methods. The median PBIAS values of MS and SCS-CN methods are found to be much higher than that of ASMA-SCS-CN and MVP methods. Further, all the four methods were also evaluated on the basis of the criteria given by Moriasi et al. (2007) and it is found that the SCS-CN, MS, MVP, and ASMA-SCS-CN methods perform very good on 50, 31, 129, and 108 watersheds, good on 17, 24, 12, and 26 watersheds, fair in 38, 39, 12, and 24 watersheds and unsatisfactory in 59, 70, 11, and 6 watersheds, respectively.

Lastly, to assess the comparative performance of the ASMA-SCS-CN, MVP, MS and SCS-CN method, the RSR statistics is also evaluated as shown in Figs. 12a and 12b and Appendix IIb It is observed from Fig. 12a that ASMA-SCS-CN has lowest median value of RSR than the MVP, MS and SCS-CN method for all the 164 watersheds. The box-whisker plots (Fig. 12b) also show that ASMA-SCS-CN has the lowest value of median RSR than the MVP, MS and SCS-CN method. The values of the 1st and 3rd quartiles of the ASMA-SCS-CN are also lower than the rest of the three methods, which supports its improved performance and lower uncertainty as compared to the other three methods. Finally, the performance of all the four methods is also rated on the basis of the criteria given by Moriasi et al. (2007) and it shows that ASMA-SCS-CN method performs very good on 87 watersheds followed by MVP (63 watersheds), MS (52 watersheds), and SCS-CN method (35 watersheds) and found to perform good on 63, 73, 55, and 55 watersheds, satisfactory on 23, 31, 30, and 38 watersheds, and unsatisfactory on 15, 23, 47, and 56 watersheds, respectively.

4.3. Performance evaluation based on watershed characteristics

The watershed characteristics such as land use, soil type, landuse and soil and their combination, catchment area and average rainfall also play an important role on runoff generation process and hence on

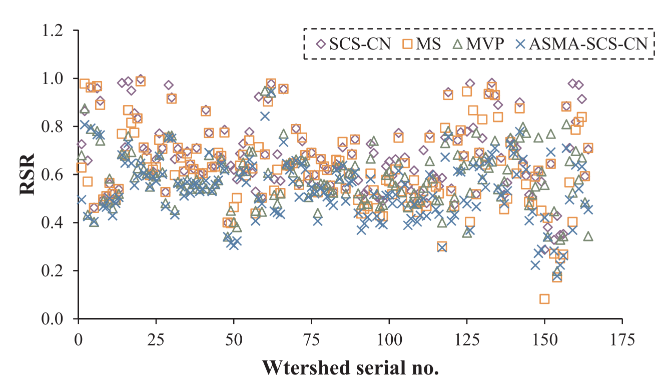

Fig. 12a. Variation of RSR for all the four methods on 164 watersheds (Watershed Sl. No. 1–164 having Watershed IDs from 9004 to 77006).

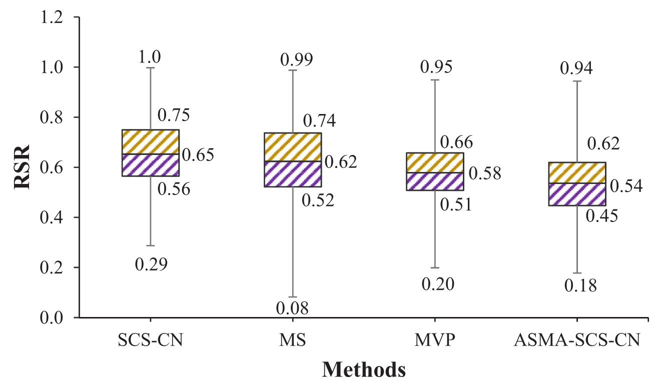

Fig. 12b. Box-whisker plots of RSR values for all the four methods. The whiskers represent the min. and max. RSR values. The height of the box portion is given by the interquartile range (IQR, 25th to 75th percentile) of the performance metrics RSR.

Table 4
Grouping of watersheds on the basis of watershed characteristics.

Watersheds categories	No. of watersheds
Based on landuse	
Mixed	37
Pasture/Range	40
Cultivated	51
Based on soil type	
Clayey	34
Silty	70
Sandy	24
Based on landuse and soil combination	
Mixed-Clayey	9
Mixed-Silty	19
Mixed-Sandy	9
Pasture/Range-Clayey	18
Pasture/Range-Silty	13
Pasture/Range-Sandy	9
Cultivated-Clayey	7
Cultivated-Silty	38
Cultivated-Sandy	6
Based on catchment area	
Catchment area < 0.01	15
0.01 ≤ Catchment area < 0.1	56
0.1 ≤ Catchment area < 1	23
1 ≤ Catchment area < 10	18
Catchment area ≥ 10	16

the performance of a model. Keeping in view of the above, all the four methods were further evaluated on the basis of the watershed characteristics as discussed here. Table 4 shows the number of watersheds grouped under different watershed characteristics.

Table 6
Comparative performance of models based on RMSE statistics for different soils.

Soil type	Model	Min.	Max.	Mean	Median	Q1	Q3	90% C.I	
								Lower	Upper
Clayey	SCS-CN	1.0	13.6	8.2	8.5	6.3	10.5	7.1	9.2
	MS	0.4	18.2	8.2	8.9	5.4	10.5	6.8	9.5
	MVP	0.9	11.8	7.4	8.3	5.3	9.5	6.5	8.4
	ASMA-SCS-CN	0.4	11.8	6.9	7.5	4.7	9.2	5.8	7.9
Sandy	SCS-CN	2.7	10.1	5.3	5.0	4.5	5.8	5.0	5.7
	MS	2.5	11.0	5.2	4.6	4.2	5.7	4.7	5.6
	MVP	1.2	10.9	4.8	4.6	4.0	5.3	4.4	5.1
	ASMA-SCS-CN	2.2	8.5	4.4	4.1	3.7	4.9	4.1	4.7
Silty	SCS-CN	3.0	10.1	6.7	6.8	5.2	7.8	6.0	7.5
	MS	2.8	8.9	5.5	5.3	4.3	6.6	4.8	6.2
	MVP	2.6	10.0	6.2	6.2	4.8	7.4	5.5	7.0
	ASMA-SCS-CN	2.0	7.6	5.1	5.1	3.9	6.1	4.4	5.7

4.3.1. Evaluation based on landuse

There are three major land use classes, i.e., mixed, pasture/range, and cultivated as shown in Table 4. A brief discussion on the performance of all the four methods for three land use classes in terms of RMSE is given here as follows.

(i) Mixed land use

For Mixed landuse class, there are 37 watersheds as given in Table 4. For these watersheds, the ASMA-SCS-CN method yields the lowest mean and median RMSE values as 5.97 mm and 5.96 mm, respectively. The inter-quartile range (3.91–7.58 mm) and bounds at 90% C.I. (5.25 mm – 6.69 mm) for ASMA-SCS-CN method are also found to be lowest amongst all methods (Table 5). Hence, ASMA-SCS-CN method works best for mixed landuse followed by MS, MVP and SCS-CN method.

(ii) Pasture/Range landuse

There are 40 watersheds having Pasture/Range landuse as given in Table 3. For these watersheds, the ASMA-SCS-CN method yields the lowest mean (4.97) and median (4.09) RMSE values amongst all the four models. The result is further supported by lowest inter-quartile range from 3.11 mm to 6.36 mm and lower and upper bounds at 90% C.I. as 4.07 mm and 5.88 mm, respectively (Table 5). Hence, ASMA-SCS-CN method performed the best for watersheds having pasture/range landuse. On the basis of mean RMSE, the methods can be ranked as ASMA-SCS-CN > MS > MVP > SCS-CN. Again, the SCS-CN method performed the poorest among all for pasture/range watersheds. The increased performance of the ASMA-SCS-CN method in this landuse

Table 5
Comparative performance of methods based on RMSE statistics for *different landuse.*

Landuse	Method	Min.	Max.	Mean	Median	Q1	Q3	90% C.I.	
								Lower	Upper
Mixed	SCS-CN	3.6	13.6	7.6	8.0	5.3	9.4	6.8	8.4
	MS	3.5	13.6	7.5	8.0	4.8	9.4	6.6	8.3
	MVP	1.2	11.4	6.2	6.2	4.2	8.3	5.4	7.0
	ASMA-SCS-CN	2.7	11.4	6.0	6.0	3.9	7.6	5.3	6.7
Pasture/Range	SCS-CN	1.0	13.2	6.1	5.3	3.9	7.9	5.2	7.0
	MS	0.4	18.2	5.9	4.7	3.5	7.8	4.8	7.1
	MVP	0.9	11.8	5.5	4.6	3.5	7.0	4.6	6.4
	ASMA-SCS-CN	0.4	11.8	5.0	4.1	3.1	6.4	4.1	5.9
Cultivated	SCS-CN	2.7	11.0	5.6	5.2	4.6	6.4	5.2	6.1
	MS	2.6	11.0	5.4	4.8	4.3	6.2	4.9	5.9
	MVP	2.5	10.9	5.3	4.8	4.3	6.1	4.8	5.7
	ASMA-SCS-CN	2.0	9.0	4.7	4.3	3.9	5.5	4.4	5.1

Table 7
Comparative performance of four methods based on RMSE statistics for different landuse soil combinations.

LULC-Soil	Model	Minimum	Maximum	Mean	Median	Q1	Q3	90% C.I	
								Lower	Upper
Mixed-Clayey	SCS-CN	6.7	13.6	9.7	9.5	8.1	10.5	8.3	11.1
	MS	6.5	13.6	9.7	9.4	8.1	10.5	8.3	11.1
	MVP	5.4	11.4	8.6	8.3	7.8	9.9	7.3	9.9
	ASMA-SCS-CN	5.0	11.4	8.2	7.8	7.3	9.3	6.9	9.5
Mixed-Silty	SCS-CN	3.6	10.1	6.6	6.6	4.9	8.1	5.8	7.4
	MS	3.5	11.0	6.6	6.5	4.4	8.4	5.6	7.6
	MVP	1.2	9.2	5.2	5.1	3.9	6.3	4.4	6.1
	ASMA-SCS-CN	2.7	8.5	5.2	4.8	3.8	6.4	4.5	6.0
Mixed-Sandy	SCS-CN	4.4	10.1	7.6	8.3	5.6	9.4	6.2	9.1
	MS	4.3	10.0	7.1	7.4	5.3	9.1	5.7	8.5
	MVP	2.9	8.9	6.1	5.9	4.3	8.3	4.6	7.6
	ASMA-SCS-CN	3.0	7.6	5.4	5.8	3.8	6.9	4.2	6.7
Pasture/Range-Clayey	SCS-CN	1.0	13.2	7.4	8.0	4.1	10.5	5.6	9.1
	MS	0.4	18.2	7.4	8.4	3.4	10.6	5.1	9.7
	MVP	0.9	11.8	6.8	7.8	4.1	10.2	5.2	8.5
	ASMA-SCS-CN	0.4	11.8	6.2	6.2	2.5	10.0	4.4	7.9
Pasture/Range-Silty	SCS-CN	2.7	6.8	4.4	4.5	3.3	5.2	3.7	5.0
	MS	2.5	7.0	4.0	3.9	3.1	4.6	3.4	4.7
	MVP	2.4	6.3	4.1	4.1	2.6	5.1	3.4	4.9
	ASMA-SCS-CN	2.2	5.8	3.7	3.7	2.5	4.3	3.1	4.3
Pasture/Range-Sandy	SCS-CN	4.2	7.9	6.1	6.3	5.1	7.2	5.2	7.0
	MS	4.3	74.7	44.6	49.0	18.4	71.6	26.2	63.0
	MVP	3.2	6.9	4.7	4.5	4.3	4.8	3.9	5.6
	ASMA-SCS-CN	3.1	7.4	4.5	4.1	3.9	4.6	3.6	5.4
Cultivated-Clayey	SCS-CN	4.8	11.0	8.2	7.8	7.6	9.4	6.8	9.7
	MS	4.3	11.0	8.1	7.8	7.6	9.4	6.6	9.7
	MVP	5.3	9.4	7.5	7.5	6.6	8.7	6.5	8.6
	ASMA-SCS-CN	4.6	9.0	7.0	7.0	6.2	8.0	5.9	8.1
Cultivated-Silty	SCS-CN	2.7	7.3	5.0	4.9	4.6	5.4	4.8	5.3
	MS	2.7	9.1	4.9	4.6	4.3	5.4	4.5	5.2
	MVP	2.5	10.9	4.8	4.6	4.2	5.1	4.4	5.2
	ASMA-SCS-CN	2.2	6.6	4.2	4.1	3.8	4.4	4.0	4.5
Cultivated-Sandy	SCS-CN	3.0	7.8	6.3	6.8	6.5	7.1	5.0	7.7
	MS	2.6	6.8	5.8	6.4	6.1	6.6	4.5	7.1
	MVP	2.8	6.6	5.7	6.4	5.9	6.4	4.6	6.9
	ASMA-SCS-CN	2.0	6.1	5.3	6.0	5.6	6.0	4.0	6.5

Table 8
Comparative performance of models based on RMSE statistics for different drainage area.

Area category	Model	Min.	Max.	Mean	Median	Q1	Q3	90% C.I	
								Lower	Upper
Area $<$ 0.01 km^2	SCS-CN	2.7	7.3	4.9	4.6	4.4	5.6	4.2	5.6
	MS	2.5	7.3	4.7	4.5	4.0	5.4	4.0	5.4
	MVP	2.4	10.9	4.7	4.2	3.5	5.5	3.6	5.8
	ASMA-SCS-CN	2.4	6.6	4.3	4.1	3.5	5.1	3.6	4.9
0.01 km^2 $\le$ Area $<$ 0.1 km^2	SCS-CN	3.2	13.2	6.4	5.5	4.9	7.5	5.8	6.9
	MS	1.8	11.8	5.8	5.0	4.4	6.6	5.2	6.4
	MVP	1.6	11.8	5.3	4.3	3.9	6.1	4.7	5.8
	ASMA-SCS-CN	1.6	18.2	6.2	5.1	4.4	7.5	5.4	7.0
0.1 km^2 $\le$ Area $<$ 1 km^2	SCS-CN	2.7	11.8	6.6	6.6	4.3	8.1	5.5	7.6
	MS	2.6	12.1	6.4	6.5	4.2	8.1	5.3	7.5
	MVP	2.5	11.4	6.0	5.4	4.5	7.3	5.0	6.9
	ASMA-SCS-CN	2.0	10.8	5.6	5.7	4.0	7.0	4.6	6.6
1 km2 $\le$ Area $<$ 10 km^2	SCS-CN	1.0	10.5	6.3	5.5	4.9	8.1	5.2	7.5
	MS	0.4	10.5	5.9	5.3	4.4	8.2	4.8	7.3
	MVP	0.9	9.9	4.9	4.5	3.7	6.4	4.0	6.1
	ASMA-SCS-CN	0.4	9.3	4.7	4.1	3.3	6.4	3.8	5.7
Area $\ge$10 km^2	SCS-CN	3.3	13.6	7.4	7.6	4.6	9.6	6.0	8.9
	MS	3.0	13.6	7.4	7.7	4.2	9.5	5.8	8.9
	MVP	2.6	11.4	6.1	5.9	4.0	8.4	4.8	7.4
	ASMA-SCS-CN	1.5	11.4	5.6	5.8	3.5	7.6	4.3	7.0

category may be attributed to be inclusion of static infiltration component in the model formulation as the vegetation tends to maintain the soil infiltration potential by preventing the sealing of the soil surface from the impacts of raindrops. It is worth highlighting that all the methods performed significantly better for the watersheds having pasture/range landuse than the mixed landuse.

(iii) Cultivated landuse

A total of 51 watersheds have been grouped in cultivated landuse as given in Table 4. For these watersheds, ASMA-SCS-CN method yields lowest values of mean (4.73 mm), median (4.32 mm), lower and upper

Table 9
Summary of the performance of the four methods based on watershed characteristics.

Watersheds characteristics	Performance Summary of the Methods (mean RMSE)			
	SCS-CN	MS	MVP	ASMA-SCS-CN
Based on landuse				
Mixed	7.60	7.50	6.20	6.00
Pasture/Range	6.10	5.90	5.50	5.00
Cultivated	5.60	5.40	5.30	4.70
Based on soil type				
Clayey	8.20	8.20	7.40	6.90
Silty	6.70	5.50	6.20	5.10
Sandy	5.30	5.20	4.80	4.40
Based on landuse and soil combination				
Mixed-Clayey	9.70	9.70	8.60	8.20
Mixed-Silty	6.60	6.60	5.20	5.20
Mixed-Sandy	7.60	7.10	6.10	5.40
Pasture/Range-Clayey	7.40	7.40	6.80	6.20
Pasture/Range-Silty	4.40	4.00	4.10	3.70
Pasture/Range-Sandy	6.10	4.60	4.70	4.50
Cultivated-Clayey	8.20	8.10	7.50	7.00
Cultivated-Silty	5.00	4.90	4.80	4.20
Cultivated-Sandy	6.30	5.80	5.70	5.30
Based on catchment area				
Area < 0.01 km^2	4.90	4.70	4.70	4.30
0.01 km^2 $\le$ Area $<$ 0.1 km^2	6.40	5.80	5.30	6.20
0.1 km^2 $\le$ Area $<$ 1.0 km^2	6.60	6.40	6.00	5.60
1.0 km^2 $\le$ Area $<$ 10.0 km^2	6.30	5.90	4.90	4.70
Area $\ge$10.0 km^2	7.40	7.40	6.10	5.60

bounds at 90% C.I. (4.35 mm − 5.11 mm) and inter-quartile range (3.86 mm − 5.50 mm), respectively, of RMSE amongst the all four methods and hence it performs the best for this landuse (Table 5). On the basis of mean RMSE, the methods can be ranked as ASMA-SCS-CN > MS > MVP > SCS-CN. The mean RMSE of ASMA-SCS-CN method in cultivated landuse is lower (4.73) than that of Pasture/Range and Mixed land uses.

4.3.2. Evaluation based on soil type

On the basis of the soil type, the watersheds are classified as clayey, silty and sandy (Table 4). Similar to the above, the performance of all the four methods has been evaluated using RMSE criteria and the results are given in Table 6.

(i) Clayey soil

Table 4 shows that 34 watersheds have clay soils. The RMSE statistics, i.e., mean (6.87 mm), median (7.49 mm), inter-quartile range (4.66 mm − 9.19 mm), and lower and upper bounds at 90% C.I. (5.81 mm − 7.92 mm) for ASMA-SCS-CN method is lower than that of SCSCN, MS and MVP for all the study watersheds (Table 6). On the basis of RMSE values, all the four methods are ranked as ASMA-SCS-CN > MVP > MS > SCS-CN.

(ii) Sandy soil

For Sandy watersheds, the RMSE statistics is given in Table 5, which shows that ASMA-SCS-CN method yields lowest values of mean (4.38 mm), median (4.10 mm), lower and upper bounds at 90% C.I. (4.07 mm − 4.68 mm) and inter-quartile range (3.66 mm − 4.87 mm) of RMSE among all the methods and hence it performs the best for this soil (Table 6). It is worth highlighting that all the models perform significantly better for the watersheds having sandy soil than those having other soils. The best performance of this model supports the significance of incorporating the effect of static infiltration on the runoff for a given rainfall, especially for watersheds with sandy soils. The reason is that the static infiltration is comparatively high for sandy soil than clayey and silty soil. The SCS-CN method again performs the poorest among all the methods. On the basis of mean RMSE values, the methods can be ranked as ASMA-SCS-CN > MS > MVP > SCS-CN.

(iii) Silty soil

For such watersheds, the ASMA-SCS-CN method performs better than the existing methods by showing lowest values of mean (5.05 m), median (5.09 mm), inter-quartile range (3.89 mm − 6.06 mm) and bounds of RMSE at 90% C.I. (4.40 mm − 5.69 mm) (Table 6). On the basis of mean RMSE, these methods can be ranked as ASMA-SCS-CN > MS > MVP > SCS-CN.

4.3.3. Landuse and soil type

The performance of all the four methods is also evaluated based on the combination of all the three land uses and three land three soils, i.e., total nine classes as shown in Table 6. The RMSE statistics resulting from the application of these methods to watersheds of different land uses and different is presented in Table 7. On the basis of RMSE statistics, all the four methods performed best for watersheds with pasture/range landuse and silty soil and poorest for watersheds with mixed landuse and clayey soils among all the combinations. For all the combinations, the ASMA-SCS-CN method performs best and SCS-CN method performs the poorest of all the methods. On the basis of mean RMSE, the suitability of the ASMA-SCS-CN method can be ranked for different landuse-soil combinations as Pasture/Range-Silty > Cultivated-Silty > Pasture/Range-Sandy > Mixed-Silty > Cultivated-Sandy > Mixed-Sandy > Pasture/Range-Clayey > Cultivated-Clayey > Mixed-Clayey.

4.3.4. Drainage area

Catchment area based evaluation of all the four methods is also conducted using RMSE statistics and the results are given in Table 7. For this purpose, all the 164 watersheds are grouped into five classes as (i) catchment area < 0.01 km^2, (ii) 0.01 $\le$ catchment area $<$ 0.1 km^2, (iii) 0.1 km^2 $\le$ catchment area $<$ 1 km^2, (iv) 1 km^2 $\le$ catchment area $<$ 10 km^2, and (v) catchment area $\ge$10 km^2 as shown in Table 7. Out of five catchment area classes, all the methods performs best for the watersheds with catchment area $<$ 0.01 km^2 with lowest RMSE statistic (mean, median, inter-quartile range and lower and upper bounds at 90% C.I.). Further, in catchment area class (i), the ASMA-SCS-CN method is found to have the lowest values of RMSE statistics such as mean (4.28 mm), median (4.10 mm), inter-quartile range ((3.52–5.14 mm) and lower and upper bounds of the 90% CI (3.63–4.93 mm) (Table 8). Notably, all the methods perform poorest for the catchments having area greater than 10 km^2 (class (v)). However, the ASMA-SCS-CN method performs best among all the methods under study for all ranges of catchment areas, whereas the SCS-CN method performed the poorest for all. Table 9 also summarises the performance of all the four methods based on all the watershed characteristics (Appendix I, Appendix II a, Appendix II b).

5. Conclusions

In this study, an activation soil moisture accounting (ASMA) based SCS-CN (ASMA-SCS-CN) method has been developed by coupling the SMA concept of Michel-Vazken-Perrin (MVP) method with the static infiltration (F_c) based Mishra-Singh (MS) method for presenting a fuller picture of SMA system to model rainfall-runoff process. The comparative performance of the ASMA-SCS-CN method is evaluated with the original SCS-CN method, MS method and MVP method by applying a large dataset of USDA watersheds (56343 storm events from 164 small to large watersheds). The goodness-of-fit statistics in terms of Nash-Sutcliffe efficiency (NSE), the root mean square error (RMSE), normalized RMSE (nRMSE), percent bias (PBIAS), mean absolute error (MAE), standard error (SE) and RMSE-observations standard deviation ratio (RSR) shows that the ASMA-SCS-CN method has the highest mean and median values of NSE and lowest mean and median values of error indices, i.e., RMSE, nRMSE, MAE and RSR as compared to the MVP, MS and SCS-CN method. The PBIAS values of the ASMA-SCS-CN and MVP

Appendix I
Optimized parameters values of SCS-CN, MS, MVP and ASMA-SCS-CN on 164 watersheds.

					SCS-CN	MS		MVP			ASMA-SCS-CN			
Sl. No.	US States	Watershed ID	Area (ha)	Number of storms	CN	fc	S	V0	Sa	S	α	β	fc	S
1	Georgia	9004	24	94	56.78	1.66	79.02	45.60	42.87	561.15	0.24	0.05	0.00	497.10
2	Georgia	10,001	7.8	32	76.52	0.00	143.44	97.71	88.32	397.75	1.30	0.06	0.00	2452.46
3	Virginia	13,008	361.4	169	67.98	1.68	44.00	280.59	270.82	510.22	0.11	0.00	0.04	463.22
4	Virginia	13,009	73.7	202	86.56	0.00	44.28	134.77	93.27	459.90	0.18	0.00	0.00	234.66
5	Virginia	13,014	157.4	89	86.30	0.15	38.17	133.21	138.63	140.79	0.02	0.04	0.00	152.43
6	Pennsylvania	16,010	40.5	325	61.92	0.00	209.36	76.32	76.25	211.28	0.12	0.05	0.00	170.81
7	Pennsylvania	16,020	56.7	325	45.16	0.73	183.75	101.75	15.45	2418.85	0.36	0.00	0.00	2500.00
8	Illinois	17,001	11	586	92.12	0.00	22.58	95.97	95.65	75.12	0.26	0.06	0.00	101.42
9	Illinois	17,002	20.2	546	91.68	0.00	23.83	90.94	90.60	79.31	0.24	0.07	0.00	98.36
10	Illinois	17,003	5.1	137	88.51	0.00	37.10	106.37	95.82	171.06	0.48	0.20	0.00	109.29
11	Illinois	17,004	117.3	608	89.03	0.00	32.57	100.11	99.28	117.19	0.20	0.04	0.00	130.15
12	Indiana	19,005	1.1	59	85.22	0.00	45.44	314.67	326.89	119.97	0.16	0.07	0.00	166.60
13	Missouri	25,001	62.32	672	93.33	0.00	20.26	100.20	99.60	61.27	0.28	0.04	0.00	94.86
14	Ohio	26,001	0.5	329	72.17	2.37	39.73	216.73	231.75	100.19	0.10	0.12	0.40	114.52
15	Ohio	26,002	0.5	273	81.16	0.90	49.40	338.76	35.94	94.46	0.18	0.16	0.79	112.84
16	Ohio	26,003	1.1	850	78.96	2.00	3.23	115.04	104.47	321.61	0.15	0.00	0.86	241.36
17	Ohio	26,004	1.1	338	63.21	2.79	58.85	389.70	399.57	248.82	0.13	0.06	0.94	228.61
18	Ohio	26,005	0.7	202	77.98	3.27	39.18	170.32	177.21	152.26	0.08	0.05	0.43	150.99
19	Ohio	26,006	1	220	87.91	0.00	38.27	101.16	99.25	175.69	0.14	0.03	0.00	202.33
20	Ohio	26,007	0.9	106	42.36	1.63	27.91	458.67	457.40	1052.56	0.08	0.01	0.25	1245.86
21	Ohio	26,010	0.6	879	91.32	0.00	28.37	102.55	98.28	112.20	0.16	0.02	0.00	115.19
22	Ohio	26,011	0.7	721	89.21	0.74	23.76	138.31	141.86	95.84	0.12	0.09	0.08	90.94
23	Ohio	26,012	0.7	584	91.33	0.00	24.67	156.45	159.37	76.02	0.13	0.08	0.00	90.97
24	Ohio	26,014	0.3	695	91.19	0.00	29.01	101.24	99.96	99.30	0.20	0.07	0.00	111.61
25	Ohio	26,015	0.5	706	87.28	0.80	31.09	147.29	153.80	104.55	0.20	0.15	0.00	108.75
26	Ohio	26,016	0.6	358	86.40	0.48	30.68	100.95	99.53	146.88	0.10	0.02	0.00	162.78
27	Ohio	26,017	0.8	1051	86.06	0.04	42.46	100.98	100.73	168.31	0.12	0.04	0.00	181.69
28	Ohio	26,018	0.5	106	90.70	0.00	25.39	106.23	85.06	173.22	0.29	0.01	0.00	155.77
29	Ohio	26,020	0.6	1289	79.32	1.64	39.38	101.97	95.25	312.04	0.10	0.00	0.01	313.07
30	Ohio	26,021	0.8	311	83.02	0.28	46.29	104.17	88.75	303.61	0.16	0.00	0.00	266.70
31	Ohio	26,023	3	504	84.07	1.08	34.17	443.78	458.17	124.02	0.15	0.13	0.14	126.80
32	Ohio	26,024	2.9	521	86.04	0.00	47.50	116.74	125.32	119.09	0.08	0.06	0.00	148.22
33	Ohio	26,025	3.1	622	84.76	0.30	39.92	134.93	137.07	179.93	0.13	0.04	0.00	202.38
34	Ohio	26,027	11.7	1620	87.83	0.00	35.51	115.04	117.82	135.06	0.15	0.06	0.00	152.82
35	Ohio	26,028	30.6	1481	88.37	0.09	31.66	123.75	129.87	100.90	0.09	0.06	0.00	119.71
36	Ohio	26,029	30	1331	89.10	0.00	30.81	114.97	118.08	109.33	0.12	0.06	0.00	116.93
37	Ohio	26,030	122.6	1924	90.72	0.00	26.80	112.01	115.70	92.58	0.10	0.05	0.00	115.85
38	Ohio	26,032	141.2	1391	85.49	0.14	41.59	88.10	89.41	190.79	0.15	0.04	0.00	210.85
39	Ohio	26,033	372.3	1173	88.05	0.00	38.17	115.11	122.20	105.91	0.10	0.07	0.00	126.05
40	Ohio	26,034	615.1	1101	88.19	0.00	36.13	117.27	125.07	96.65	0.13	0.09	0.00	115.81
41	Ohio	26,035	1040	65	86.23	0.02	40.53	115.82	103.75	234.43	0.01	0.00	0.00	178.89
42	Ohio	26,036	1853.5	138	90.02	0.00	30.45	119.84	122.63	97.22	0.09	0.03	0.00	130.41
43	Ohio	26,040	28.2	1509	89.87	0.00	29.70	99.67	99.94	123.02	0.08	0.02	0.00	120.12
44	Ohio	26,041	32.05	1248	87.97	0.00	35.57	99.90	99.62	169.89	0.09	0.03	0.00	176.23
45	Ohio	26,711	118.6	1324	89.68	0.00	36.58	114.23	120.49	87.16	0.12	0.08	0.00	113.32
46	Ohio	26,791	32.1	1475	94.09	0.00	18.82	99.75	100.66	61.31	0.25	0.07	0.00	82.46
47	Ohio	26,828	1.08	577	82.52	0.55	46.80	162.42	165.29	183.37	0.10	0.05	0.00	184.93
48	Ohio	26,863	0.2	197	96.30	0.00	10.86	109.88	101.73	66.14	0.15	0.00	0.00	52.41
49	Wisconsin	31,001	133.55	724	66.36	4.83	65.47	442.17	461.74	348.54	0.24	0.08	2.81	274.61
50	Wisconsin	31,003	21.25	80	66.82	6.76	75.42	476.62	498.30	414.65	0.24	0.08	1.89	370.17
51	Wisconsin	31,004	69.2	114	70.85	3.10	77.95	357.72	371.28	354.80	0.24	0.10	0.76	305.80
52	Oklahoma	34,001	0.9	258	90.39	1.77	17.42	102.10	97.53	112.01	0.19	0.00	0.78	104.74
53	Oklahoma	34,006	0.7	275	89.76	1.07	20.20	102.06	97.69	122.31	0.27	0.06	0.81	84.13
54	Oklahoma	34,007	0.8	262	90.68	2.04	23.70	101.45	98.51	96.88	0.22	0.04	1.26	125.95
55	Oklahoma	34,008	1.9	231	87.56	0.00	41.76	101.33	98.44	146.47	0.32	0.11	0.00	146.15
56	Oklahoma	34,013	0.8	52	87.68	0.90	12.88	138.68	112.14	356.76	0.32	0.27	0.69	32.99
57	Oklahoma	35,001	13.5	158	92.41	2.16	15.24	100.17	102.94	55.02	0.08	0.00	0.20	122.51
58	Oklahoma	35,002	1.3	151	87.68	0.02	21.76	101.57	97.58	129.58	0.21	0.16	0.00	80.57
59	Oklahoma	35,003	1.3	107	92.14	0.00	193.11	99.01	106.32	37.89	0.58	0.01	0.00	2500.00
60	Oklahoma	35,004	2.3	26	56.23	0.33	47.03	416.07	377.78	1450.05	0.07	0.01	0.00	200.49
61	Oklahoma	35,005	2.1	128	82.11	0.00	225.58	99.72	99.30	174.70	0.02	0.01	0.00	409.50
62	Oklahoma	35,006	1	31	54.47	1.10	220.33	425.75	384.07	1043.12	0.23	0.01	0.00	2500.00
63	Oklahoma	35,008	3.7	129	80.50	0.89	29.28	98.70	101.19	115.45	0.13	0.02	0.00	129.24
64	Oklahoma	35,009	5.4	120	83.62	0.93	37.93	97.58	98.81	98.99	0.30	0.09	0.08	154.25
65	Oklahoma	35,010	6.4	113	79.91	0.00	194.39	97.56	100.06	126.80	0.17	0.00	0.00	814.88
66	Oklahoma	35,011	38.4	99	57.49	0.00	25.37	53.27	26.72	861.97	0.19	0.12	0.00	78.80
67	Oklahoma	37,001	6.8	195	92.01	0.00	31.04	93.19	93.45	72.83	0.32	0.06	0.00	151.82
68	Oklahoma	37,002	37.2	388	89.42	0.00	61.38	122.54	125.88	87.07	0.21	0.00	0.00	420.32
69	Texas	42,003	449.2	487	88.67	0.02	32.25	104.24	95.36	153.84	0.24	0.00	0.00	173.42
70	Texas	42,004	1772.5	125	88.96	0.25	28.54	145.93	100.78	300.45	0.36	0.15	0.00	98.23
71	Texas	42,006	70.4	819	89.05	0.00	34.94	103.02	104.19	97.17	0.22	0.00	0.00	149.83
72	Texas	42,007	52.6	148	90.28	0.00	41.30	105.72	95.02	141.61	0.30	0.08	0.00	130.94

(*continued on next page*)

Appendix I (*continued*)

					SCS-CN	MS		MVP			ASMA-SCS-CN			
Sl. No.	US States	Watershed ID	Area (ha)	Number of storms	CN	fc	S	V0	Sa	S	α	β	fc	S
73	Texas	42,008	17.1	162	88.64	0.00	28.12	100.59	99.00	117.36	0.19	0.00	0.00	108.48
74	Texas	42,010	8	224	92.26	0.00	39.85	104.09	93.36	109.86	0.15	0.01	0.00	161.05
75	Texas	42,011	125	287	87.44	0.00	28.58	101.75	95.73	163.88	0.17	0.07	0.00	101.99
76	Texas	42,012	53.4	277	90.23	0.58	12.78	102.05	102.66	93.11	0.22	0.12	0.03	54.16
77	Texas	42,013	32.3	36	93.93	0.00	39.73	93.43	95.36	53.45	0.15	0.04	0.00	148.20
78	Texas	42,014	6.6	273	87.65	0.00	23.83	100.00	97.55	152.49	0.22	0.05	0.00	89.33
79	Texas	42,015	16.2	128	91.76	0.00	41.52	105.90	105.98	68.96	0.23	0.04	0.00	155.38
80	Texas	42,016	8.4	293	86.35	0.16	23.70	101.92	99.66	151.56	0.31	0.09	0.00	99.61
81	Texas	42,017	7.5	237	91.09	0.32	17.43	100.05	98.86	87.94	0.43	0.36	0.00	44.96
82	Texas	42,023	1.31	80	92.79	0.00	24.00	108.45	108.66	59.33	0.27	0.04	0.00	79.95
83	Texas	42,024	1.2	252	93.54	0.00	27.03	102.37	95.59	76.87	0.16	0.08	0.00	75.60
84	Texas	42,028	1.2	263	92.80			100.62	100.50	68.48	0.38	1.00	0.00	9.34
85	Texas	42,035	1.3	163	91.21	1.48	0.01	111.10	88.15	171.13	0.29	0.00	0.00	132.12
86	Texas	42,037	4.6	181	88.77	0.00	35.25	181.74	187.75	74.61	0.37	0.21	0.00	93.16
87	Texas	42,038	2.3	158	89.30	0.20	33.61	104.83	96.96	124.39	0.30	0.26	0.00	88.74
88	Texas	42,039	4	237	87.96	0.00	38.02	98.32	103.09	100.44	0.31	0.35	0.00	71.59
89	Texas	42,040	4.6	226	87.98	1.55	17.14	134.45	145.43	78.16	0.30	0.14	1.48	59.54
90	Nebraska	44,001	194.7	407	89.86	1.30	26.84	105.13	105.23	112.54	0.37	0.26	1.13	69.18
91	Nebraska	44,002	166.3	482	86.65	1.02	27.44	111.39	116.63	127.30	0.28	0.04	1.07	120.99
92	Nebraska	44,003	844.2	235	87.00	0.99	31.91	102.31	96.29	196.71	0.25	0.11	0.61	123.12
93	Nebraska	44,004	1412.4	349	84.85	5.19	38.88	112.06	114.43	175.30	0.36	0.57	3.51	54.11
94	Nebraska	44,005	1.5	135	78.56	5.85	24.41	418.32	449.73	56.66	0.51	0.91	7.00	24.76
95	Nebraska	44,006	1.4	149	83.49	1.31	10.86	210.89	229.10	80.68	0.38	0.25	1.31	29.07
96	Nebraska	44,007	1.5	524	94.13	1.84	9.55	99.85	100.12	53.67	0.31	0.21	1.53	29.09
97	Nebraska	44,008	1.5	515	93.73	1.87	15.58	95.26	94.87	63.15	0.33	0.21	1.61	43.98
98	Nebraska	44,009	1.6	537	91.21	1.88	14.16	129.03	130.20	85.98	0.33	0.12	1.54	57.94
99	Nebraska	44,010	1.6	537	91.96	2.67	14.36	101.00	99.40	88.66	0.35	0.10	2.13	67.35
100	Nebraska	44,011	1.7	486	90.63	1.97	21.50	101.78	99.63	106.83	0.30	0.28	1.58	49.15
101	Nebraska	44,012	1.59	355	88.79	1.85	19.13	145.07	153.41	78.69	0.19	0.03	1.30	95.74
102	Nebraska	44,013	1.5	248	89.86	0.51	27.38	101.99	97.40	135.80	0.23	0.01	1.78	112.91
103	Nebraska	44,014	1.6	262	89.22	1.35	14.08	106.29	96.03	187.27	0.27	0.12	0.79	56.88
104	Nebraska	44,015	1.6	295	92.60	1.40	12.50	92.48	91.38	80.63	0.24	0.00	0.49	90.72
105	Nebraska	44,016	1.5	309	93.23	2.36	12.63	103.38	91.91	121.53	0.32	0.14	1.71	52.80
106	Nebraska	44,017	1.4	276	92.02	0.94	15.82	99.71	97.98	84.08	0.32	0.13	0.67	62.28
107	Nebraska	44,018	1.4	274	92.71	3.19	7.79	98.49	96.31	77.86	0.25	0.01	1.30	69.83
108	Nebraska	44,019	1.5	303	93.60	1.55	11.87	104.00	94.42	106.12	0.32	0.22	1.39	34.33
109	Nebraska	44,020	1.4	281	93.23	1.41	12.74	100.48	100.95	63.12	0.30	0.16	1.09	43.84
110	Nebraska	44,021	1.6	321	93.18	3.28	15.98	95.89	95.02	67.78	0.17	0.13	1.78	61.83
111	Nebraska	44,022	1.5	320	88.10	0.58	17.06	92.38	97.85	91.32	0.27	0.20	0.38	48.25
112	Nebraska	44,023	1.7	258	92.63	0.87	22.82	100.82	101.16	38.55	0.33	0.00	1.50	144.41
113	Nebraska	44,024	1.6	264	90.00	1.30	17.03	115.50	66.50	38.71	0.29	0.10	1.36	60.42
114	Nebraska	44,025	1.6	238	91.21	1.34	15.04	101.95	98.57	101.90	0.25	0.19	0.58	51.45
115	Nebraska	44,026	1.5	241	92.34	1.09	14.76	197.52	199.43	68.62	0.33	0.28	0.64	42.64
116	Nebraska	44,028	1.8	269	92.68	5.97	42.77	236.71	239.41	62.75	0.27	0.21	0.00	138.18
117	Nebraska	44,029	0.9	16	66.36			275.38	332.38	0.10	0.19	0.14	0.00	68.98
118	Illinois	61,003	157.8	463	85.08	0.00	61.90	102.70	100.14	20.72	0.26	0.01	0.00	387.69
119	Illinois	61,004	25.5	342	82.36	0.29	47.62	123.90	103.33	495.53	0.16	0.00	0.00	427.53
120	Mississippi	62,001	809.37	236	78.40	0.39	60.74	66.87	71.93	206.43	0.26	0.08	0.00	251.11
121	Mississippi	62,002	404.7	136	90.74	0.27	22.80	201.59	203.19	72.41	0.42	0.17	0.00	88.04
122	Mississippi	62,003	2237.9	28	89.03	0.00	33.47	100.13	100.19	120.92	0.43	0.30	0.00	80.68
123	Mississippi	62,004	9226.9	22	89.82	0.00	32.97	109.37	117.43	78.99	0.42	1.00	0.00	30.79
124	Mississippi	62,005	12990.5	92	78.83	0.19	62.89	81.90	61.53	322.05	0.59	0.19	0.00	492.31
125	Mississippi	62,008	437.1	19	81.82	0.00	102.00	432.99	477.96	13.19	0.08	0.17	0.00	138.11
126	Mississippi	62,010	8093.7	104	88.65	0.18	29.68	107.12	96.76	148.64	0.27	0.01	0.00	159.52
127	Mississippi	62,012	3055.4	35	87.58	0.00	55.60	75.30	37.87	346.71	0.34	0.02	0.00	206.80
128	Mississippi	62,014	0.6	134	94.93	0.00	13.94	105.39	94.76	32.80	0.41	0.18	0.00	52.46
129	Mississippi	62,017	1295	26	89.04	0.19	30.17	227.07	248.36	41.96	0.46	1.00	0.00	35.08
130	Mississippi	62,018	441.1	59	89.35	0.00	50.48	100.59	98.88	125.11	0.08	0.03	0.00	128.09
131	New Mexico	64,001	17,353	14	45.82	2.39	160.81	314.75	337.17	220.27	0.19	0.02	0.00	957.83
132	Vermont	67,003	836.5	125	81.36	0.12	55.40	75.36	62.64	427.77	0.01	0.00	0.00	331.26
133	Vermont	67,004	4351.2	61	79.79	0.48	41.52	203.40	166.87	752.29	0.16	0.00	0.00	509.62
134	Vermont	67,005	11116.4	247	79.01	0.00	66.70	125.48	83.27	834.79	0.30	0.00	0.00	600.64
135	Vermont	67,009	46.9	58	75.75	0.81	43.67	118.35	118.76	337.21	0.01	0.00	0.00	375.45
136	Oklahoma	69,030	7.2	161	83.57	0.30	43.72	172.20	181.39	124.61	0.09	0.06	0.00	170.73
137	Oklahoma	69,032	17.9	198	89.70	0.91	21.42	130.81	139.32	67.81	0.39	0.42	0.88	38.77
138	Oklahoma	69,033	12.1	156	88.64	1.09	23.10	111.77	121.27	72.91	0.35	0.28	0.99	53.60
139	Oklahoma	69,034	5.2	94	83.88	0.46	43.10	79.36	72.77	250.61	0.18	0.03	0.00	243.05
140	Oklahoma	69,035	5.26	116	85.00	1.01	33.41	100.61	98.67	192.21	0.22	0.08	0.42	138.35
141	Oklahoma	69,036	10.7	113	84.84	1.53	28.71	96.22	103.19	134.95	0.31	0.22	1.42	66.84
142	Oklahoma	69,037	11	123	77.29	0.77	57.63	201.55	211.00	179.25	0.08	0.09	0.00	213.89
143	Oklahoma	69,042	9.6	85	76.94	0.72	65.96	408.89	397.08	448.78	0.48	0.13	0.63	255.43
144	Oklahoma	69,043	11	127	78.04	1.00	59.06	204.57	210.02	248.53	0.59	0.39	0.77	109.82
145	Oklahoma	69,044	7.8	225	90.81	0.84	20.50	102.26	99.20	106.65	0.24	0.03	0.58	100.37

(*continued on next page*)

Appendix I (*continued*)

					SCS-CN	MS		MVP			ASMA-SCS-CN			
Sl. No.	US States	Watershed ID	Area (ha)	Number of storms	CN	fc	S	V0	Sa	S	α	β	fc	S
146	Oklahoma	69,045	11.1	250	86.91	0.87	31.62	106.17	108.68	128.12	0.25	0.10	0.45	116.18
147	Texas	70,002	717.9	8	35.39	4.07	87.87	500.00	500.00	1173.39	0.27	0.01	2.56	2500.00
148	Texas	70,003	2182.1	9	44.61	0.00	327.52	223.96	230.24	425.49	0.56	0.13	2.01	460.89
149	Texas	70,004	4365.4	12	45.74	1.80	127.58	246.19	264.90	259.31	0.28	0.07	0.00	503.28
150	Texas	70,006	277.6	14	82.44	0.85	38.63	0.00	1.62	283.40	0.51	0.25	1.30	132.96
151	Texas	70,007	4.1	25	76.30	0.00	131.38	131.39	162.82	23.61	0.42	0.37	0.00	95.68
152	Texas	70,008	3.5	23	87.71	0.00	35.48	102.08	99.28	153.28	0.32	0.08	0.00	153.38
153	Texas	70,009	2.7	18	68.86	1.76	57.18	346.90	415.75	0.11	0.58	0.59	0.80	87.00
154	Texas	70,010	1.8	9	31.86	6.71	94.42	118.49	214.64	11.82	0.54	0.83	3.75	92.69
155	Texas	70,011	2.9	41	71.59	1.77	42.00	199.93	222.56	59.51	0.37	0.20	0.00	147.82
156	Texas	70,012	2.8	15	46.89	3.58	65.22	303.40	328.41	129.92	0.28	0.20	0.00	218.82
157	Iowa	71,001	30.1	979	68.13	0.61	107.42	18.68	3.02	575.98	0.28	0.03	3.29	261.98
158	Iowa	71,002	33.51	1120	79.85	4.10	26.27	130.02	131.09	240.89	0.33	0.13	3.51	108.29
159	Iowa	71,005	157.43	375	48.90	6.05	43.48	442.45	500.00	588.56	0.26	0.15	5.39	156.83
160	Georgia	74,003	1566.94	284	73.55	0.64	60.99	95.27	93.71	404.53	0.22	0.08	0.49	215.43
161	Georgia	74,008	1665.28	349	50.05	1.29	51.85	12.15	10.30	466.60	0.16	0.03	0.00	468.20
162	Georgia	74,009	261.43	202	68.37	1.16	66.61	460.60	432.68	768.85	0.21	0.00	0.00	719.51
163	Hawaii	77,003	2.8	248	46.79	0.00	296.20	477.92	488.00	218.11	0.09	0.05	0.00	264.67
164	Hawaii	77,006	2.9	118	30.80	4.24	18.62	175.51	12.58	2451.61	0.10	0.00	0.37	752.13

methods are also lower than that of MS and SCS-CN method. These lower values of error indices and higher values of NSE also indicate that the ASMA-SCS-CN method has lowest uncertainty as compared to the SCS-CN, MS and MVP method. A comparative performance of all the methods based on landuse (cultivated, pasture/range, mixed) and soil type (sandy, silty clayey) shows that the ASMA-SCS-CN method performs significantly better for the watersheds with cultivated land use than those having mixed or pasture/range land use. Enhanced performance has been also observed for the watersheds having sandy soil than those having clayey or silty soils. This could be further attributed to the consideration of static infiltration in the model formulation. The results show that the concept of activation soil moisture (i.e. coupling of SMA with static infiltration component) provides a more complete assessment of SMA system.

6. Limitations and potential for future research

Though the ASMA concept present the fuller picture of SMA in rainfall-runoff modelling. However, it lacks the storm intensity and duration in its formulation. Efforts may be put to address this issue. Secondly, the model also ignores the watershed slope and hence it may be an innovative idea to couple the 'ASMA-INTENSITY-SLOPE' concept in SCS-CN based rainfall-runoff modelling. It will also be a good idea to develop erosion and sediment yield model based on ASMA concept, where it may play a greater role. Of course, the slope concept may also be coupled with ASMA-sediment yield model for improved performance. Finally, there exists a large scope for harnessing of satellite soil moisture products to devise the components of ASMA system for rainfall-runoff modelling.

CRediT authorship contribution statement

S. Verma: Investigation, Formal analysis, Writing - original draft, Validation. **P.K. Singh:** Conceptualization, Methodology, Investigation. **S.K. Mishra:** Conceptualization, Data curation, Writing - review & editing. **V.P. Singh:** Methodology, Writing - review & editing. **Vishal Singh:** Investigation, Visualization, Writing - review & editing. **A. Singh:** Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Equations (15) and (16) are re-written here as:

$$V = V_0 + P - \left[\frac{(P - I_a - F_c)^2}{(P - I_a - F_c + S)}\right] \tag{A1}$$

$$q = \frac{(P - I_a - F_c)(P - I_a - F_c + 2S)}{(P - I_a - F_c + S)^2} p \text{ if } P > (I_a + F_c) \tag{A2}$$

P can be derived from Eq. (A1) as:

$$P = \frac{(I_a + F_c - S)(V_0 - V) + (I_a + F_c)^2}{(V_0 - V + I_a + F_c + S)} \tag{A3}$$

Using Eq. (A3), different terms of Eq. (A2) can be written as

Appendix II a

Comparison of NSE, RMSE and PBIAS resulting from applications of all the four methods to 164 US watersheds.

Sl. No.	State	Watershed ID	Area (ha)	Number of storm events	NSE				RMSE				PBIAS (%)			
					SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN
1	Georgia	9004	24	94	0.47	0.60	0.54	0.75	2.96	2.56	2.77	2.02	71.73	54.51	0.95	24.3
2	Georgia	10,001	7.8	32	0.25	0.04	0.23	0.35	6.50	7.35	6.58	6.07	33.24	75.38	1.59	8.18
3	Virginia	13,009	73.7	169	0.57	0.67	0.81	0.82	4.98	4.31	3.27	3.21	66.07	59.04	6.85	12.79
4	Virginia	13,014	157.4	202	0.07	0.07	0.38	0.37	8.16	8.15	6.69	6.72	40.75	48.26	0.81	18.37
5	Virginia	16,010	40.5	89	0.79	0.79	0.84	0.84	7.34	7.31	6.39	6.42	21.13	22.23	7.68	11.42
6	Pennsylvania	16,020	56.7	325	0.08	0.06	0.39	0.41	3.06	3.09	2.50	2.45	86.36	91.75	−7.45	−0.17
7	Pennsylvania	17,001	11	325	0.18	0.21	0.45	0.42	2.04	2.00	1.67	1.72	86.37	83.14	−24.02	12.59
8	Illinois	17,002	20.2	586	0.75	0.75	0.76	0.78	6.23	6.22	6.15	5.87	10.51	12.12	0.46	4.4
9	Illinois	17,003	5.1	546	0.74	0.74	0.77	0.78	6.56	6.54	6.20	5.96	9.95	11.22	0.14	5.26
10	Illinois	17,004	117.3	137	0.69	0.68	0.66	0.75	5.82	5.86	6.05	5.19	23.15	30.96	−3.74	6.12
11	Illinois	19,005	1.1	608	0.73	0.73	0.79	0.82	5.38	5.36	4.74	4.43	18.81	20.75	0.58	0.57
12	Indiana	25,001	62.32	59	0.75	0.76	0.75	0.77	5.61	5.59	5.61	5.44	9.39	11.11	21.83	5.62
13	Missouri	26,001	0.5	672	0.71	0.71	0.72	0.74	8.20	8.21	7.91	7.70	8.5	15.11	2.79	7.82
14	Ohio	26,002	0.5	329	0.04	0.41	0.53	0.53	4.52	3.55	3.16	3.14	62.46	38.7	23.69	11.4
15	Ohio	26,003	1.1	273	0.49	0.54	0.54	0.58	2.66	2.54	2.53	2.42	28.07	25.86	33.73	4.49
16	Ohio	26,004	1.1	850	0.02	0.25	0.42	0.47	4.17	3.66	3.21	3.08	67.98	57.46	−0.31	6.55
17	Ohio	26,005	0.7	338	0.10	0.33	0.52	0.58	3.25	2.80	2.38	2.22	76.47	58.43	16.12	12.77
18	Ohio	26,006	1	202	0.27	0.40	0.65	0.69	3.93	3.56	2.70	2.55	56.16	57.05	13.09	10.43
19	Ohio	26,007	0.9	220	0.30	0.30	0.61	0.65	3.05	3.04	2.29	2.17	29.37	37.2	−0.91	64.77
20	Ohio	26,010	0.6	106	0.01	0.02	0.56	0.58	1.61	1.60	1.07	1.05	86.9	86.25	7.58	4.65
21	Ohio	26,011	0.7	879	0.50	0.49	0.61	0.63	4.79	4.82	4.20	4.10	22.64	34.71	0.55	4.15
22	Ohio	26,012	0.7	721	0.51	0.56	0.63	0.65	4.59	4.38	3.97	3.91	17.76	22.53	63.22	8.01
23	Ohio	26,014	0.3	584	0.64	0.64	0.70	0.70	4.33	4.32	3.98	3.97	17.72	18.18	7.81	15.64
24	Ohio	26,015	0.5	695	0.62	0.62	0.63	0.65	4.46	4.50	4.41	4.30	21.68	34.69	0.71	8.19
25	Ohio	26,016	0.6	706	0.56	0.60	0.65	0.67	3.61	3.43	3.22	3.11	25.31	32.63	14.92	23
26	Ohio	26,017	0.8	358	0.41	0.45	0.53	0.54	3.84	3.70	3.40	3.37	43.25	40.48	1.12	10.44
27	Ohio	26,018	0.5	1051	0.50	0.50	0.63	0.64	3.50	3.48	3.00	2.96	39.25	42.39	2.03	10.05
28	Ohio	26,020	0.6	106	0.72	0.72	0.77	0.78	4.63	4.60	4.23	4.11	38.64	36.22	−3.57	13.13
29	Ohio	26,021	0.8	1289	0.05	0.14	0.42	0.43	3.33	3.18	2.61	2.58	70.86	66.66	2.37	5.29
30	Ohio	26,023	3	311	0.15	0.16	0.42	0.44	6.14	6.10	5.08	5.00	49.17	46.88	40.74	7.76
31	Ohio	26,024	2.9	504	0.56	0.64	0.80	0.81	2.75	2.48	1.88	1.79	24.92	26.64	28.75	15.03
32	Ohio	26,025	3.1	521	0.50	0.49	0.68	0.68	4.67	4.69	3.76	3.72	19.31	32.85	6.1	1.84
33	Ohio	26,027	11.7	622	0.53	0.55	0.68	0.70	3.16	3.08	2.58	2.52	41.1	40.62	10.45	12.54
34	Ohio	26,028	30.6	1620	0.62	0.63	0.72	0.74	2.39	2.38	2.07	1.99	33.01	32.18	5.78	13.9
35	Ohio	26,029	30	1481	0.52	0.53	0.67	0.68	2.87	2.83	2.39	2.35	51.37	23.49	8.44	2.92
36	Ohio	26,030	122.6	1331	0.59	0.59	0.71	0.73	2.83	2.82	2.38	2.30	31.41	28.82	5.36	4.72
37	Ohio	26,032	141.2	1924	0.61	0.61	0.69	0.69	3.25	3.24	2.91	2.91	20.53	21.9	4.46	8.25
38	Ohio	26,033	372.3	1391	0.49	0.50	0.67	0.68	2.90	2.89	2.36	2.30	38.41	41	−0.96	12.85
39	Ohio	26,034	615.1	1173	0.64	0.64	0.71	0.72	3.39	3.39	3.04	2.98	63.6	27.64	5.65	3.82
40	Ohio	26,035	1040	1101	0.63	0.63	0.69	0.71	3.54	3.53	3.27	3.15	17.22	22.28	6.18	6.95
41	Ohio	26,036	1853.5	65	0.24	0.25	0.71	0.67	6.18	6.14	3.86	4.09	36.44	35.74	0.56	21.92
42	Ohio	26,040	28.2	138	0.40	0.40	0.54	0.52	6.59	6.58	5.81	5.89	12.21	18.41	4.84	14.87
43	Ohio	26,041	32.05	1509	0.60	0.60	0.71	0.72	2.99	2.98	2.53	2.50	25.52	27.42	−0.98	−5.6
44	Ohio	26,711	118.6	1248	0.60	0.60	0.69	0.69	2.41	2.40	2.13	2.12	35.44	36.15	−1.75	11.79
45	Ohio	26,791	32.1	1324	0.54	0.52	0.67	0.67	3.93	4.01	3.35	3.35	16.23	37.75	5.58	14.74
46	Ohio	26,828	1.08	1475	0.55	0.54	0.56	0.59	4.20	4.25	4.17	4.04	15.26	28.92	0.48	8.84
47	Ohio	26,863	0.2	577	0.38	0.40	0.61	0.62	3.46	3.40	2.75	2.72	49.93	53.88	16.73	17.8
48	Ohio	26,891	0.5	197	0.84	0.84	0.88	0.88	3.50	3.52	3.00	3.00	15.24	20.83	−4.05	7.58
49	Wisconsin	31,001	133.55	724	0.59	0.84	0.80	0.90	2.26	1.37	1.60	1.07	19	42.93	20.28	2.83
50	Wisconsin	31,003	21.25	80	0.62	0.78	0.84	0.91	5.16	3.84	3.35	2.53	6.93	34.62	15.14	1.09
51	Wisconsin	31,004	69.2	114	0.66	0.75	0.85	0.90	5.08	4.40	3.34	2.84	8.31	24.01	10.17	3.19
52	Oklahoma	34,001	0.9	258	0.53	0.59	0.62	0.65	6.47	5.99	5.78	5.54	10.62	17.05	−1.3	−3.15
53	Oklahoma	34,006	0.7	275	0.47	0.54	0.58	0.62	7.13	6.67	6.37	6.01	12.25	13.56	−0.53	−1.91
54	Oklahoma	34,007	0.8	262	0.61	0.64	0.62	0.68	6.55	6.25	6.44	5.95	6.94	10.53	−0.6	−1.14
55	Oklahoma	34,008	1.9	231	0.40	0.45	0.51	0.56	7.10	6.78	6.39	6.06	12.28	13.55	−0.34	−1.78
56	Oklahoma	34,013	0.8	52	0.63	0.61	0.52	0.60	4.53	4.66	5.19	4.74	23.69	37.13	−2.3	19.68
57	Oklahoma	35,001	13.5	158	0.72	0.81	0.80	0.83	7.80	6.46	6.62	6.00	0.63	4.18	2.27	−2.48
58	Oklahoma	35,002	1.3	151	0.15	0.49	0.74	0.75	7.90	6.11	4.32	4.27	15.59	14.37	0.21	2.96
59	Oklahoma	35,003	1.3	107	0.74	0.75	0.80	0.77	7.82	7.78	6.89	7.40	−2.11	−2.22	3.23	26.56
60	Oklahoma	35,004	2.3	26	0.53	0.53	0.10	0.29	3.85	3.85	5.35	4.75	45.94	43.78	11.32	–23.36
61	Oklahoma	35,005	2.1	128	0.16	0.18	0.63	0.65	7.16	7.07	4.75	4.64	23.93	21.8	0.92	2.09
62	Oklahoma	35,006	1	31	0.04	0.04	0.12	0.11	6.39	6.40	6.15	6.17	64.49	68.07	0.42	22.67
63	Oklahoma	35,008	3.7	129	0.66	0.72	0.73	0.80	5.09	4.67	4.51	3.92	29.25	21.1	−0.72	1.85
64	Oklahoma	35,009	5.4	120	0.53	0.62	0.77	0.80	6.30	5.71	4.41	4.07	24.32	15.06	−0.42	−4.69
65	Oklahoma	35,010	6.4	113	0.67	0.73	0.73	0.81	5.19	4.73	4.71	3.93	27.05	19.38	−0.12	−3.87
66	Oklahoma	35,011	38.4	99	0.09	0.09	0.41	0.46	4.17	4.18	3.36	3.21	68.89	71.04	−6.3	4.41
67	Oklahoma	37,001	6.8	195	0.60	0.59	0.59	0.58	10.50	10.55	10.61	10.68	7.91	17.12	1.1	20.09
68	Oklahoma	37,002	37.2	388	0.59	0.60	0.58	0.62	9.00	8.99	9.19	8.75	12.89	14.07	4.59	5.21
69	Texas	42,003	449.2	487	0.58	0.58	0.63	0.67	10.53	10.49	9.87	9.26	5.81	7.06	−2.38	3.47
70	Texas	42,004	1772.5	125	0.37	0.38	0.56	0.57	13.64	13.60	11.42	11.35	8.31	9.46	−0.45	12.91
71	Texas	42,006	70.4	819	0.69	0.69	0.67	0.74	8.11	8.05	8.27	7.32	7.67	8.79	0.49	−1.81

(continued on next page)

Appendix II a (*continued*)

Sl. No.	State	Watershed ID	Area (ha)	Number of storm events	NSE				RMSE				PBIAS (%)			
					SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN
72	Texas	42,007	52.6	148	0.45	0.43	0.56	0.58	11.66	11.90	10.42	10.19	5.29	22.59	0.87	8.82
73	Texas	42,008	17.1	162	0.54	0.52	0.57	0.61	11.84	12.10	11.38	10.79	1.1	19.5	0.12	4.31
74	Texas	42,010	8	224	0.67	0.64	0.74	0.74	9.85	10.16	8.62	8.63	65.93	22.79	−1.09	9.68
75	Texas	42,011	125	287	0.52	0.52	0.68	0.70	8.03	8.02	6.62	6.37	11.12	17.26	−1.09	0.3
76	Texas	42,012	53.4	277	0.64	0.64	0.72	0.73	8.80	8.77	7.81	7.65	−0.1	1.6	0.37	6.35
77	Texas	42,013	32.3	36	0.70	0.72	0.81	0.83	6.72	6.45	5.40	4.99	−4.47	−2.24	−1.05	−1.92
78	Texas	42,014	6.6	273	0.56	0.56	0.68	0.70	7.79	7.79	6.60	6.38	3.59	11.81	−3.07	−1.52
79	Texas	42,015	16.2	128	0.60	0.60	0.69	0.72	9.46	9.43	8.32	7.82	−1.4	0.5	−0.24	2.21
80	Texas	42,016	8.4	293	0.61	0.62	0.69	0.74	7.37	7.33	6.59	6.02	6.01	7.72	−1.62	−6.89
81	Texas	42,017	7.5	237	0.69	0.69	0.71	0.76	9.14	9.10	8.79	7.97	1.82	2.16	−0.43	−1.3
82	Texas	42,023	1.31	80	0.72	0.72	0.73	0.78	12.76	12.65	12.62	11.36	−2.14	−1.31	0.79	−1.41
83	Texas	42,024	1.2	252	0.59	0.56	0.60	0.62	11.23	11.53	11.01	10.80	5.4	23.68	0.71	7.18
84	Texas	42,028	1.2	263	0.60	0.57	0.66	0.66	10.32	10.67	9.47	9.45	−0.77	21.04	−0.14	10.7
85	Texas	42,035	1.3	163	0.49	0.46	0.59	0.59	13.16	13.58	11.78	11.77	7.39	27.79	−1.08	11.07
86	Texas	42,037	4.6	181	0.70	0.71	0.73	0.76	7.81	7.77	7.48	7.03	−0.2	0.8	6.69	9.51
87	Texas	42,038	2.3	158	0.64	0.63	0.63	0.68	10.77	10.84	10.86	10.14	3.15	12.72	0.98	16.09
88	Texas	42,039	4	237	0.53	0.53	0.64	0.67	9.72	9.66	8.53	8.08	−4.54	−2.66	1.95	16.32
89	Texas	42,040	4.6	226	0.44	0.44	0.59	0.63	11.01	10.98	9.39	8.99	−9.88	−2.42	7.05	14.93
90	Nebraska	44,001	194.7	407	0.67	0.76	0.73	0.81	5.07	4.35	4.59	3.87	11.21	13.76	1.33	1.29
91	Nebraska	44,002	166.3	482	0.74	0.81	0.77	0.86	4.23	3.65	3.96	3.07	8.16	10.3	3.62	3.31
92	Nebraska	44,003	844.2	235	0.73	0.79	0.75	0.84	5.26	4.62	5.06	4.01	16.21	18.96	1.42	1
93	Nebraska	44,004	1412.4	349	0.71	0.78	0.77	0.82	4.66	4.06	4.15	3.67	16.83	18.3	1.91	1.23
94	Nebraska	44,005	1.5	135	0.47	0.64	0.56	0.66	4.49	3.73	4.12	3.59	8.43	9.76	33.03	18.57
95	Nebraska	44,006	1.4	149	0.52	0.71	0.45	0.73	5.88	4.56	6.32	4.42	−4.37	3.54	16.54	11.37
96	Nebraska	44,007	1.5	524	0.74	0.79	0.73	0.82	4.92	4.46	5.04	4.14	8.04	13.31	2.9	−5.91
97	Nebraska	44,008	1.5	515	0.75	0.82	0.78	0.84	5.32	4.60	5.01	4.27	8.18	14.06	3	−2.59
98	Nebraska	44,009	1.6	537	0.76	0.82	0.78	0.85	4.33	3.76	4.18	3.45	13.06	18.59	5.89	−5.66
99	Nebraska	44,010	1.6	537	0.60	0.67	0.64	0.74	4.92	4.47	4.64	3.98	15.05	22.93	2.04	−0.31
100	Nebraska	44,011	1.7	486	0.57	0.67	0.62	0.73	5.01	4.37	4.70	3.95	17.89	28.3	0.84	−2.8
101	Nebraska	44,012	1.59	355	0.65	0.73	0.68	0.77	4.61	4.01	4.38	3.72	4.16	10.7	12.72	−3.44
102	Nebraska	44,013	1.5	248	0.56	0.61	0.69	0.73	4.62	4.33	3.86	3.60	20.47	25.48	0.78	1.12
103	Nebraska	44,014	1.6	262	0.40	0.43	0.58	0.62	5.44	5.30	4.58	4.34	23.97	25.54	−1.24	−0.84
104	Nebraska	44,015	1.6	295	0.69	0.72	0.72	0.77	4.93	4.67	4.64	4.23	9.52	14.2	0.65	−0.74
105	Nebraska	44,016	1.5	309	0.55	0.58	0.65	0.69	5.89	5.68	5.17	4.90	16.43	20.04	−4.18	−3.7
106	Nebraska	44,017	1.4	276	0.69	0.78	0.78	0.85	4.84	4.09	4.06	3.41	10.81	18.63	1.5	1.1
107	Nebraska	44,018	1.4	274	0.72	0.75	0.77	0.83	4.92	4.66	4.49	3.86	10.44	14.31	1.32	−1.07
108	Nebraska	44,019	1.5	303	0.62	0.67	0.73	0.77	5.11	4.77	4.32	3.94	12.25	22.71	−2.87	−2.84
109	Nebraska	44,020	1.4	281	0.76	0.80	0.77	0.84	4.48	4.05	4.37	3.68	7.98	10.74	2.13	−3.18
110	Nebraska	44,021	1.6	321	0.72	0.76	0.76	0.81	4.68	4.31	4.37	3.82	11.34	14.11	2.33	−1.45
111	Nebraska	44,022	1.5	320	0.51	0.72	0.70	0.75	5.19	3.92	4.03	3.70	7.57	13.07	−1.14	0.47
112	Nebraska	44,023	1.7	258	0.77	0.78	0.68	0.82	4.52	4.40	5.32	4.01	9.28	9.41	−35.37	2.42
113	Nebraska	44,024	1.6	264	0.41	0.43	0.57	0.64	5.52	5.42	4.73	4.32	29.34	30.43	−6.35	2.97
114	Nebraska	44,025	1.6	238	0.64	0.68	0.66	0.74	5.36	5.06	5.21	4.56	15.91	17.84	2.03	−0.74
115	Nebraska	44,026	1.5	241	0.66	0.70	0.76	0.79	5.44	5.11	4.59	4.23	0.16	4.6	5.1	−0.01
116	Nebraska	44,028	1.8	269	0.70	0.73	0.76	0.81	5.38	5.07	4.81	4.24	0.95	3.39	5.36	1.85
117	Nebraska	44,029	0.9	16	0.66	0.91	0.84	0.91	6.05	3.11	4.13	3.05	38.04	13.33	28.82	−0.92
118	Illinois	61,003	157.8	463	0.43	0.37	0.47	0.55	3.38	3.55	3.27	3.01	40.1	62.62	9.18	15.74
119	Illinois	61,004	25.5	342	0.11	0.13	0.39	0.43	4.29	4.23	3.55	3.45	48.66	46.06	3.61	18.12
120	Mississippi	62,001	809.37	236	0.71	0.72	0.78	0.83	4.40	4.31	3.76	3.30	19.19	17.28	−1.5	−1.05
121	Mississippi	62,002	404.7	136	0.77	0.78	0.74	0.81	8.34	8.23	8.86	7.58	5.83	6.37	2.21	0.9
122	Mississippi	62,003	2237.9	28	0.45	0.45	0.53	0.62	9.08	9.06	8.34	7.52	4.05	8.88	0.91	10.62
123	Mississippi	62,004	9226.9	22	0.40	0.39	0.61	0.63	7.34	7.41	5.90	5.77	−2.25	11.19	2.54	17.38
124	Mississippi	62,005	12990.5	92	0.54	0.54	0.59	0.76	9.43	9.35	8.84	6.83	29.69	28.38	−1.42	−2.89
125	Mississippi	62,008	437.1	19	0.39	0.11	0.87	0.77	7.80	9.47	3.59	4.79	−10.77	60.02	18.21	13.96
126	Mississippi	62,010	8093.7	104	0.70	0.71	0.74	0.78	9.93	9.83	9.23	8.53	11.53	10.42	−0.27	−1
127	Mississippi	62,012	3055.4	35	0.37	0.25	0.57	0.59	10.13	11.04	8.36	8.12	22.74	55.67	−2.8	2.75
128	Mississippi	62,014	0.6	134	0.73	0.73	0.40	0.78	7.33	7.33	10.94	6.60	4.04	4.56	−56.15	4.83
129	Mississippi	62,017	1295	26	0.52	0.52	0.57	0.60	8.66	8.62	8.18	7.91	−6.07	−4.5	11.84	17.72
130	Mississippi	62,018	441.1	59	0.44	0.31	0.66	0.66	8.08	8.91	6.24	6.30	13.89	53.62	−1.17	12.18
131	New Mexico	64,001	17,353	14	0.55	0.59	0.55	0.70	1.48	1.42	1.49	1.21	51.82	52.21	15.72	4.95
132	Vermont	67,003	836.5	125	0.12	0.13	0.61	0.57	4.81	4.79	0.16	3.36	59.33	60.59	0.29	24.86
133	Vermont	67,004	4351.2	61	0.04	0.07	0.57	0.53	4.35	4.27	2.90	3.03	59.19	52.67	4.48	23.28
134	Vermont	67,005	11116.4	247	0.14	0.13	0.45	0.50	3.57	3.57	2.84	2.72	76.9	75.75	0.53	49.59
135	Vermont	67,009	46.9	58	0.21	0.30	0.71	0.70	6.52	6.14	3.95	3.99	49.93	38.08	7.63	13.27
136	Oklahoma	69,030	7.2	161	0.55	0.57	0.74	0.74	4.62	4.53	3.51	3.55	14.33	10.35	10.89	15.36
137	Oklahoma	69,032	17.9	198	0.73	0.79	0.67	0.77	4.15	3.66	4.60	3.85	4.04	5.21	5.49	3.34
138	Oklahoma	69,033	12.1	156	0.68	0.75	0.61	0.72	4.84	4.27	5.32	4.55	1.96	4.46	4.93	−0.72
139	Oklahoma	69,034	5.2	94	0.44	0.46	0.43	0.47	5.62	5.51	5.64	5.45	18.04	18.74	−0.01	13.98
140	Oklahoma	69,035	5.26	116	0.47	0.53	0.48	0.52	5.51	5.15	5.46	5.20	15.32	16.13	−0.64	−0.2
141	Oklahoma	69,036	10.7	113	0.50	0.64	0.53	0.64	5.15	4.38	4.95	4.36	8.87	6.05	−0.3	−16.68
142	Oklahoma	69,037	11	123	0.19	0.23	0.43	0.39	4.38	4.25	3.66	3.78	29.36	24.21	6.03	43.88
143	Oklahoma	69,042	9.6	85	0.58	0.60	0.36	0.56	4.85	4.69	5.95	4.94	26.62	28.43	−2.01	7.65

(*continued on next page*)

Appendix II a (*continued*)

Sl. No.	State	Watershed ID	Area (ha)	Number of storm events	NSE				RMSE				PBIAS (%)			
					SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN
144	Oklahoma	69,043	11	127	0.65	0.69	0.40	0.61	3.93	3.69	5.11	4.10	19.13	22.62	4.65	0.69
145	Oklahoma	69,044	7.8	225	0.73	0.76	0.78	0.83	4.45	4.19	4.08	3.52	16.05	17.91	0.3	−1.69
146	Oklahoma	69,045	11.1	250	0.74	0.77	0.73	0.80	3.46	3.25	3.53	3.04	18.69	20.94	1.89	0.22
147	Texas	70,002	717.9	8	0.65	0.65	0.70	0.95	0.92	0.91	0.86	0.35	48.19	48.15	10.34	3.84
148	Texas	70,003	2182.1	9	0.62	0.62	0.43	0.93	3.30	3.31	4.05	1.46	49.6	52.48	9.4	2.76
149	Texas	70,004	4365.4	12	0.68	0.80	0.62	0.92	3.77	2.97	4.05	1.91	46.05	28.95	6.09	4.19
150	Texas	70,006	277.6	14	0.92	0.96	0.69	0.82	1.46	0.42	2.82	2.13	9.4	−1.33	−10.25	4.29
151	Texas	70,007	4.1	25	0.85	0.82	0.88	0.88	8.10	8.92	7.27	7.24	16.48	43.09	9.47	6.87
152	Texas	70,008	3.5	23	0.58	0.58	0.41	0.52	7.85	7.85	9.37	8.45	−3.26	−5.29	2.2	−0.33
153	Texas	70,009	2.7	18	0.89	0.93	0.80	0.92	6.10	5.03	8.31	5.24	18.26	4.26	40.54	−5.79
154	Texas	70,010	1.8	9	0.82	0.97	0.96	0.97	3.90	1.57	1.81	1.62	15.67	17.19	23.54	10.37
155	Texas	70,011	2.9	41	0.88	0.94	0.89	0.95	5.57	4.02	5.25	3.57	28.95	6.02	12.83	−4.13
156	Texas	70,012	2.8	15	0.88	0.93	0.88	0.93	4.67	3.53	4.54	3.47	34.37	4.65	14.44	5.57
157	Iowa	71,001	30.1	979	0.22	0.22	0.34	0.50	2.71	2.70	2.48	2.17	70.49	71.16	−25.53	−20.6
158	Iowa	71,002	33.51	1120	0.49	0.68	0.57	0.75	3.23	2.58	2.98	2.25	32.42	33.11	3.15	2.35
159	Iowa	71,005	157.43	375	0.04	0.84	0.72	0.86	2.30	0.95	1.23	0.87	85	51.66	60.98	37.11
160	Georgia	74,003	1566.94	284	0.33	0.38	0.51	0.59	3.21	5.23	4.65	4.26	16.69	25.07	−2.94	−1.46
161	Georgia	74,008	1665.28	349	0.05	0.33	0.66	0.71	5.54	4.66	3.30	3.08	81.24	35.04	−3.38	−1.56
162	Georgia	74,009	261.43	202	0.16	0.30	0.55	0.60	6.66	6.11	4.89	4.61	47.56	43.23	−4.85	2.96
163	Hawaii	77,003	2.8	248	0.65	0.65	0.76	0.77	2.99	2.99	2.45	2.40	51.9	53.61	22.58	17.53
164	Hawaii	77,006	2.9	118	0.50	0.50	0.88	0.79	2.80	2.82	1.37	1.80	75.02	68.25	7.37	43.67

$$(P - I_a - F_c) = \frac{S(V - V_{et})}{(V_{et} + S - V)} \tag{A4}$$

$$(P - I_a - F_c + 2S) = \frac{S(V_{et} - V + 2S)}{(V_{et} + S - V)} \tag{A5}$$

$$(P - I_a - F_c + S) = \frac{S^2}{(V_{et} + S - V)} \tag{A6}$$

Using Eqs. (A4)–(A6) into Eq. (A2) and then simplifying the result is

$$q = \frac{(V - V_{et})(2S - V + V_{et})}{S^2}p; \text{ if } V > V_{et}, \tag{A7}$$

$q = 0$, otherwise

Eq. (A7) can be rewritten as

$$q = \left(\frac{V - V_{et}}{S}\right)\left[2 - \left(\frac{V - V_{et}}{S}\right)\right]p \text{ if } V > V_{et}, \tag{A8}$$

$q = 0$, otherwise

Appendix B

Coupling of Eq. (17) and Eq. (18) results into

$$\frac{dV}{dt} = \left[1 - \left(\frac{V - V_{et}}{S}\right)\left(2 - \frac{V - V_{et}}{S}\right)\right]p \tag{B1}$$

After re-arranging, Eq. (B1) can be expressed as:

$$\frac{dV}{dt} = \frac{(V - V_{et} - S)^2}{S^2}p \tag{B2}$$

Re-arranging Eq. (B2) and applying appropriate lower and upper limits of integration the results is:

$$\int_{V_0}^{V} \frac{dV}{(V - V_{et} - S)^2} = \frac{1}{S^2}\int_0^t pdt \tag{B3}$$

After integration, we get

$$\frac{1}{V_{et} + S - V} - \frac{1}{V_{et} + S - V_0} = \frac{P}{S^2} \tag{B4}$$

Now, replacing the value of V derived from Eq. (14) into Eq. (B4), rearranging yields

Appendix II b
Comparison of MAE, RSR and nRMSE resulting from applications of all the four methods to 164 US watersheds.

Sl. No.	State	Watershed ID	MAE				RSR				nRMSE			
			SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN
1	Georgia	9004	0.03	0.03	0.02	0.03	0.73	0.63	0.68	0.50	1.21	1.04	1.13	0.82
2	Georgia	10,001	0.01	0.01	0.13	0.01	0.86	0.98	0.88	0.81	1.18	1.34	1.20	1.10
3	Virginia	13,008	0.00	0.00	0.01	0.00	0.66	0.57	0.43	0.43	1.26	1.09	0.83	0.81
4	Virginia	13,009	0.10	0.11	0.08	0.10	0.96	0.96	0.79	0.79	1.33	1.33	1.09	1.09
5	Virginia	13,014	0.01	0.01	0.01	0.01	0.46	0.46	0.40	0.40	0.99	0.98	0.86	0.86
6	Pennsylvania	16,010	0.02	0.02	0.01	0.01	0.96	0.97	0.78	0.77	2.95	2.98	2.41	2.36
7	Pennsylvania	16,020	0.00	0.00	0.00	0.00	0.91	0.89	0.74	0.76	2.56	2.51	2.09	2.16
8	Illinois	17,001	0.00	0.00	0.00	0.00	0.50	0.50	0.49	0.47	1.11	1.11	1.10	1.05
9	Illinois	17,002	0.00	0.00	0.00	0.00	0.51	0.51	0.48	0.46	1.17	1.16	1.10	1.06
10	Illinois	17,003	0.02	0.02	0.01	0.02	0.56	0.56	0.58	0.50	1.19	1.19	1.23	1.06
11	Illinois	17,004	0.00	0.00	0.00	0.00	0.52	0.52	0.46	0.43	1.19	1.19	1.05	0.98
12	Indiana	19,005	0.16	0.16	0.14	0.12	0.50	0.49	0.50	0.48	1.13	1.13	1.13	1.10
13	Missouri	25,001	0.04	0.04	0.04	0.04	0.54	0.54	0.52	0.51	0.98	0.98	0.95	0.92
14	Ohio	26,001	0.00	0.00	0.00	0.00	0.98	0.77	0.69	0.68	2.76	2.16	1.93	1.92
15	Ohio	26,002	0.00	0.00	0.00	0.00	0.71	0.68	0.68	0.65	2.45	2.33	2.32	2.22
16	Ohio	26,003	0.00	0.00	0.00	0.00	0.99	0.87	0.76	0.73	2.06	1.81	1.59	1.52
17	Ohio	26,004	0.00	0.00	0.00	0.00	0.95	0.82	0.69	0.65	2.27	1.95	1.66	1.55
18	Ohio	26,005	0.00	0.00	0.00	0.00	0.86	0.77	0.59	0.56	2.03	1.84	1.40	1.32
19	Ohio	26,006	0.02	0.02	0.01	0.02	0.83	0.83	0.63	0.59	1.69	1.69	1.27	1.20
20	Ohio	26,007	0.00	0.00	0.01	0.01	1.00	0.99	0.66	0.65	2.04	2.02	1.35	1.33
21	Ohio	26,010	0.00	0.00	0.00	0.00	0.71	0.71	0.62	0.61	1.28	1.28	1.12	1.09
22	Ohio	26,011	0.01	0.01	0.01	0.01	0.70	0.67	0.60	0.60	1.86	1.78	1.61	1.59
23	Ohio	26,012	0.00	0.00	0.00	0.00	0.60	0.60	0.55	0.55	1.49	1.48	1.37	1.37
24	Ohio	26,014	0.00	0.00	0.00	0.00	0.61	0.62	0.61	0.59	1.34	1.36	1.33	1.30
25	Ohio	26,015	0.00	0.00	0.00	0.00	0.66	0.63	0.59	0.57	2.01	1.92	1.80	1.74
26	Ohio	26,016	0.00	0.00	0.00	0.00	0.77	0.74	0.68	0.68	1.87	1.80	1.65	1.64
27	Ohio	26,017	0.01	0.01	0.00	0.01	0.71	0.71	0.61	0.60	2.00	1.99	1.72	1.70
28	Ohio	26,018	0.01	0.01	0.00	0.00	0.53	0.53	0.48	0.47	0.91	0.91	0.83	0.81
29	Ohio	26,020	0.00	0.00	0.00	0.00	0.97	0.75	0.76	0.75	2.65	2.05	2.07	2.05
30	Ohio	26,021	0.02	0.02	0.02	0.02	0.92	0.92	0.76	0.75	1.86	1.85	1.54	1.52
31	Ohio	26,023	0.00	0.00	0.00	0.00	0.66	0.60	0.45	0.43	2.26	2.03	1.54	1.47
32	Ohio	26,024	0.00	0.00	0.00	0.00	0.71	0.71	0.57	0.56	2.29	2.30	1.84	1.82
33	Ohio	26,025	0.00	0.00	0.00	0.00	0.69	0.67	0.56	0.55	2.08	2.03	1.70	1.66
34	Ohio	26,027	0.01	0.01	0.01	0.01	0.62	0.61	0.53	0.51	2.59	2.57	2.24	2.15
35	Ohio	26,028	0.00	0.00	0.00	0.00	0.70	0.69	0.58	0.57	2.71	2.68	2.25	2.22
36	Ohio	26,029	0.00	0.00	0.00	0.00	0.64	0.64	0.54	0.52	2.10	2.09	1.76	1.70
37	Ohio	26,030	0.00	0.00	0.00	0.00	0.62	0.62	0.56	0.56	2.40	2.39	2.15	2.15
38	Ohio	26,032	0.00	0.00	0.00	0.00	0.71	0.71	0.58	0.56	2.61	2.60	2.12	2.07
39	Ohio	26,033	0.00	0.00	0.00	0.00	0.60	0.60	0.54	0.53	2.07	2.07	1.86	1.82
40	Ohio	26,034	0.00	0.00	0.00	0.00	0.61	0.61	0.56	0.54	1.99	1.98	1.84	1.77
41	Ohio	26,035	0.03	0.03	0.00	0.02	0.87	0.86	0.54	0.57	1.05	1.05	0.66	0.70
42	Ohio	26,036	0.01	0.01	0.01	0.01	0.77	0.77	0.68	0.69	1.35	1.35	1.19	1.21
43	Ohio	26,040	0.00	0.00	0.00	0.00	0.63	0.63	0.54	0.53	2.05	2.04	1.73	1.71
44	Ohio	26,041	0.00	0.00	0.00	0.00	0.63	0.63	0.56	0.56	2.07	2.06	1.82	1.82
45	Ohio	26,711	0.00	0.00	0.00	0.00	0.68	0.69	0.58	0.58	2.25	2.30	1.92	1.92
46	Ohio	26,791	0.00	0.00	0.00	0.00	0.67	0.68	0.66	0.64	2.02	2.04	2.01	1.94
47	Ohio	26,828	0.01	0.01	0.01	0.01	0.79	0.77	0.63	0.62	2.31	2.28	1.84	1.82
48	Ohio	26,863	0.01	0.01	0.00	0.01	0.40	0.40	0.34	0.34	0.76	0.77	0.65	0.65
49	Wisconsin	31,001	0.00	0.00	0.00	0.00	0.64	0.40	0.45	0.32	3.74	2.34	2.64	1.85
50	Wisconsin	31,003	0.00	0.00	0.00	0.00	0.62	0.46	0.40	0.31	1.66	1.24	1.08	0.82
51	Wisconsin	31,004	0.00	0.00	0.00	0.00	0.58	0.50	0.38	0.32	1.63	1.41	1.07	0.91
52	Oklahoma	34,001	0.00	0.00	0.01	0.00	0.69	0.64	0.61	0.59	1.15	1.06	1.03	0.98
53	Oklahoma	34,006	0.03	0.02	0.01	0.02	0.73	0.68	0.65	0.61	1.33	1.24	1.19	1.12
54	Oklahoma	34,007	0.00	0.00	0.01	0.00	0.62	0.60	0.61	0.57	1.06	1.01	1.04	0.96
55	Oklahoma	34,008	0.02	0.01	0.00	0.01	0.78	0.74	0.70	0.66	1.50	1.43	1.35	1.28
56	Oklahoma	34,013	0.13	0.07	0.11	0.13	0.61	0.62	0.70	0.63	0.85	0.88	0.98	0.89
57	Oklahoma	35,001	0.01	0.01	0.00	0.01	0.53	0.44	0.45	0.41	0.85	0.71	0.73	0.66
58	Oklahoma	35,002	0.05	0.05	0.02	0.03	0.92	0.71	0.51	0.50	1.38	1.07	0.76	0.75
59	Oklahoma	35,003	0.02	0.02	0.00	0.01	0.51	0.50	0.45	0.48	0.85	0.85	0.75	0.81
60	Oklahoma	35,004	0.01	0.01	0.15	0.06	0.68	0.68	0.95	0.84	1.24	1.24	1.72	1.52
61	Oklahoma	35,005	0.00	0.00	0.01	0.01	0.91	0.90	0.61	0.59	1.69	1.67	1.12	1.10
62	Oklahoma	35,006	0.57	0.60	0.60	0.62	0.98	0.98	0.94	0.94	1.94	1.94	1.86	1.87
63	Oklahoma	35,008	0.00	0.00	0.00	0.00	0.58	0.53	0.52	0.45	1.18	1.08	1.05	0.91
64	Oklahoma	35,009	0.23	0.28	0.12	0.14	0.68	0.62	0.48	0.44	1.24	1.12	0.87	0.80
65	Oklahoma	35,010	0.05	0.06	0.03	0.02	0.57	0.52	0.52	0.43	1.18	1.07	1.07	0.89
66	Oklahoma	35,011	0.02	0.02	0.03	0.04	0.96	0.96	0.77	0.73	1.83	1.83	1.47	1.41
67	Oklahoma	37,001	0.00	0.00	0.01	0.00	0.64	0.64	0.64	0.65	1.24	1.25	1.26	1.26
68	Oklahoma	37,002	0.01	0.01	0.01	0.01	0.64	0.64	0.65	0.62	1.49	1.49	1.52	1.45
69	Texas	42,003	0.02	0.01	0.00	0.01	0.65	0.65	0.61	0.57	1.09	1.09	1.02	0.96
70	Texas	42,004	0.04	0.04	0.00	0.02	0.79	0.79	0.66	0.66	0.84	0.84	0.71	0.70
71	Texas	42,006	0.00	0.00	0.00	0.00	0.56	0.56	0.57	0.51	1.21	1.20	1.23	1.09
72	Texas	42,007	0.04	0.04	0.01	0.02	0.74	0.75	0.66	0.65	0.95	0.97	0.85	0.83

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Appendix II b (*continued*)

Sl. No.	State	Watershed ID	MAE				RSR				nRMSE			
			SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN
73	Texas	42,008	0.01	0.01	0.00	0.00	0.68	0.68	0.65	0.62	1.01	1.01	0.97	0.92
74	Texas	42,010	0.00	0.00	0.00	0.00	0.58	0.60	0.51	0.51	0.80	0.83	0.70	0.70
75	Texas	42,011	0.01	0.01	0.01	0.01	0.69	0.69	0.57	0.55	1.21	1.21	1.00	0.96
76	Texas	42,012	0.01	0.01	0.00	0.01	0.60	0.60	0.53	0.52	1.11	1.11	0.99	0.96
77	Texas	42,013	0.05	0.11	0.01	0.02	0.55	0.53	0.44	0.41	0.73	0.70	0.59	0.54
78	Texas	42,014	0.00	0.00	0.01	0.00	0.66	0.66	0.56	0.54	1.35	1.35	1.14	1.10
79	Texas	42,015	0.03	0.03	0.00	0.01	0.64	0.63	0.56	0.53	0.91	0.91	0.80	0.76
80	Texas	42,016	0.00	0.00	0.00	0.00	0.62	0.62	0.56	0.51	1.24	1.24	1.11	1.01
81	Texas	42,017	0.00	0.00	0.00	0.00	0.56	0.55	0.54	0.49	0.95	0.94	0.91	0.83
82	Texas	42,023	0.19	0.18	0.06	0.08	0.53	0.53	0.52	0.47	0.67	0.67	0.67	0.60
83	Texas	42,024	0.00	0.00	0.00	0.00	0.64	0.66	0.63	0.62	1.01	1.04	0.99	0.97
84	Texas	42,028	0.02	0.02	0.01	0.01	0.64	0.66	0.58	0.58	1.10	1.14	1.01	1.01
85	Texas	42,035	0.02	0.01	0.05	0.04	0.71	0.74	0.64	0.64	1.05	1.09	0.94	0.94
86	Texas	42,037	0.02	0.02	0.04	0.02	0.54	0.54	0.52	0.49	1.08	1.08	1.04	0.98
87	Texas	42,038	0.01	0.00	0.05	0.01	0.60	0.60	0.61	0.57	0.90	0.91	0.91	0.85
88	Texas	42,039	0.01	0.01	0.02	0.01	0.69	0.68	0.60	0.57	1.41	1.40	1.24	1.17
89	Texas	42,040	0.01	0.01	0.02	0.00	0.75	0.75	0.64	0.61	1.58	1.58	1.35	1.29
90	Nebraska	44,001	0.01	0.01	0.02	0.01	0.58	0.49	0.52	0.44	1.18	1.01	1.07	0.90
91	Nebraska	44,002	0.00	0.00	0.00	0.00	0.51	0.44	0.47	0.37	1.29	1.12	1.21	0.94
92	Nebraska	44,003	0.01	0.01	0.01	0.00	0.52	0.46	0.50	0.40	0.76	0.66	0.73	0.58
93	Nebraska	44,004	0.00	0.00	0.00	0.00	0.54	0.47	0.48	0.42	1.18	1.03	1.05	0.93
94	Nebraska	44,005	0.00	0.00	0.00	0.00	0.73	0.60	0.67	0.58	2.04	1.69	1.87	1.63
95	Nebraska	44,006	0.03	0.02	0.03	0.02	0.69	0.53	0.74	0.52	1.90	1.47	2.04	1.42
96	Nebraska	44,007	0.01	0.00	0.01	0.00	0.51	0.46	0.52	0.43	1.00	0.91	1.03	0.84
97	Nebraska	44,008	0.00	0.00	0.00	0.00	0.50	0.43	0.47	0.40	1.11	0.96	1.05	0.89
98	Nebraska	44,009	0.00	0.00	0.00	0.00	0.49	0.43	0.47	0.39	1.25	1.08	1.20	0.99
99	Nebraska	44,010	0.00	0.00	0.01	0.00	0.63	0.58	0.60	0.51	1.28	1.17	1.21	1.04
100	Nebraska	44,011	0.00	0.00	0.00	0.00	0.65	0.57	0.61	0.52	1.38	1.20	1.29	1.09
101	Nebraska	44,012	0.00	0.00	0.00	0.00	0.59	0.52	0.57	0.48	1.47	1.28	1.40	1.18
102	Nebraska	44,013	0.00	0.00	0.01	0.01	0.66	0.62	0.55	0.52	1.23	1.15	1.02	0.96
103	Nebraska	44,014	0.00	0.00	0.02	0.01	0.77	0.75	0.65	0.62	1.47	1.44	1.24	1.17
104	Nebraska	44,015	0.00	0.00	0.01	0.01	0.56	0.53	0.53	0.48	1.14	1.08	1.07	0.98
105	Nebraska	44,016	0.00	0.00	0.01	0.01	0.67	0.65	0.59	0.56	1.27	1.22	1.11	1.06
106	Nebraska	44,017	0.00	0.01	0.01	0.01	0.55	0.47	0.46	0.39	1.06	0.90	0.89	0.75
107	Nebraska	44,018	0.00	0.00	0.01	0.01	0.53	0.50	0.48	0.42	0.98	0.93	0.89	0.77
108	Nebraska	44,019	0.00	0.01	0.01	0.01	0.62	0.58	0.52	0.48	1.11	1.04	0.94	0.85
109	Nebraska	44,020	0.00	0.01	0.01	0.01	0.49	0.44	0.48	0.40	0.96	0.87	0.93	0.79
110	Nebraska	44,021	0.00	0.00	0.00	0.00	0.53	0.49	0.49	0.43	1.08	1.00	1.01	0.88
111	Nebraska	44,022	0.01	0.01	0.00	0.00	0.70	0.53	0.55	0.50	1.64	1.24	1.27	1.17
112	Nebraska	44,023	0.00	0.00	0.00	0.00	0.48	0.47	0.57	0.43	0.91	0.88	1.07	0.81
113	Nebraska	44,024	0.00	0.00	0.01	0.00	0.77	0.75	0.66	0.60	1.28	1.26	1.10	1.00
114	Nebraska	44,025	0.00	0.00	0.01	0.01	0.60	0.57	0.58	0.51	1.14	1.08	1.11	0.97
115	Nebraska	44,026	0.00	0.00	0.01	0.00	0.58	0.55	0.49	0.46	1.23	1.15	1.04	0.96
116	Nebraska	44,028	0.00	0.00	0.00	0.00	0.55	0.52	0.49	0.44	1.23	1.16	1.10	0.97
117	Nebraska	44,029	0.01	0.01	0.01	0.01	0.59	0.30	0.40	0.30	1.14	0.59	0.78	0.58
118	Illinois	61,003	0.00	0.00	0.00	0.00	0.75	0.79	0.73	0.67	1.50	1.58	1.45	1.34
119	Illinois	61,004	0.00	0.00	0.00	0.00	0.94	0.93	0.78	0.76	1.35	1.33	1.12	1.09
120	Mississippi	62,001	0.00	0.00	0.00	0.00	0.54	0.53	0.46	0.41	1.51	1.48	1.30	1.14
121	Mississippi	62,002	0.04	0.04	0.01	0.03	0.48	0.47	0.51	0.43	0.69	0.68	0.73	0.63
122	Mississippi	62,003	0.07	0.08	0.04	0.01	0.74	0.74	0.68	0.61	0.85	0.85	0.78	0.70
123	Mississippi	62,004	0.01	0.04	0.06	0.10	0.78	0.78	0.62	0.61	0.86	0.87	0.69	0.67
124	Mississippi	62,005	0.04	0.04	0.04	0.03	0.68	0.68	0.64	0.49	0.88	0.87	0.82	0.64
125	Mississippi	62,008	0.09	0.10	0.10	0.04	0.78	0.95	0.36	0.48	1.42	1.72	0.65	0.87
126	Mississippi	62,010	0.00	0.00	0.00	0.00	0.98	0.40	0.52	0.37	3.95	1.62	2.12	1.49
127	Mississippi	62,012	0.11	0.16	0.06	0.03	0.80	0.87	0.66	0.64	1.08	1.17	0.89	0.86
128	Mississippi	62,014	0.01	0.00	0.08	0.02	0.52	0.52	0.77	0.47	0.59	0.59	0.87	0.53
129	Mississippi	62,017	0.04	0.03	0.01	0.04	0.69	0.69	0.65	0.63	1.12	1.11	1.06	1.02
130	Mississippi	62,018	0.01	0.01	0.03	0.01	0.75	0.83	0.58	0.59	1.29	1.42	0.99	1.00
131	New Mexico	64,001	0.04	0.04	0.03	0.05	0.67	0.64	0.67	0.55	0.73	0.70	0.73	0.59
132	Vermont	67,003	0.02	0.02	0.01	0.00	0.94	0.94	0.63	0.66	1.03	1.02	0.69	0.72
133	Vermont	67,004	0.09	0.09	0.02	0.06	0.98	0.96	0.65	0.68	0.83	0.82	0.55	0.58
134	Vermont	67,005	0.01	0.01	0.00	0.00	0.93	0.93	0.74	0.71	1.45	1.45	1.16	1.11
135	Vermont	67,009	0.18	0.18	0.16	0.16	0.89	0.84	0.54	0.54	1.31	1.24	0.80	0.80
136	Oklahoma	69,030	0.00	0.00	0.02	0.01	0.67	0.66	0.51	0.51	1.74	1.71	1.33	1.34
137	Oklahoma	69,032	0.00	0.00	0.00	0.00	0.52	0.46	0.57	0.48	0.98	0.87	1.09	0.91
138	Oklahoma	69,033	0.00	0.00	0.00	0.00	0.57	0.50	0.62	0.53	1.06	0.94	1.17	1.00
139	Oklahoma	69,034	0.01	0.01	0.05	0.02	0.75	0.74	0.75	0.73	1.21	1.19	1.22	1.18
140	Oklahoma	69,035	0.00	0.01	0.03	0.01	0.73	0.68	0.72	0.69	1.33	1.25	1.32	1.26
141	Oklahoma	69,036	0.01	0.01	0.04	0.03	0.71	0.60	0.68	0.60	1.27	1.08	1.22	1.08
142	Oklahoma	69,037	0.01	0.01	0.02	0.00	0.90	0.88	0.75	0.78	2.06	2.00	1.73	1.78
143	Oklahoma	69,042	0.03	0.02	0.05	0.09	0.65	0.63	0.80	0.66	1.21	1.17	1.49	1.23
144	Oklahoma	69,043	0.01	0.00	0.03	0.07	0.60	0.56	0.77	0.62	1.46	1.37	1.89	1.52
145	Oklahoma	69,044	0.01	0.02	0.03	0.02	0.52	0.49	0.47	0.41	0.82	0.77	0.75	0.65

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Appendix II b (*continued*)

Sl. No.	State	Watershed ID	MAE				RSR				nRMSE			
			SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN	SCS-CN	MS	MVP	ASMA-SCS-CN
146	Oklahoma	69,045	0.00	0.01	0.02	0.03	0.51	0.48	0.52	0.45	1.08	1.01	1.10	0.95
147	Texas	70,002	0.01	0.01	0.06	0.01	0.59	0.59	0.55	0.22	0.78	0.78	0.73	0.30
148	Texas	70,003	0.08	0.08	0.00	0.02	0.61	0.62	0.75	0.27	0.85	0.85	1.04	0.38
149	Texas	70,004	0.06	0.06	0.01	0.00	0.57	0.45	0.61	0.29	0.76	0.60	0.82	0.39
150	Texas	70,006	0.01	0.01	0.01	0.01	0.29	0.08	0.56	0.42	0.48	0.14	0.94	0.71
151	Texas	70,007	0.02	0.02	0.02	0.00	0.38	0.42	0.34	0.34	0.88	0.97	0.79	0.79
152	Texas	70,008	0.01	0.02	0.15	0.18	0.64	0.64	0.77	0.69	1.03	1.03	1.23	1.11
153	Texas	70,009	0.00	0.00	0.00	0.00	0.33	0.27	0.45	0.28	0.69	0.57	0.94	0.59
154	Texas	70,010	0.00	0.04	0.00	0.05	0.43	0.17	0.20	0.18	0.83	0.34	0.39	0.35
155	Texas	70,011	0.00	0.00	0.00	0.00	0.35	0.25	0.33	0.22	0.97	0.70	0.92	0.63
156	Texas	70,012	0.13	0.15	0.53	0.35	0.35	0.27	0.34	0.26	0.72	0.54	0.70	0.53
157	Iowa	71,001	0.00	0.00	0.00	0.00	0.89	0.88	0.81	0.71	3.36	3.35	3.07	2.69
158	Iowa	71,002	0.00	0.00	0.00	0.00	0.71	0.57	0.66	0.50	3.11	2.48	2.87	2.16
159	Iowa	71,005	0.00	0.00	0.00	0.00	0.98	0.40	0.52	0.37	3.95	1.62	2.12	1.49
160	Georgia	74,003	0.00	0.00	0.00	0.00	0.82	0.79	0.70	0.64	1.73	1.66	1.47	1.35
161	Georgia	74,008	0.00	0.00	0.00	0.00	0.97	0.82	0.58	0.54	2.08	1.75	1.24	1.16
162	Georgia	74,009	0.00	0.00	0.02	0.01	0.91	0.84	0.67	0.63	1.38	1.26	1.01	0.95
163	Hawaii	77,003	0.00	0.00	0.00	0.00	0.59	0.59	0.48	0.48	2.27	2.27	1.85	1.82
164	Hawaii	77,006	0.05	0.05	0.01	0.04	0.70	0.71	0.34	0.45	1.68	1.69	0.82	1.08

$$\frac{(P-Q)}{(V_{et}+S-(V_0+P-Q))(V_{et}+S-V_0)}=\frac{P}{S^2} \tag{B5}$$

$$Q=P\left[1-\frac{(V_{et}+S-V_0)^2}{(S^2+(V_{et}+S-V_0)P)}\right] \tag{B6}$$

References

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