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Sensitivity and fuzzy uncertainty analyses in the determination of SCS-CN parameters from rainfall–runoff data

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ABSTRACT
Spatial and seasonal variations of curve number (CN) and initial abstraction ratio (λ) in a watershed can result in inaccurate runoff volume estimations when using the US Natural Resources Conservation Service (SCS-CN) method with constant values for these parameters. In this paper, parameters of CN and λ are considered as calibration parameters and the sensitivity of estimated runoff to these parameters using the SCS-CN method is scrutinized. To incorporate the uncertainty associated with CN and λ, fuzzy linear regression (FLR) is applied to derive the relationships of CN and λ with rainfall depth (P) by employing a large dataset of storm events from four watersheds in Iran. Results indicate that the proposed approach provides more accuracy in estimation of runoff volume compared to the SCS method with constant values of CN and λ, and gives a straightforward technique for evaluating the hydrological effects of CN, λ, and P on runoff volume.

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1 Introduction

The runoff curve number (SCS-CN) method proposed by US Natural Resources Conservation Service, formerly the Soil Conservation Service, is a well-established method for estimating direct runoff volume due to its simplicity, predictability, stability, responsiveness to runoff-producing watershed properties, and following the parsimony criterion by summarizing environmental factors affecting runoff production all in one parameter of curve number (CN). Additionally, this method is computationally efficient, since the potential maximum soil moisture retention (S) of the watershed from which the CN is derived is a function of land use and treatment, hydrological soil group (HSG) and antecedent soil moisture (NRCS 1997), which are readily available. Also, this method produces satisfactory runoff estimates for many agricultural and urban watersheds with different sizes (e.g. Hawkins *et al.* 2009, Wang *et al.* 2009, Yuan *et al.* 2014, Hosseini *et al.* 2016). In addition to above-mentioned advantages of the SCS-CN model, the main weaknesses associated with this method can be summarized as follows: The SCS-CN method does not consider the impact of rainfall intensity on runoff. Also, it does not consider the effect of spatial distribution of parameters such as soil depth, bulk density, moisture content, saturated hydraulic conductivity, and permeability in heterogeneous watersheds (Li and Shao 2006, Xiao *et al.* 2009). Additionally, it is very sensitive to the value of selected CN and considers a constant value for initial abstraction ratio (λ) of 0.2, which may not be applicable for watersheds with different hydrological properties (e.g. Banasik *et al.* 2014). A good review of the advantages and drawbacks of this method was reported by Ponce and Hawkins (1996).

To take into account the effect of spatial heterogeneity factors in producing runoff, Soulis and Valiantzas (2012) introduced the concept of a two-CN heterogeneous system to model the observed CN–rainfall variations by reducing CN spatial variability to two classes. Runoff estimated by the SCS-CN model is highly sensitive to changes in the values of its parameters (CN and λ) which can occur due to human activities. The values of CN calculated from measured rainfall–runoff data vary significantly from storm to storm in any watershed. However, antecedent moisture condition (AMC), depending on the soil moisture in the previous 5–30 days, was initially assumed to be the primary cause of parameter variations. There are no guidelines clearly stating how to determine soil moisture following antecedent rainfall of a certain duration (Hawkins *et al.* 2010). Soulis *et al.* (2009) discussed that CN values, according to AMC category alone, cannot justify the variability of observed CN values in every case. Additionally, there are uncertainties in considering the

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effect of AMC on the CN value that need to be addressed (McCuen 2003, Michel *et al.* 2005, Soulis and Valiantzas 2012). The main inconsistency in the original SCS-CN method arises from confusion between the intrinsic parameter of soil moisture content and initial condition (Michel *et al.* 2005, Sahu *et al.* 2010). Since the SCS-CN method was developed using data of small catchments and was originally designed for use in mid-sized rural watersheds (Johnson 1998), its extension to large watersheds requires validation and calibration. Ponce (1989) suggested that this method should not be used for watersheds larger than 250 km^2 without catchment subdivisions. However, Johnson (1998) stated that the size of the watershed is not a key factor in application of the SCS-CN method, while the rainfall distribution over the area plays the main role. Furthermore, there are no guidelines clearly stating the appropriate watershed area for application of the SCS-CN method (Ajmal *et al.* 2015).

The uncertainty of the parameter λ, which mainly depends on climate condition, should be appropriately incorporated (Mishra and Singh 2003, Baltas *et al.* 2007a, Ajmal *et al.* 2015). This parameter is often set equal to 0.20, according to experiments done in different regions of North America. However, the validity and applicability of using this assumption in other regions and from storm to storm have frequently been questioned (Shi *et al.* 2009). Woodward *et al.* (2004) determined the value of parameter λ to be 0.05 using rainfall and runoff measurements in 327 watersheds in the USA. Tedela *et al.* (2012) obtained the value of this parameter as 0.2 for 10 mountainous watersheds in the Eastern USA. Some researchers have proposed that considering the value of λ between 0.01 and 0.05 can be realistic for all regions (e.g. Yuan *et al.* 2014). Mishra *et al.* (2003, 2005) correlated the value of λ with potential maximum retention and the amount of precipitation. The upper bound of λ is approximately 1.0 for watersheds that have never experienced runoff.

According to the classification of the United Nations Environment Programme (UNEP 1997), only 15% of the total surface area of Iran has a humid and Mediterranean climate. Since potential maximum retention (S) and initial abstraction ($I_a = \lambda\ S$) are large fractions of rainfall (Baltas *et al.* 2007b), and the soil moisture memory has variable effects on the AMC, in some part of Iran with arid and semi-arid climate, estimation of runoff volume by the SCS-CN method provides inaccurate results. However, the available maps (especially soil maps) required for determining the CN value of a watershed are often imprecise or are not of high resolution (up to the scale of 1:1 000 000). In the gauged watersheds of such regions, more accurate values for these parameters can be obtained using recoded rainfall–runoff data. However, these parameters are strongly correlated with rainfall depth, which definitely varies from storm to storm (Soulis and Valiantzas 2012). The value of the median or geometric mean of calibrated CNs obtained from recorded rainfall–runoff data is frequently used as a single value for this parameter (e.g. Viji *et al.* 2015). However, in heterogeneous watersheds or those undergoing land-use changes, considering a single value of CN can result in unreliable estimations (Grunwald and Norton 2000).

To take into account variations of CN with rainfall depth (P), some researchers have used CN as an exponential function, variable order decay function and complementary error function of P (Banasik *et al.* 2014), or have developed a new method based on SCS-CN (Woodward *et al.* 2003, Mishra *et al.* 2006, Ajmal *et al.* 2015). Due to the impacts of CN and λ on runoff estimated by the SCS-CN model and the variability of these parameters, especially in semi-arid regions, it is necessary to determine the influence of these parameters on the runoff volume, and to appropriately estimate values of these parameters. In this paper, sensitivity coefficients related to the parameters of the SCS-CN method (i.e. CN and λ) are derived and scrutinized to characterize the uncertainty of outputs with respect to each parameter. This analysis is useful to acquire an insight into the relationship of rainfall with the parameters CN and λ in the watershed. Then, the values of CN and λ are optimized through the calibration phase based on several recorded rainfall–runoff datasets for four small watersheds located in the humid region of northern Iran. In the next step, using the calibration datasets, the relationship of the optimized values of CN with logarithmic rainfall depth ($\ln P$) as well as the relationships of the optimum value of λ with $\ln P$ are derived for each study area. Fuzzy linear regression (FLR) with an asymmetric triangular membership function is used to indicate the uncertainty incorporated in the CN–$\ln P$ and λ–$\ln P$ relationships. Then, using the verification data, the values of the parameters CN and λ obtained from the FLRs are defuzzified and verified to estimate the runoff volume resulting from rainfalls with different return periods (2–100 years). Finally, the results of the developed SCS-CN method are compared with those of the SCS-CN with linear regression (without incorporating the fuzzy concept) as well as those of the SCS-CN with constant values of CN and λ in each watershed.

2 Materials and methods

2.1 Study watersheds

Four watersheds, Sulaghan, Kiga, Rendan and Keshar, in the north of Tehran (capital of Iran), with an area of less than 150 km^2, were used to investigate the proposed approach (Fig. 1). The geomorphological properties of these watersheds were obtained using a 1:25 000-scale topographic map and are listed in Table 1. In total, 387 hourly rainfall–runoff records for the four watersheds over 10 years (2004–2013) were collected from the Iranian Water Resources Management Company and the storms with return periods (T) of 2–100 years were selected. Based on available rainfall–runoff data, the mean annual precipitation (MAP) of the watersheds ranges between 409.3 mm (for Rendan) and 739.8 mm (for Kiga). The dry season lasts from June to September for the four watersheds (Fig. 2). The average annual discharge of the watersheds ranges from 8.83 MCM (for Rendan) to 77.0 MCM (for Sulaghan), where MCM stands for m^3 × 10^6. The studied watersheds have not undergone land-use changes over recent decades (Fig. 3). Only 4% and 1% of the total area of the watersheds are covered by orchards and residential regions, respectively.

2.2 Sensitivity analysis of CN and λ

In this section, a sensitivity analysis on the SCS-CN parameters (CN and λ) is conducted to determine how they affect runoff estimation. This provides directions for further research in order to reduce parameter uncertainties and increase model accuracy (Hamby 1994). To assess the effect of CN and λ on estimated runoff (Q), direct sensitivity analysis of these

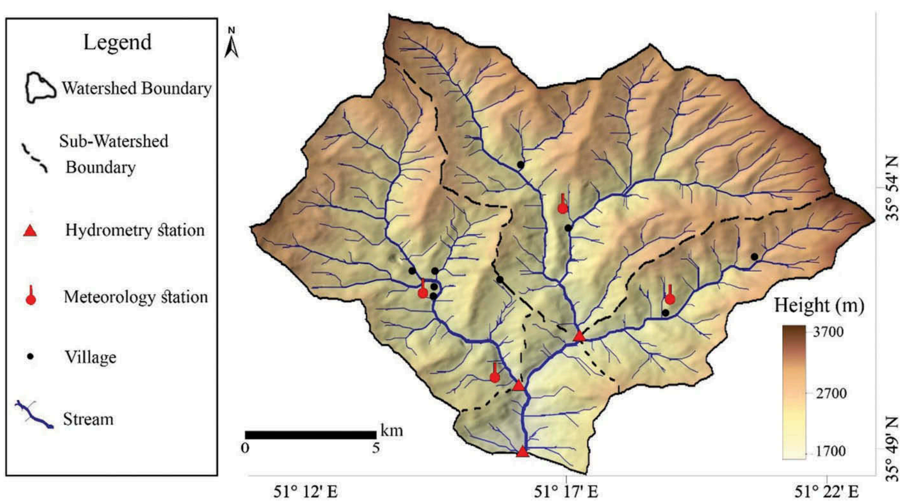

Figure 1. Locations of stations and drainage network of the studied watersheds.

Table 1. Physiographic and climatic characteristics of the studied watersheds.

Character (unit)	Sub-watershed			
	Sulaghan	Kiga	Rendan	Keshar
Area, A (km^2)	152.50	23.78	66.85	47.13
Perimeter, P (km)	71.30	31.10	52.60	42.90
Maximum height, H_{max} (m)	3811.5	3811.5	3724.7	3357.4
Minimum height, H_{min} (m)	1610.6	1772.5	1773.0	1685.8
Length of main river, L (km)	17.47	10.71	15.30	12.70
Slope of watershed, S (%)	8.60	16.60	11.0	9.70
Time of concentration*, T_c (h)	1.40	0.26	0.67	0.43
Average annual precipitation, P (mm)	425.1	739.8	409.3	537.2
Average annual discharge, Q (m^3/s)	2.44	0.30	0.28	1.04
Total number of used events, n_t (-)	127	120	66	74
Specific discharge, Q_s (m^3 year^{-1} km^{-2})	39.2 × 10^4	39.6 × 10^4	15.0 × 10^4	92.6 × 10^4
Date of events	2004–2012	2006–2011	2006–2008	2006–2013
Number of events used for calibration, N_c (-)	97	95	42	59
Number of events used for validation, N_v (-)	30	25	14	15
Climate	Semi-humid	Humid	Mediterranean	Semi-humid

*Time of concentration was calculated by the Kirpich formula.

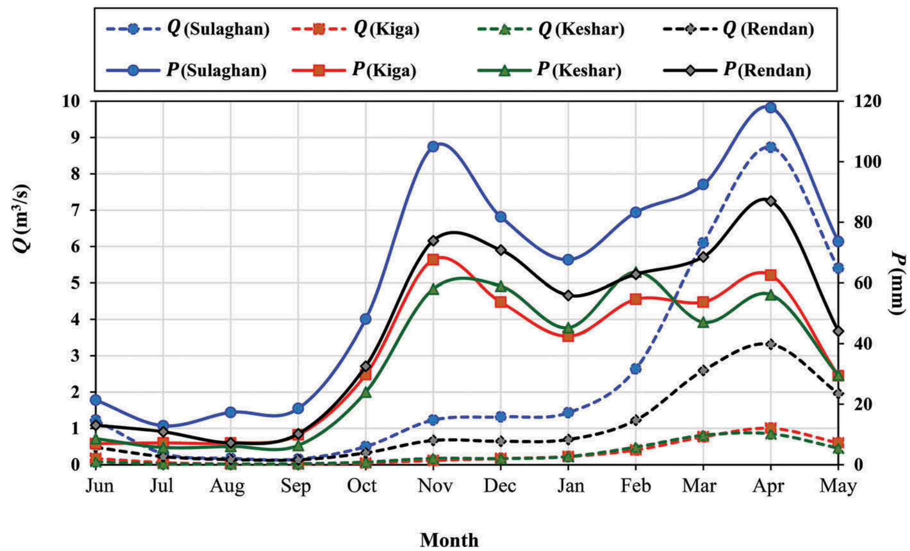

Figure 2. Average monthly variations of rainfall and discharge in the four studied areas.

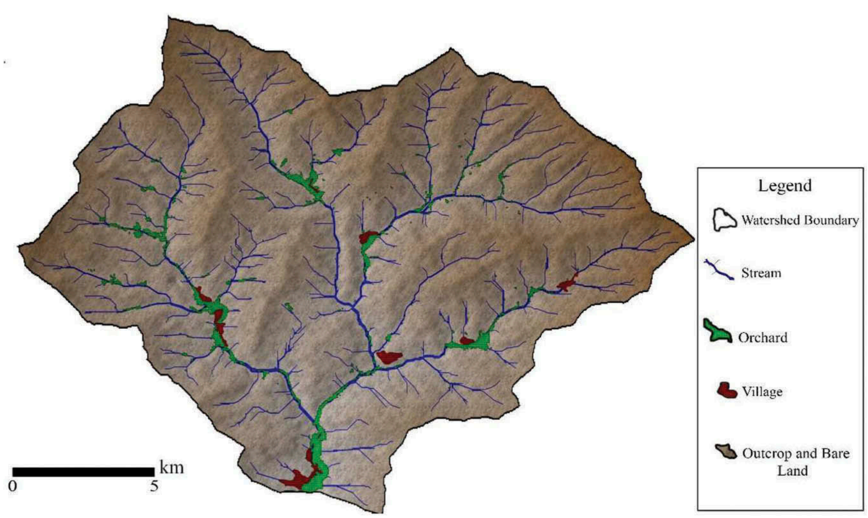

Figure 3. Current land-use map of the study areas.

parameters is done using partial differential equations of the estimated runoff with respect to each parameter:

$$SC_{CN} = \frac{\partial Q}{\partial CN} \times \frac{CN}{Q} = \frac{\partial Q}{\partial S} \times \frac{\partial S}{\partial CN} \times \frac{CN}{Q} \tag{1}$$

$$SC_{\lambda} = \frac{\partial Q}{\partial \lambda} \times \frac{\lambda}{Q} \tag{2}$$

where SC_{CN} and SC_{λ} are dimensionless sensitivity coefficients of CN and λ estimated based on the SCS-CN model, respectively, S is the potential maximum retention of the watershed (mm), P is rainfall depth (mm) and Q is direct runoff depth (mm), which are calculated as follows (USDA SCS 1985):

$$Q = \begin{cases} \frac{(P-I_a)^2}{(P-I_a)+S} & \text{for } P > I_a \\ 0 & \text{for } P \leq I_a \end{cases} \tag{3}$$

$$S = \frac{25400}{CN} - 254 \tag{4}$$

$$I_a = \lambda \times S \tag{5}$$

where I_a and λ are initial abstraction (mm) and initial abstraction ratio, respectively. The functions SC_{CN} and SC_{λ} can be obtained using the following equations:

$$\frac{\partial Q}{\partial S} = \frac{(-2\lambda(P - \lambda S)) \times [P + (1-\lambda)S] - (1-\lambda) \times (r - \lambda S)^2}{[P + (1-\lambda)S]^2} \tag{6}$$

$$\frac{\partial S}{\partial \mathrm{CN}} = -\frac{25400}{(\mathrm{CN})^2} \tag{7}$$

$$\mathrm{SC}_{\mathrm{CN}} = \frac{25400 \times \left[P^2(1+\lambda) - \lambda^2\ S^2\ (1-\lambda) - 2\lambda PS\right]}{\mathrm{CN}^2\ [P + (1-\lambda)S](P - \lambda\ S)^2} \tag{8}$$

$$\frac{\partial Q}{\partial \lambda} = \frac{\begin{array}{c}(-2S(P-\lambda S)) \times [P + (1-\lambda)S] \\ -(-S) \times (P - \lambda S)^2\end{array}}{[P + (1-\lambda)S]^2} \tag{9}$$

$$\mathrm{SC}_{\lambda} = \frac{2P\lambda^3\ (\lambda - 1) +\ \lambda^2\ S^3(2-\lambda) - P^2\lambda S}{[P + (1-\lambda)S]\ (P - \lambda\ S)^2} \tag{10}$$

A finite difference approximation of Equations (1) and (2), which gives variations of estimated runoff as a result of small changes in CN and λ (maximum ±30% of nominal values), has frequently been used (ASCE/EWRI Curve Number Hydrology Task Committee 2009, Yuan *et al.* 2014). This approach neglects the nonlinear relationship between the input and output variables and therefore usually produces valid results only for small changes in input variables (Hamby 1994). Equations (8) and (10) allow a comprehensive assessment of the effect of wide ranges of CN and λ values on the estimated Q.

2.3 Estimation of CN and λ parameters

Eighty percent of the available rainfall (P) and runoff (Q) events were selected randomly for estimating the λ and CN parameters corresponding to each storm in the four watersheds. During the calibration step, the parameters CN and λ have been estimated for each storm by adopting a multi-steps fitting procedure as follows:

Step 1. Available storms for each watershed are categorized into 12 groups, according to their time of occurrence (i.e. month). Then, single values for CN and λ are estimated based on the storms occurring in each month by minimizing the sum of squared differences between observed runoff volumes and their corresponding estimated values ($\mathrm{SSR}_i,\ i = 1,\ 2, \ldots,\ n$) and applying the constraints $0 < \mathrm{CN} < 100$ and $0 < \lambda < 1$, using a constrained least squares fitting method:

$$\mathrm{SSR}_i = \left[(Q_i)_{\mathrm{obs}} - (Q_i)_{\mathrm{est}}\right]^2 = \left((Q_i)_{\mathrm{obs}} - \frac{\left(P_i - \lambda_i \times \left(\frac{25400}{\mathrm{CN}_i} - 254\right)\right)^2}{P_i + (1-\lambda_i) \times \left(\frac{25400}{\mathrm{CN}_i} - 254\right)}\right)^2 \tag{11}$$

where CN = 0 corresponds to low runoff and high potential retention storage and CN = 100 corresponds to no infiltration and maximum potential retention storage are respectively implied.

Step 2. Next, the available storms in each watershed are categorized into five groups based on the rainfall depths, P (<10, 10–20, …, and 40–50 mm). Then, single values for CN and λ are estimated based on the storms occurring in each group by minimizing Equation (11).

Step 3. Considering the results of the two previous steps, initial narrow ranges are estimated for parameters CN and λ for storms placed in the same category based on their depths and times of occurrence. Considering the mentioned ranges for CN and λ, Equation (11) is applied for pairs of P–Q data to specify appropriate values of CN and λ for the storms. The calibration phase adjusts single values for CN and λ parameters that are valid for a set of P–Q data.

After obtaining optimized values for CN and λ using the calibration data, relationships between runoff (P) and these two parameters are derived (CN–ln$P$ and λ–ln$P$) in each watershed using the FLR. The following section describes details of the FLR.

2.4 Fuzzy linear regression analysis (FLR)

In this paper, FLR analysis is used for estimating the linear relationships CN–ln$P$ and λ–ln$P$ in the studied watersheds. In the fuzzy regression analysis, the vectors of fuzzy output variables ($\widetilde{\mathbf{CN}}_i$ and $\tilde{\lambda}_i$ $(i = 1,\ 2, \ldots,\ 12)$) are related to the vector of non-fuzzy input variable $\boldsymbol{P}_i$ $(i = 1,\ 2, \ldots,\ 12)$ using fuzzy regression coefficients $\tilde{\boldsymbol{A}} = \left[\tilde{A}_0,\ \tilde{A}_1\right]$ and $\tilde{\boldsymbol{B}} = \left[\tilde{B}_0,\ \tilde{B}_1\right]$, respectively (Yen *et al.* 1999, Zahraie and Hosseini 2009, Hosseini and Mahjouri 2014):

$$\widetilde{\mathbf{CN}}_i(\mathrm{CN}^c, \mathrm{CN}^s, k, h) = \tilde{\mathrm{A}}_0\left(a_0^c, a_0^s, k_0, h\right) + \tilde{\mathrm{A}}_1\left(a_1^c, a_1^s, k_1, h\right).\boldsymbol{P}_i \tag{12}$$

$$\tilde{\lambda}_i(\lambda^c, \lambda^s, k', h') = \tilde{\mathrm{B}}_0\left(b_0^c, b_0^s, k_2, h'\right) + \tilde{\mathrm{B}}_1\left(b_1^c, b_1^s, k_3, h'\right).\boldsymbol{P}_i \tag{13}$$

Asymmetric triangular membership functions with skew factor k_i $(i = 0,\ 1,\ 2,\ 3)$ at optimal confidence levels of h and h' are considered for determining the fuzzy regression coefficients of $\tilde{\boldsymbol{A}}$ and $\tilde{\boldsymbol{B}}$ (Fig. 4).

A linear programming problem (LPP) based on Tanaka *et al.* (1982) is formulated to determine the parameters of fuzzy number coefficients (centre and spread). The LPP has two objectives of minimizing

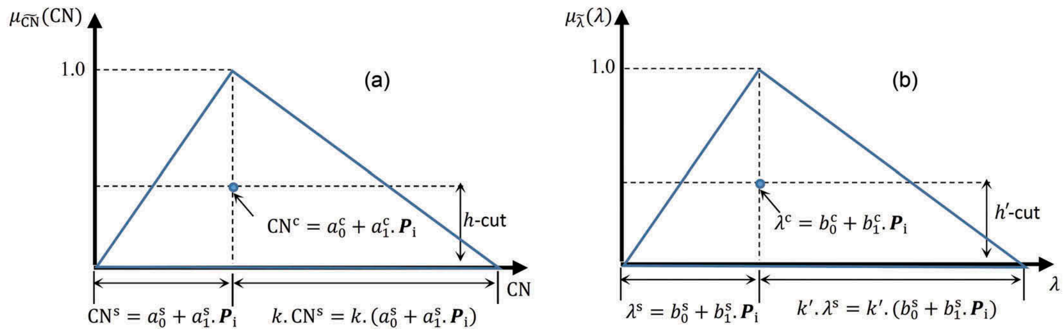

Figure 4. Asymmetric triangular fuzzy membership function of (a) CN with h-level (h-cut) and (b) λ with h'-level (h'-cut).

the spreads of the regression coefficients and bringing the h- and h'-cut of the estimated values of response as close as possible to the h- and h'-cut of the observed value:

$$\text{Minimize } Z_{CN} = (1+k_0)a_0^s + (1+k_1)a_1^s\sum_{i=1}^{N_c}\ln P_i \tag{14}$$

$$\text{Subject to}\begin{cases}(1-h)a_0^s + (1-h)a_1^s P_i + a_0^c + a_1^c P_i \geq CN_i\\ (1-h)k_0 a_0^s + (1-h)k_1 a_1^s P_i - a_0^c - a_1^c P_i \geq -CN_i\end{cases} \tag{15}$$

$$i = 1,\ 2, \ldots,\ N_c;\ a_0^s, a_1^s, a_0^c,\ a_1^c,\ k_0,\ k_1,\ h \geq 0;\ h \leq 1$$

$$\text{Minimize } Z_\lambda = (1+k_2)b_0^s + (1+k_3)b_1^s\sum_{i=1}^{N_c}\ln P_i \tag{16}$$

$$\text{Subject to}\begin{cases}(1-h')b_0^s + (1-h')b_1^s P_i + b_0^c + b_1^c P_i \geq \lambda_i\\ (1-h')k_2 b_0^s + (1-h')k_3 b_1^s P_i - b_0^c - b_1^c P_i \geq -\lambda_i\end{cases} \tag{17}$$

$$i = 1,\ 2, \ldots,\ N_c;\ b_0^s, b_1^s, b_0^c,\ b_1^c,\ k_2,\ k_3,\ h' \geq 0;\ h' \leq 1$$

where $a_0^s, a_1^s,\ b_0^s$ and b_1^s are the spread of fuzzy numbers, $a_0^c,\ a_1^c,\ b_0^c$ and b_1^c are the centres of fuzzy numbers, k_i ($i = 0,\ 1,\ 2,\ 3$) denotes skew factors of fuzzy numbers, and h and h' are target levels of belief of fuzzy output numbers (this term is considered as a measure of goodness of fit). Also, N_c is the number of data used for the calibration phase. It is assumed that any fuzzy coefficient having a membership level higher than a given level h or $h' \in (0, 1)$ is in the certainty domain (Fig. 3). A centroid defuzzifier method (Runkler 1996) is used to convert fuzzy parameters of $\widetilde{CN}$ and $\tilde{\lambda}$, obtained using FLRs, to the corresponding crisp values.

2.5 Model evaluation and performance criteria

Using rainfall depth data in the verification mode ($P_i,\ i = 1, 2, \ldots, N_v$), corresponding CN_i and λ_i values are calculated based on the adopted FLR in each watershed. Then, Equations (3)–(5) are used to estimate runoff volume (Q_i) corresponding to P_i, CN_i and λ_i. The following criteria are chosen to determine the goodness of fit of the proposed model in runoff estimation:

Average percentage error in runoff volume ($\%PE_V$):

$$\%PE_V = \frac{1}{N_v}\sum_{i=1}^{N_v}\frac{(V_i)_{obs} - (V_i)_{est}}{(V_i)_{obs}} \times 100 \tag{18}$$

where V_{obs} and V_{est} are the observed and estimated runoff volumes, respectively; N_v is the number of data used in the verification mode in every watershed. Ritter and Muñoz-Carpena (2013) proposed four model performance classes based on the criteria of the number of times that the model predictions are greater than the mean error (n_t), the Nash and Sutcliffe coefficient of efficiency (NSE) (Nash and Sutcliff 1970), which is a dimensionless goodness-of-fit indicator, variability of the observations based on their standard deviation (SD), and the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}\left[(Q_i)_{obs} - (Q_i)_{est}\right]^2}{m}} \tag{19}$$

$$SD = \sqrt{\frac{\sum_{i=1}^{m}\left[(Q_i)_{obs} - \bar{Q}_{obs}\right]^2}{m}} \tag{20}$$

$$n_t = \frac{SD}{RMSE} - 1 \tag{21}$$

$$NSE = 1 - \left(\frac{RMSE}{SD}\right)^2 = 1 - \left(\frac{1}{1+n_t}\right)^2 \tag{22}$$

where $\bar{Q}_{obs}$ is the value of average recorded runoff. These categories were defined as Unsatisfactory for SD < 1.7RMSE, n_t < 0.8, NSE < 0.65; Acceptable for SD = 1.2–1.7RMSE, n_t = 0.7–1.2, NSE = 0.65–0.8; Good for SD = 2.2–3.2RMSE, n_t = 1.2–2.2, NSE = 0.8–0.9; and Very good for SD > 3.2RMSE, n_t > 2.2, NSE > 0.9. Ritter and Muñoz-Carpena (2013) derived the NSE probability distribution by the block bootstrapping method and applied the test statistical hypotheses on the model goodness-of-fit (at 95% confidence level). This technique allows defining the probability of the goodness-of-fit to be within each proposed performance class.

3 Results and discussions

3.1 Sensitivity analysis of the parameters CN and λ

To determine the impact of CN and λ parameters on runoff (Q) in the SCS-CN method, the variation of sensitivity coefficients SC_{CN} and SC_{λ} based on different values for the above-mentioned parameters are estimated as shown in Figures 5 and 6. According to Figure 5(a), theoretically, when the initial abstraction ratio of a watershed is equal to zero ($\lambda = 0$), the sensitivity of the estimated runoff volume to the parameter CN (SC_{CN}) decreases as the CN of the watershed increases, especially for great rainfall depths (i.e. $P \geq 100$ mm). In such conditions, the effects of interception and surface storage before runoff begins are not considered and therefore runoff begins immediately ($Q < P$). It can also be observed, for small CN values (less than 30), sensitivity of the estimated runoff volume to rainfall depth is negligible due to the high capacity of infiltration occurring after runoff begins.

Low initial abstraction ratios of the watershed (λ) can be attributed to impervious areas due to urbanization, characterized by high runoff coefficient. The runoffs from these areas reach the outlet of the watershed quickly and result in the rapid start of direct runoff, at the early stages of the storm. This is stimulated by the low surface retention of the watershed (i.e. high CN).

For a higher initial abstraction ratio (i.e. λ = 0.2), which was frequently suggested in previous works for natural watersheds, the sensitivity of the estimated runoff to the value of CN (SC_{CN}) increases as the CN increases up to a certain value and then decreases (Fig. 5(b) and (c)). This means that the sensitivity of the runoff to the CN values increases as the infiltration and retention of a watershed after runoff production increases and the rainfall depth (P) decreases. For a larger rainfall depth (i.e. P = 100 mm), the effect of watershed CN on the runoff volume produced is limited to the lower values of this parameter (i.e. CN = 35), whereas for lower rainfall depths (i.e. P = 20 mm), larger values of CN (i.e. CN = 75) have more impact on SC_{CN} values.

Comparing the obtained values of SC_{CN} for the two cases of $\lambda = 0$ and $\lambda = 0.2$ (see the vertical lines in Fig. 5(a) and (b)), it can be concluded that the initial abstraction ratio has a predominant effect on the runoff production process compared to CN.

As the initial abstraction ratio of the watershed increases ($\lambda = 0.2$ to $\lambda = 0.5$) due to vegetation cover (i.e. range lands or pastures) or lack of impervious areas, more rainfall is intercepted and therefore the runoff coefficient of the watershed decreases (Fig. 5(b) and (c)).

As observed in Figure 5(b) and (c), for a given initial abstraction ratio (λ), the estimated runoff volume is more sensitive to the CN than the rainfall depth (P). This is similar to what has been reported in former research (Hawkins 1983).

Variation of the sensitivity of the estimated runoff to initial abstraction ratio (SC_{λ}) is dependent on the CN of the watershed and also rainfall depth (P), as shown in Figure 5(d) and (c). For watersheds with lower CN (e.g. CN = 30), the effect of the rainfall depth is dominated by the CN value (Fig. 5(d)) due to the high potential of the surface of the watersheds to store water after runoff is produced. The augmentation effect of initial losses due to intercepting and retaining a greater part of the rainfall (i.e. high values of λ) is the main reason for SC_{λ} growth (Fig. 5(d)). A decrease in SC_{λ} value is observed after a certain λ value, which depends on rainfall depth and surface storage potential (i.e. CN). As shown in Figure 5(e), decreasing the surface retention capacity or increasing the CN value of the watershed (i.e. CN = 70) results in increasing the sensitivity of runoff volume to initial abstraction ratio only for small rainfall depths (i.e. $P \leq$ 100 mm). For high rainfall depths (i.e. P = 200 and 300 mm), when the potential of the watershed surface for water storage is small (or CN is great), as observed in watersheds with high impervious areas, the initial loss significantly decreases and therefore the runoff produced is not sensitive to λ (Fig. 5(e)).

For the extreme case of CN = 100, the surface potential of the watershed to retain and store rainfall is zero, and therefore rainfall is completely transformed to runoff (Fig. 5(f)). In this case, the initial abstraction ratio has a negligible effect on runoff generation. Comparing the results shown in Figure 5(a)–(f), it can be concluded that the effect of surface storage of the watershed (i.e. CN) on the estimated runoff volume is greater than the initial abstraction ratio (λ) and the

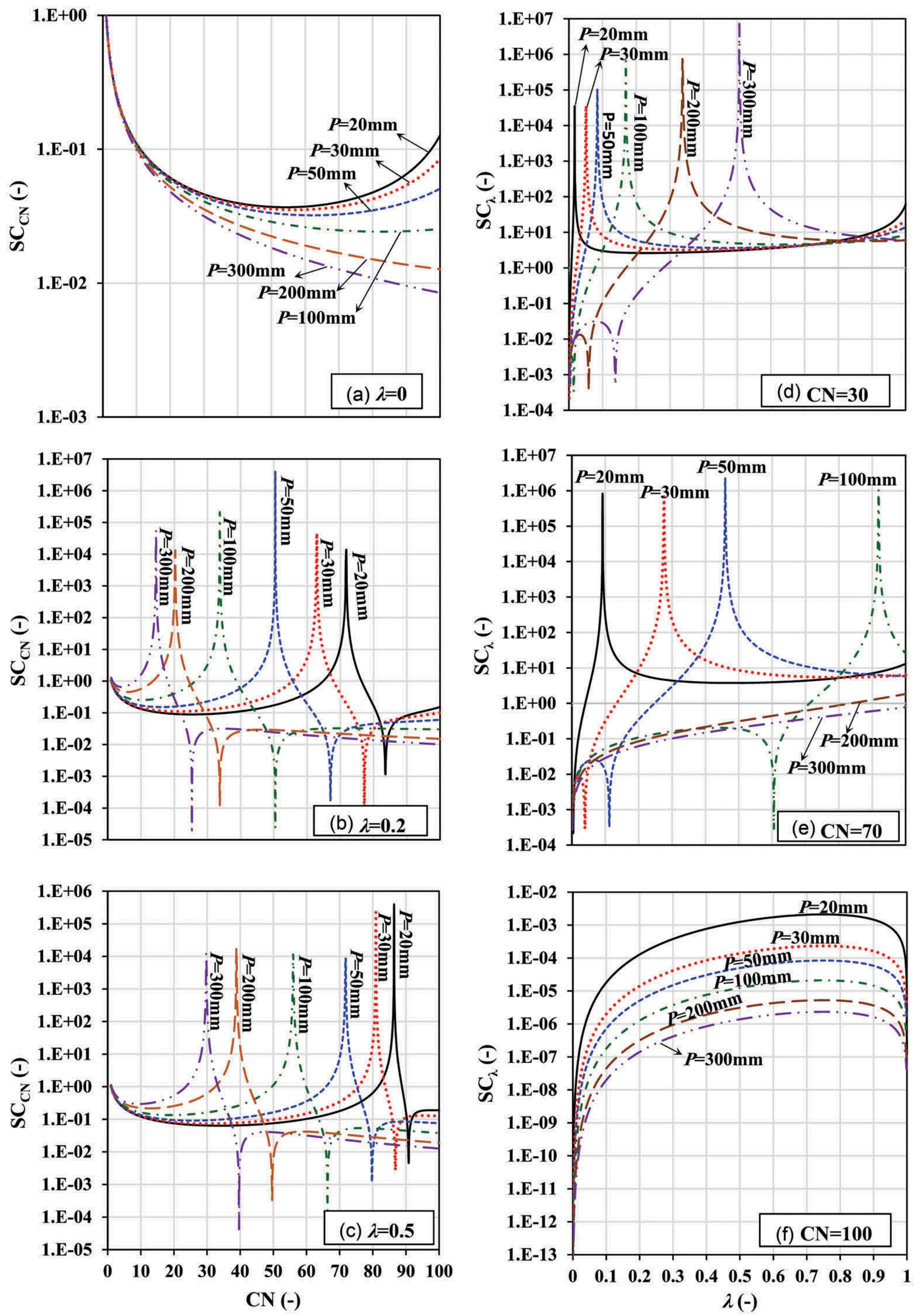

Figure 5. Sensitivity of estimated runoff using the SCS method to the CN (a)–(c), and to λ (d)–(f) for different rainfall depths (P) using the SCS method.

rainfall depth (P). This is consistent with findings of previous studies related to the Walnut Gulch watershed in southeastern Arizona, with an area of 148 km^2, CN = 85 and $P \leq$ 25 mm (e.g. Woodward *et al.* 2004, Yuan *et al.* 2014). Also, Hawkins (1975) and Boughton (1989) emphasized the high sensitivity of runoff estimated using the SCS-CN method to CN rather than to P up to 20 mm, considering λ = 0.2 (a variation of 10% in CN leads to a variation of 50% in Q).

Figure 6(a) shows the relationship of the CN values of the watershed, having maximum sensitivity of the estimated runoff volume to CN (maxSC_{CN}), with initial abstraction ratio (λ) for different rainfall depths.

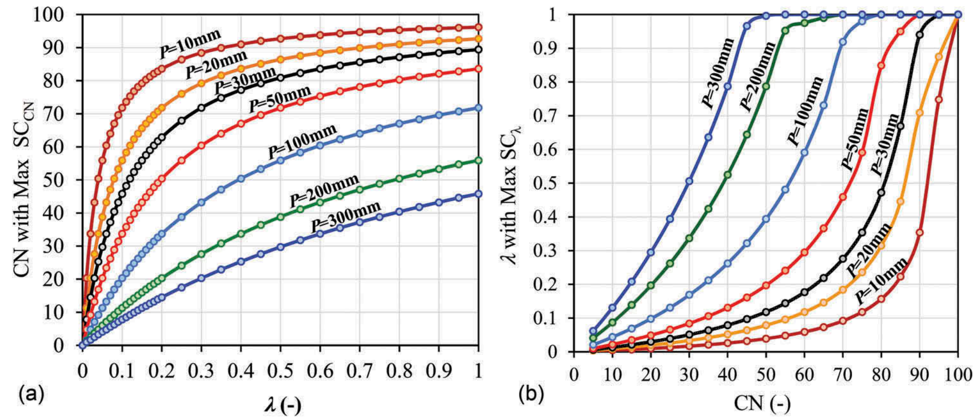

Figure 6. (a) Relationship of the watershed CN with maximum sensitivity of the estimated runoff to this parameter (maxSC_{CN}), initial abstraction ratio of the watershed (λ), and rainfall depth (P). (b) Relationship of the watershed λ with maximum sensitivity of the estimated runoff to this parameter (maxSC_λ), CN, and P.

Variations of the λ of the watershed, having the maximum sensitivity of the estimated runoff to λ (maxSC_λ), *versus* CN for different rainfall depths is also given in Figure 6(b). For smaller rainfall depths (i.e. $P < 100$ mm), a nonlinear relationship is observed between maxSC_{CN} and λ and also between maxSC_λ and CN, whereas a linear trend is observed for high rainfall depths (i.e. $P = 300$ mm).

The curves shown in Figure 6(a) indicate that the effect of variation in CN on runoff decreases as rainfall depth increases, but the inverse is valid for parameter λ (Fig. 6(b)). These findings support the conclusions of Hawkins (1975) and Bondelid *et al.* (1982) that errors in estimation of CN are dangerous for rainfalls with depth near the threshold value for runoff generation.

The above-mentioned findings can give a more practical insight into the effects of initial losses (i.e. λ), rainfall depth (P), and surface factors affecting hydrological conditions of a watershed (i.e. CN) on runoff volume estimation. These findings can be used directly for evaluating the hydrological effect of existing uncertainties in estimated CN and λ values.

3.2 Relationship of runoff with CN and λ

The parameters λ and CN were adjusted using the adopted multi-step fitting procedure (as described in Section 2.3) and rainfall–runoff event data of each watershed considered for the calibration phase. The average estimated values of λ and CN and number of P–Q data considered in every category in each calibration step are given in Table 2. Almost all obtained values of λ and CN in the four watersheds range from 0.08 to 0.22, and from 40 to 80, respectively. Interestingly, the average value of λ for all watersheds is less than 0.2, which is consistent with values obtained in previous research (e.g. Hawkins *et al.* 2002, Mishra *et al.* 2004). For each watershed, a logarithmic function was fitted between the calculated values of λ and CN and the values of P. The rainfall depths with return periods between 2 and 100 years were estimated using the four-parameter generalized gamma distribution at the significance level α = 0.05 and corresponding to 6–80 mm, as shown in Figure 7. Figure 8(a)–(d) shows the relationships λ–P and CN–P in the four watersheds. In some previous research (e.g. Hawkins 1993, Gundalia and Dholakia 2014), different functions such as exponential correlation, variable order decay function or complementary error function peak were fitted between calibrated CN data and corresponding P values. In these fitted curves, CN decreases to a constant value with a definite rate. Kohnová *et al.* (2015) obtained a linear correlation between initial abstraction ratio (λ) and rainfall depth (P) in a watershed located in Slovakia. Soulis and Valiantzas (2012) found a second-order relationship between calculated CN and rainfall depth in the Little River watershed in the USA with total area of 15.2 km^2 and the Lykorrema watershed in Greece with total area of 15.7 km^2. In the current paper, the calibrated CNs obtained in the four watersheds, do not show exactly an exponential or a linear correlation with rainfall depth, but a logarithmic relationship seems to be more realistic, since all obtained R^2 values are statistically significant (according to Student's t-test at $\alpha = 0.05$). The slope of CN–P and λ–P curves in different watersheds tend to decrease as P increases. In the studied watersheds, when the CN values decrease, initial abstraction also increases. This indicates that the initial abstraction of the watersheds is not affected by the impervious area (residential areas). This is in accordance with the land-use map of the study watersheds (Fig. 3). It is also found that, in these watersheds, the retention and initial abstraction ratio

Table 2. Average values of SCS-CN model parameters (initial abstraction ratio, λ, and curve number, CN) adjusted in two calibration steps for the study watersheds. Number of P–Q data (N_c) considered in two calibration steps is also given.

Calibration Step 1													
Sub-watershed	Variable	Month											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Sulaghan	λ	0.098	0.121	0.137	0.167	0.118	0.084	0.127	0.128	0.156	0.122	0.143	0.133
	CN	73.18	66.34	63.80	53.60	67.04	71.50	65.76	69.91	59.81	67.41	59.82	68.41
	N_c	8	11	9	16	7	4	4	4	5	5	10	14
Kiga	λ	0.142	0.130	0.153	0.172	0.149	0.117	0.133	0.112	0.149	0.129	0.155	0.152
	CN	67.90	64.51	65.72	56.68	65.55	66.38	66.39	76.85	62.45	69.91	64.02	68.45
	N_c	12	10	10	10	14	5	3	4	3	3	12	9
Rendan	λ	0.115	0.139	0.140	0.146	0.139	0.101	0.186	0.092	0.143	0.132	0.152	0.115
	CN	67.0	75.22	69.78	62.96	66.83	79.43	53.36	74.08	63.55	66.53	66.10	66.96
	N_c	3	5	5	3	4	4	2	2	2	5	4	3
Keshar	λ	0.115	0.134	0.141	0.158	0.159	0.105	0.160	0.107	0.126	0.156	0.115	0.156
	CN	68.96	70.23	71.87	62.0	64.88	79.03	53.34	74.05	66.75	66.10	68.96	66.10
	N_c	5	8	5	7	6	3	3	2	2	9	5	4

Calibration Step 2						
Sub-watershed	Variable	Precipitation range (mm)				
		[0, 10)	[10, 20)	[20, 30)	[30, 40)	[40, 50)
Sulaghan	λ	0.095	0.153	0.18	0.21	0.22
	CN	75.69	62.03	52.06	43.00	40.85
	N_c	38	40	12	4	3
Kiga	λ	0.104	0.145	0.18	0.19	0.22
	CN	74.40	66.65	54.60	49.10	45.20
	N_c	31	43	11	5	5
Rendan	λ	0.1165	0.195	0.175	0.155	-
	CN	77.93	45.55	52.95	61.45	-
	N_c	16	18	6	2	-
Keshar	λ	0.215	0.185	0.155	0.115	-
	CN	45.55	55.5	61.23	76.75	-
	N_c	20	28	9	2	-

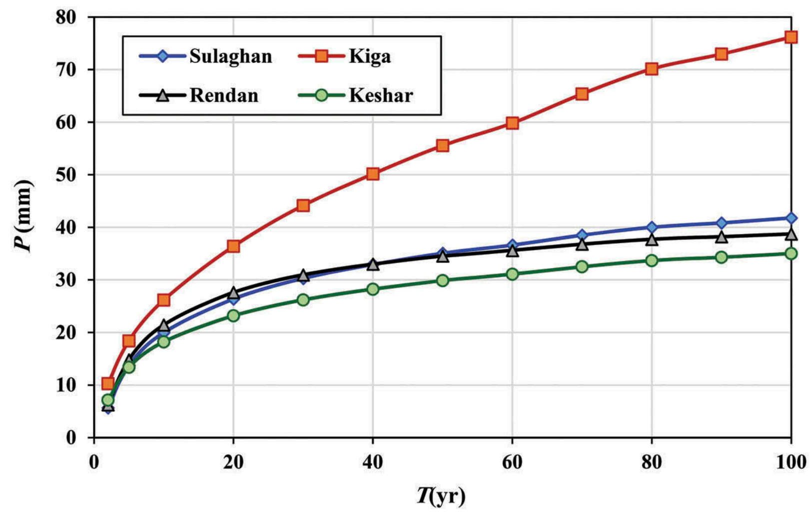

Figure 7. Variation of storm rainfall depth with return period for the studied watersheds estimated using the four-parameter generalized gamma distribution.

increase with rainfall depth. This is mainly associated with the type of land cover, which is mostly bare lands (95% of total watershed area). However, the lower value of parameter λ for these watersheds (0.13–0.14) is associated with the lower retention capacity associated with poor land cover.

According to the calculated values for the coefficient of determination (R^2), in the Keshar watershed (Fig. 8 (d)), weaker correlation is observed in CN–P and λ–P relationships. This is in accordance with a higher specific discharge value for this watershed (i.e. 0.93 MCM km^{-2} year^{-1}) in comparison to other watersheds (0.15–0.40 MCM km^{-2} year^{-1}).

3.3 FLR analysis

Possible sources of temporal variability of CN and λ are the effect of antecedent moisture condition (AMC), temporal and spatial variability of storm and watershed properties, and the quality of the measured data (Ponce and Hawkins 1996, Michel *et al.* 2005, Soulis *et al.* 2009). According to the latest version of the *National Engineering Handbook* (NEH-4), the effect of AMC on variability of CN can be incorporated by considering CN as a random variable and the AMC-I and AMC-III categories as bounds of a probability distribution that measure the dispersion around AMC-II (Soulis and Valiantzas 2012). Tedela *et al.* (2012) demonstrated that in forested watersheds the curve number method is too uncertain to distinguish seasonal effects for at least four of the 10 studied watersheds. In the current study, to take into account the uncertainty accompanied by parameters CN and λ (especially due to the effect of the AMC), fuzzy linear regression (FLR) analysis is carried out for CN–ln$P$ and λ–ln$P$ datasets obtained in the four watersheds. Using the calibration rainfall–runoff datasets and the linear programming problems given in Equations (14)–(17), the related parameters including spreads ($a_0^s, a_1^s, b_0^s, b_1^s$) and centres ($a_0^s, a_1^s, b_0^s, b_1^s$) of the fuzzy coefficients, skewness factors of fuzzy coefficients (k_i), and target levels of regression belief (h, h') in the watersheds are optimized, separately. The optimized values of these parameters for λ–ln$P$ and CN–ln$P$ relationships in each watershed are listed in Table 3.

The FLR analysis for λ–ln$P$ gives a low value for the skewness factor (k) for watershed D-M (equal to 0.004), whereas a high value of k for CN–P is obtained for watershed P-K (equal to 0.11). This means that the asymmetric triangular fuzzy membership function provides better fitting to λ–P and especially CN–P in comparison to a symmetrical shape (when $k = 0$). The average values for confidence level (h-cut), which indicate the degree of acceptable uncertainty and fitness between input and output data (Shakouri-Ganjavi and Nadimi 2009), are in the range of 0.16–0.55 for λ–P and 0.05–0.11 for CN–P. Smaller values of the h-cut for corresponding fuzzy coefficients in the CN–P relationship can be interpreted by the uncertainty associated with CN values as a result of vagueness in AMC values.

3.4 Runoff estimation and evaluation of model performance

Considering the optimized values of the fuzzy parameters corresponding to λ–ln$P$ and CN–ln$P$ relationships through the FLR analysis (Table 2), the values of CN and λ using the verification rainfall–runoff data are calculated. Knowing the fuzzy values of CN and λ for

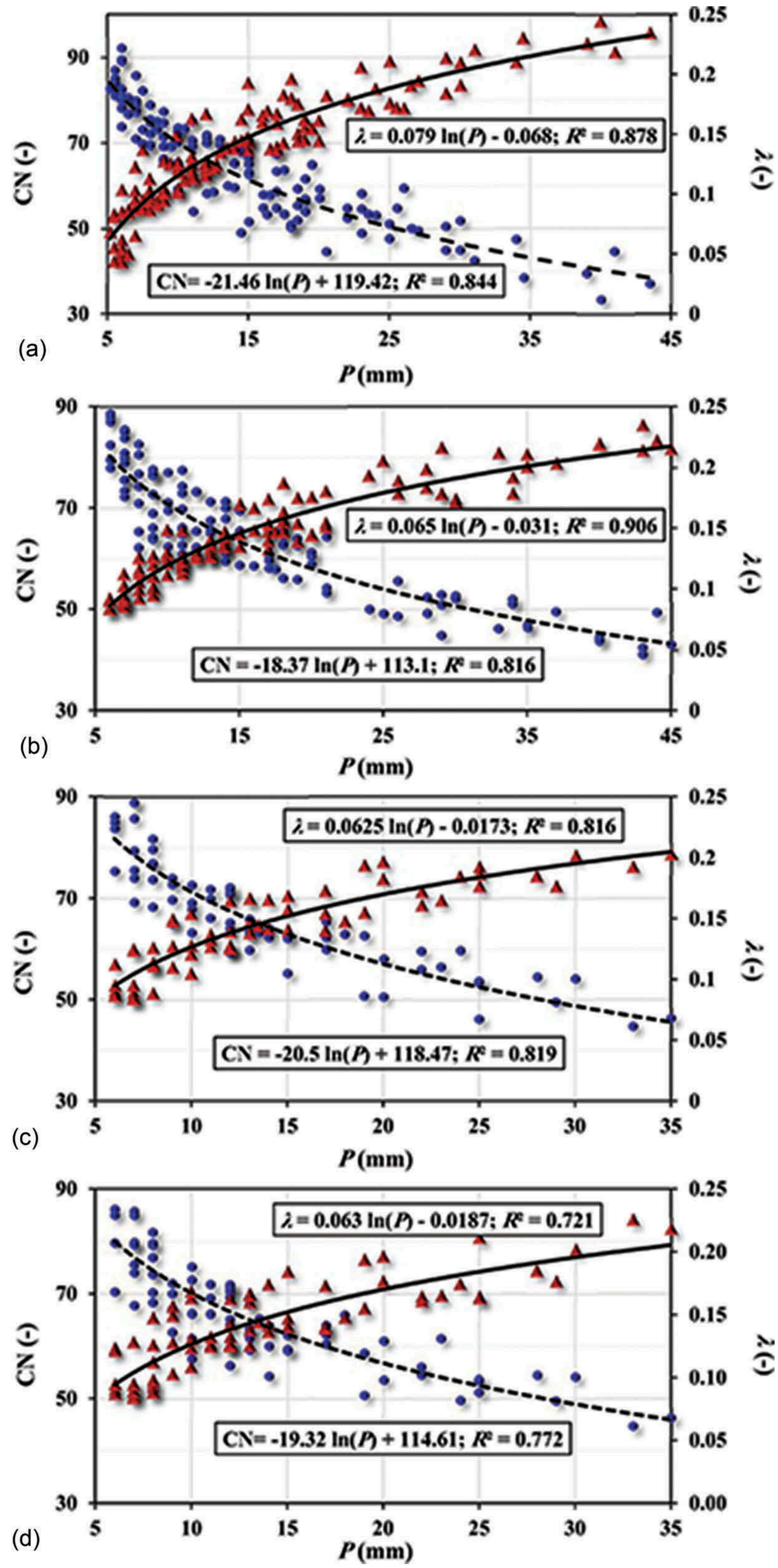

Figure 8. Relationship of the curve number (CN) and initial abstraction ratio (λ) with rainfall depth (P) in the studied watersheds: (a) Sulaghan, (b) Kiga, (c) Rendan and (d) Keshar (R^2 values denote the coefficient of determination of the fitted curves).

Table 3. Optimized parameters of the coefficients in the membership functions of the FLR for the λ–ln$P$ and CN–ln$P$ relationships.

Parameter	Sub-watershed			
	Sulaghan	Keshar	Kiga	Rendan
a_0^s	21.823	39.726	22.105	28.453
a_1^s	17.676	32.136	25.051	18.786
a_0^c	30.310	55.960	33.492	47.932
a_1^c	0.001	0.002	0.001	0.003
k_0	0.001	0.008	0.016	0.001
k_1	5.200	2.823	4.165	8.118
h	0.004	0.001	0.004	0.005
b_0^s	0.185	0.108	0.017	0.062
b_1^s	0.013	0.028	0.042	0.008
b_0^c	0.007	0.009	0.051	0.040
b_1^c	0.002	0.001	0.003	0.005
k_2	0.027	0.241	0.001	0.001
k_3	0.004	0.001	0.005	0.007
h'	0.085	0.001	0.017	0.024

each event in the verification phase, the fuzzy ordinates of runoff volume are estimated using the SCS-CN method. The centroid defuzzification technique is used to convert the fuzzy values of runoff to corresponding crisp values. The performance of the proposed model is evaluated by comparing the obtained runoffs with corresponding runoff volumes estimated using the SCS-CN method considering linear regression relationship between $\lambda - \ln P$ and $\mathrm{CN} - \ln P$. In addition, the SCS-CN method with constant values for CN and λ (median of calibrated values) in each watershed is used as a benchmark model. The median values of CN and λ are calculated, respectively, as 65.12 and 0.136 for Sulaghan, 64.51 and 0.135 for Kiga, 65.43 and 0.141 for Rendan, and 66.50 and 0.138 for Keshar. The observed and simulated runoff volumes obtained using the proposed model as well as the SCS-CN method based on linear regression and constant parameters are shown in Figure 9(a)–(d).

According to Figure 9, the simulated upper and lower fuzzy bounds completely encompass the observed runoff volumes. As observed, the fuzzy spectrum of the higher runoff volumes has a larger spread than that of the lower values.

Mostly, the runoff volumes estimated using the SCS-CN method with constant parameters have more discrepancies than the corresponding observed values. This has also been reported by other researchers (e.g. Grunwald and Norton 2000, Soulis and Valiantzas 2012). The SCS-CN method developed based on linear regression analysis has more advantages over the constant parameter SCS-CN method. It reveals the efficiency of the SCS-CN method with rainfall depth-based varying parameters.

As seen in Figure 9, the proposed model is more efficient than the SCS-CN method based on linear regression and also constant parameters in predicting runoff volumes. The SCS-CN method with constant parameters gives more erroneous results in the estimation of runoff volumes even though the study watersheds do not undergo land-use changes. Generally, the proposed model is advantageous over the SCS-CN method with constant parameters in simulating runoff volume and it provides more accurate predictions of runoff corresponding to a wider range of rainfall depths.

To quantify the goodness of fit of the three approaches (SCS-CN method based on FLR, linear regression and constant parameters) in simulating the runoff volume, the criteria of PE_V, RMSE and the probability distributions of NSE (Equations (18)–(22)) are used for verification (Fig. 10). The results given in Figure 10 indicate that, in general, runoff volumes simulated using the proposed model show better fitness to the observed ones in terms of percentage of error in runoff volume, $\%\mathrm{PE}_V$ (between 2.94% and 19.26%), and the RMSE in all four watersheds.

The obtained NSE values for the proposed model can be classified mostly as Good or Very good. Whereas the results simulated by the SCS-CN method with constant parameters fall mostly in Unsatisfactory regions and rarely fall within the Acceptable region. The NSE values for the SCS-CN method based on linear regressions of λ–ln$P$ and CN–ln$P$ fall within a broad range between Unsatisfactory and Good.

In a watershed with “standard” or “complacent” behaviour (Hjelmfelt 1991, Hawkins 1993, Soulis and Valiantzas 2012), correlating the CN and λ with rainfall depth through LR or FLR leads to more accurate estimates of direct runoff volume by the SCS-CN method in comparison with when a constant value for CN is considered.

4 Conclusions

Sensitivity analysis on CN and λ in the SCS-CN model can be helpful to estimate these parameters based on

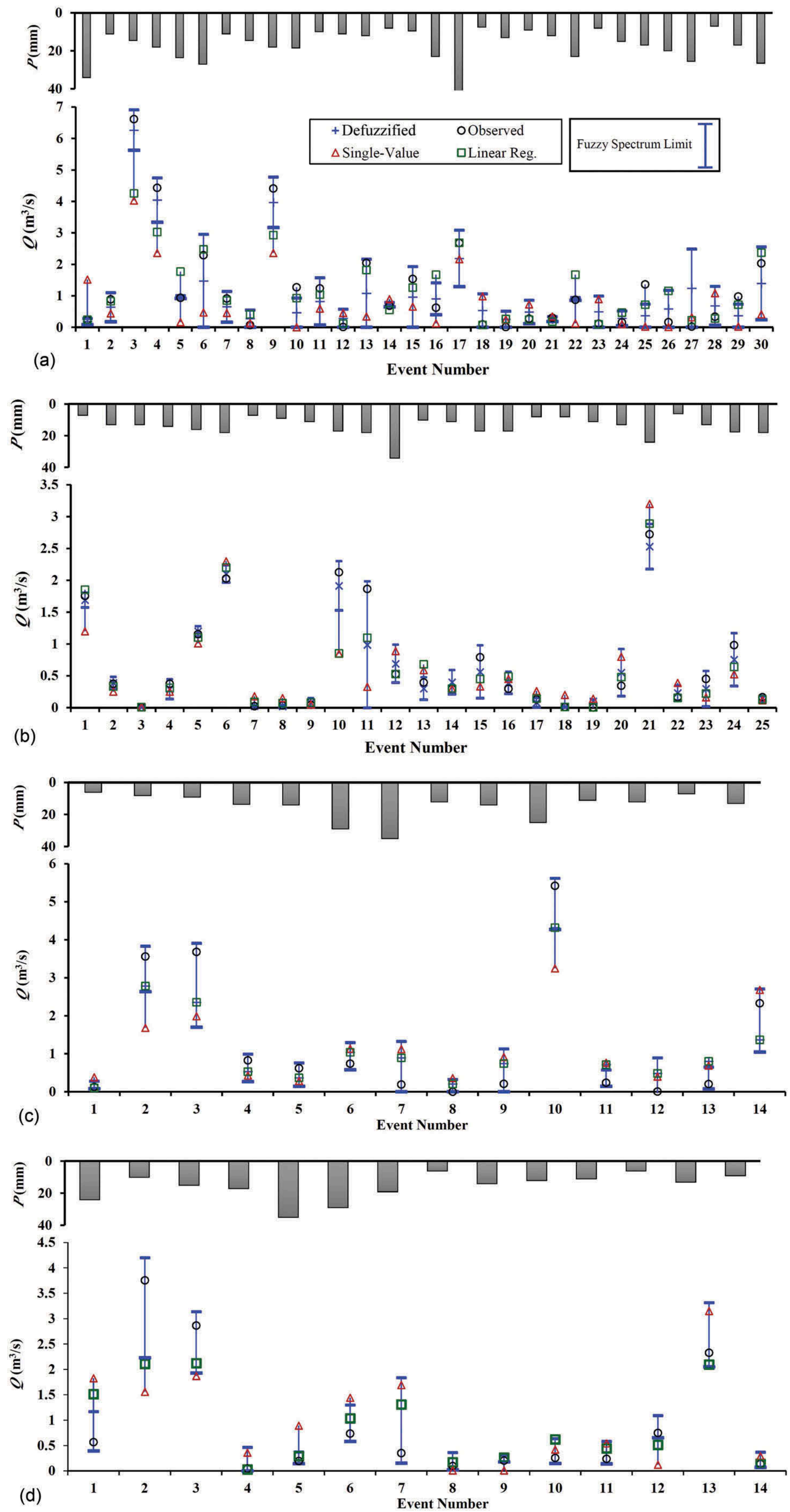

Figure 9. The observed and simulated runoff volume of events considered for the verification phase using the SCS-CN method based on FLR model, linear regression method, and constant parameters in the four watersheds: (a) Sulaghan, (b) Kiga, (c) Rendan and (d) Keshar (vertical blue lines show fuzzy spectrum corresponding to each estimated runoff volume).

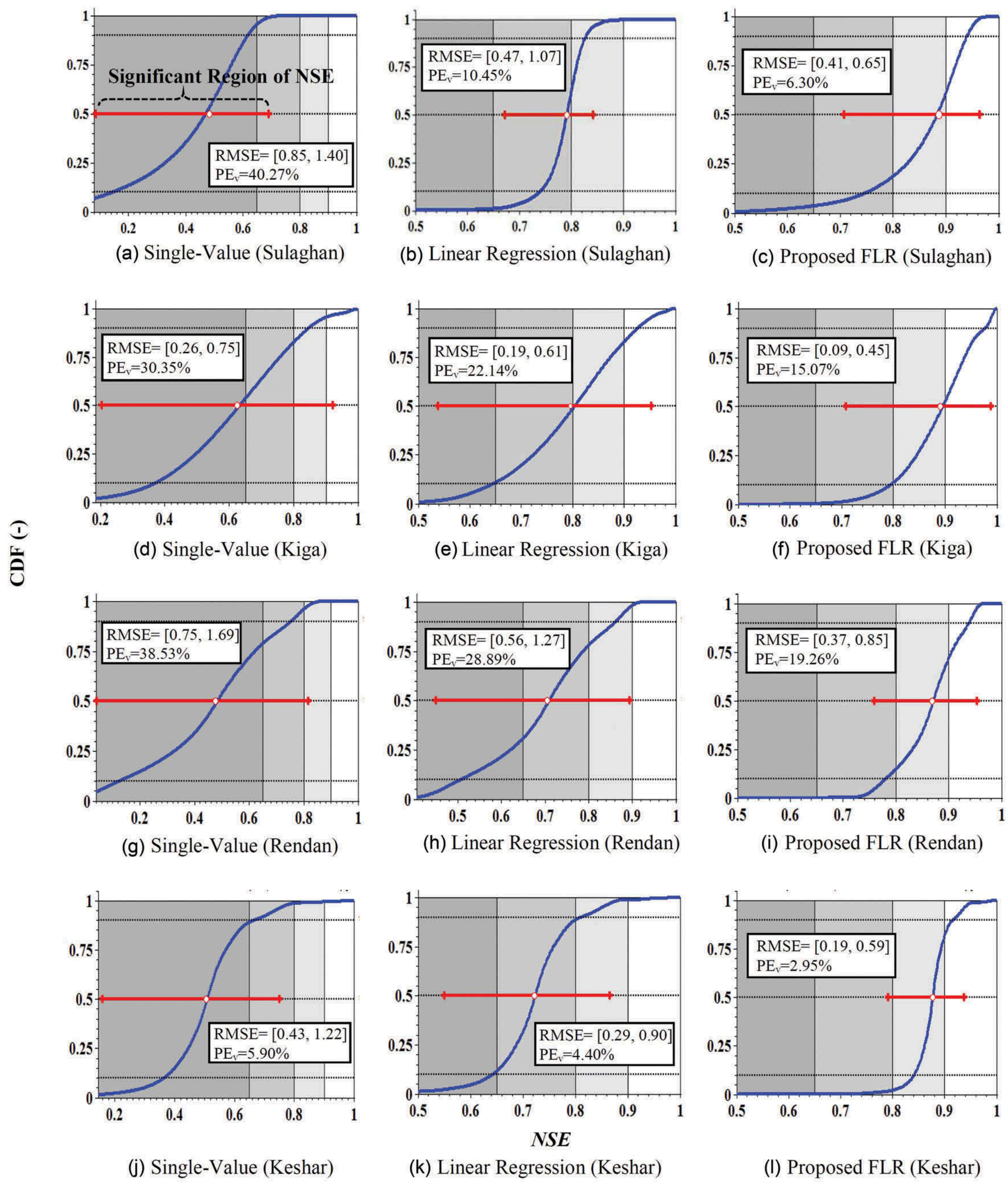

Figure 10. NSE probability distribution obtained by bootstrapping technique, the significant region of RMSE (at α= 0.05), and the percentage of error in runoff volume estimation (%PE$_V$) applied for the simulation results of validation data by the single-value SCS, linear regression and the proposed FLR models in the four studied watersheds.

watershed characteristics such as land cover and vegetation, land-use patterns, soil conditions, surface retention and also storm depth for more accurate runoff estimation. In this paper, considering CN–P and λ–P relationships, the efficiency of the SCS-CN model in estimating runoff volume increased in comparison with the SCS-CN model with constant parameters, especially for areas not undergoing land-use changes. Therefore, attention to variability of CN and λ parameters by storm depth in a gauged watershed is essential to have accurate runoff estimation through the SCS-CN method. Furthermore, it has been shown that incorporating fuzzy logic for considering uncertainties in CN–P and λ–P relationships also could significantly improve the capability of the SCS-CN model in estimation of flood volume. This was done through incorporating the vagueness associated with CN and λ using FLR analysis, which enhanced the efficiency of the traditional SCS-CN method in estimating runoff volume resulting from a wide range of rainfall depths. Therefore, the precision of runoff volume predictions during storm increases. It should be noted that in the proposed model the number of parameters increases, and more effort is needed to adjust the unknown parameters and, as a result, the SCS-CN model with constant parameters is more parsimonious.

The correlation between the CN and λ values and rainfall depth in a watershed is strongly attributed to the spatial variability of the soil and land cover of the watershed. Being aware of these relationships is useful for precise estimation of runoff volume in heterogeneous watersheds undergoing less land-use change over time and those with imprecise information about spatial variations of soil and land cover.

Finally, more research is called for to investigate the proposed approach in heterogeneous watersheds with different climates and also those with a high rate of land-use change due to human activities.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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