Revised runoff curve number for runoff prediction in the Loess Plateau of China

Wenhai Shi[a, b*], Ni Wang[a, b]

[a] Key Laboratory of Subsurface Hydrology and Ecological Effects in Arid Region, Chang'an University, Ministry of Education, China

[b] School of Water and Environment, Chang'an University, China

*Corresponding author:

Tel.: +86-29-82339291

Fax: +86-29-82339291

E-mail: shiwenhai@chd.edu.cn

ABSTRACT

The Soil Conservation Service Curve Number (SCS-CN), one of the most commonly used methods for surface runoff prediction, was developed by the United States Department of Agriculture (USDA). For many years, the direct application of the *CN* look-up table derived from USDA in regions elsewhere with different characteristics was questionable, because it could lead to a large error in runoff prediction. To eliminate this error, some studies suggested that *CN* entries should be revised based on measured data, whereas others indicated that major factors affecting runoff should be considered for application in specified regions. In this study, the above-mentioned *CN* revision approaches were compared to adjust *CN* values using a large amount of rainfall-runoff observation data for 43 study sites across the Loess Plateau region. The results showed that the average *CN* values of each watershed obtained from the measured rainfall-runoff data are quite different from the tabulated CN_2 values. However, the calculated average *CN* values produce little improvement in runoff estimation with the SCS-CN method, due to large *CN* value variation. Therefore, three factors—soil moisture, rainfall depth, and intensity—were identified as influencing the *CN* values under field conditions in the Loess Plateau, and a new *CN* value with a CN_2 value in the conventional SCS-CN method was developed. The reliability of the proposed method was tested with data from three watersheds on the Loess Plateau. High Nash–Sutcliffe efficiency (*NSE* = 74.70%) and low root mean square error (*RMSE* = 3.08 mm) indicated that the proposed method could accurately estimate runoff and was more reliable than the standard SCS-CN method (*NSE* =

19.26%; *RMSE* = 5.51 mm). Moreover, the factors incorporated in the proposed method seem to more effectively reflect the large *CN* value variations than the revised CN_2 value based on measured dataset in the Loess Plateau region.

Key words: Soil moisture; Rainfall depth; Rainfall intensity; Soil Conservation Service Curve Number method; Runoff prediction

1 Introduction

Runoff prediction is becoming an essential part of many hydrologic applications, such as water resource management, flood control design, and water and soil conservation . Accordingly, multiple rainfall-runoff models have been developed to predict runoff using readily available rainfall data. One of the most common methods used for estimating runoff as a response to rainfall is the Soil Conservation Service Curve Number (SCS-CN) method . This method has evolved well beyond its original scope of storm runoff evaluation and expanded to other areas, such as rainfall-infiltration, soil loss, and non-point source pollution (Shi et al., 2018b). Furthermore, the method has become an integral part of more complex, long-term simulation models (Kaffas et al., 2015) including SWAT (Soil and Water Assessment Tool) (Neitsch et al., 2011), EPIC (Environmental Policy Integrated Climate) (, and AnnAGNPS (Annualized Agricultural Non-Point Source Pollution Model) (Baginska et al., 2003).

The *CN* method is simple and convenient and only has a single parameter, *CN*, making it the most widespread and accepted method for estimating runoff in ungauged watersheds. The *CN* value is determined by the *CN* value (CN_2) of the average moisture condition (AMC 2)—which depends on land cover, land management, and the hydrologic soil group, as per a table from the SCS handbook (SCS, 1972)—and is converted to AMC 1 or AMC 3 based on 5-day prior rainfall depth . Error analysis and sensitivity calculations indicated that the sensitivity of runoff calculated by the *CN* method to the *CN* value was greater than that to rainfall depth, with runoff changing from 45% to 55% when the *CN* value varies by ±10% (Hawkins, 1975). Numerous studies have shown that the *CN* method performs better with the empirically calculated *CN* values obtained from observed rainfall-runoff data as compared with the theoretical *CN* values as well as those derived from the *CN* look-up table, warranting a need for improvement (Banasik and Woodward, 2010; Ebrahimian et al., 2012; Lal et al., 2017; Soulis and Valiantzas, 2013; Walega and Salata, 2019).

The accuracy of the tabulated *CN* value of the *CN* method plays a vital role in runoff prediction. Key factors that impact the tabulated *CN* value can be divided into two parts, i.e. AMC and CN_2. The antecedent moisture condition (AMC) is a major factor determining the initial abstraction of runoff. The AMC was defined in three levels: dry (AMC 1), average (AMC 2), and wet (AMC 3), with 5-day antecedent precipitation prior to an individual rainfall-runoff event in the traditional *CN* method. However, the definition of three discrete AMC levels will cause the *CN* value to suddenly shift from one level to another (Hawkins, 1978). Soil moisture proved to be a more appropriate indicator to define AMC values than the 5-day antecedent rainfall depth and strengthened knowledge of the relationship between soil moisture; the *CN* value greatly improved the runoff estimation of the SCS-CN method (Wood, 1976; Michele and Salvadori, 2002). The relationship between soil moisture and the *CN* value has been confirmed by many studies; several functions, such as the step function (Saxton,1992) and the linear function (Koelliker, 1994), which were developed using multi-source soil moisture data measured in situ (Huang et al., 2007), modelled (Shi et al., 2017), and derived from satellites (Jacobs et al., 2003).

The CN_2 value corresponds to the field conditions of the watershed (soil, slope, and land use). The *CN* look-up table was obtained and organised according to the monitored rainfall-runoff events of 150 watersheds across a wide range of terrain, soil, land use, and management conditions in the United States. However, the application of the *CN* method to regions with different geographical characteristics, land use, and soil infiltration ability produces a large error between *CN* values from the look-up table and the measured values (Lian et al., 2020). The CN_2 values from the handbook tables accurately predict runoff in traditional agricultural basins in the United States, but may generate unreliable flood parameters when applied to other countries and regions (Walega et al., 2019). Therefore, local application of the *CN* method must be verified to reduce the uncertainty of modelling results and promote a more widespread use of this method.

In addition to the tabulated *CN* value, rainfall characteristics such as rainfall depth and intensity also greatly impact runoff prediction; these are not considered in the *CN* look-up table. In most watersheds, the *CN* value calculated based on measured rainfall runoff events eventually approaches a constant value as the rainfall depth increases, which can be regarded as a characteristic of a specific watershed. In the study of determining asymptotic *CN*s using measured rainfall-runoff events, Hawkins (1993) indicated the typical presence of a secondary systematic between calculated *CN* values and rainfall depth in the watersheds. Soulis and Valiantzas (2012) developed a two-*CN* heterogeneous system to calculate runoff in the watersheds characterised by heterogeneous land use; the predicted results were very similar to the measured runoff.

Rainfall intensity has an important influence on the rainfall-runoff process, and thereby on the runoff estimation . However, the rainfall intensity factor is not considered in the SCS-CN, method, which will inevitably produce runoff prediction uncertainty due to spatiotemporal variability of rainfall . Several modified *CN* methods have been developed to compensate for neglecting rainfall intensity. Jain et al. (2006) proposed a modified model with a rainfall intensity-based rainfall adjustment. Mishra et al. (2008) suggested a rainfall intensity-dependent procedure by developing a new *CN* value equation with an introduced minimum *CN* and rainfall duration. Shi et al. (2017) introduced static infiltration into soil moisture accounting (SMA) based on the SCS-CN method to improve runoff prediction in the Loess Plateau. However, none of these methods have contact with the *CN* value of the original SCS-CN method, limiting the application of the models.

The Loess Plateau, located in the middle reaches of the Yellow River, covers an area of 620,000 km^2 across five provinces of China; it is one of the most erodible regions (Fu et al., 2004; Tian et al., 2016). The severe soil erosion and deposition in this area is primarily due to heavy rainstorms occurring over a short duration, steep slopes, and sparse vegetation (Zhang and Liu, 2005). Since the 1970s, a number of soil and water conservation measures, such as the Grain-for-Green project, have been adopted to strengthen vegetation restoration, control soil erosion, and improve environmental quality. Current research on the rainfall erosion process shows that runoff is one of the primary driving factors in soil erosion modelling. Thus, it is necessary to develop an appropriate method for predicting surface runoff from the design of soil and water conservation measures in this region.

Verifying the applicability of the SCS-CN model under different hydrological and climatic conditions on the Loess Plateau region is crucial to reduce modelling uncertainty and promote wider application in the engineering practice. To obtain revised *CN* values that better reflect actual hydrological conditions on the Loess Plateau, three objectives were defined: (i) to compare *CN* values derived from SCS handbook tables with the calculated *CN* values based on the monitored rainfall-runoff data; (ii) to identify the key factors influencing *CN* values under the hydrological conditions of the Loess Plateau; and (iii) to develop a revised *CN* value with the tabulated CN_2 value to identify key factors influencing the *CN* values in the conventional SCS-CN method.

2. Material and methods

2.1 Overview of the SCS-CN method

The SCS-CN method was originally developed based on two fundamental hypotheses and one simple water balance equation; the general form is expressed as follows:

$$Q = \begin{cases} 0 & (P \le 0.2S) \\ \dfrac{(P-0.2S)^2}{(P+0.8S)} & (P > 0.2S) \end{cases}, \tag{1}$$

where *P* and *Q* are the depth of observed rainfall and direct runoff, respectively (mm);

S is the potential maximum retention (mm), which can be calculated by:

$$S = \frac{25400}{CN} - 254 \tag{2}$$

where CN varies from 0 to 100 (dimensionless. The CN value is determined by the CN value (CN_2) of AMC 2, which depends on land cover, soil group, and the hydrologic conditions from the SCS handbook table (SCS, 1972); this is then converted to the values for AMC 1 or AMC 3 based on the 5-day prior rainfall depth.

CN values can be derived from Equation (2) after S is calculated from Equation (1) using available observed rainfall and runoff data (Hawkins, 1973):

$$S = 5\left[(P + 2Q) - \sqrt{Q(4Q + 5P)}\right] \tag{3}$$

2.2 Data Collection

In this study, a total of 43 watersheds were selected using existing data from monitoring rainfall-runoff events in the Loess Plateau region; the distribution of each study site is shown in Fig. 1. Data for 1479 monitored rainfall-runoff events from the 43 experimental watersheds were collected to revise the CN value. The observed events, period, land use, and other attributes for these watersheds are shown in Table 1. The meteorological data were derived from the China Meteorological Data Service Center and provided by the Chinese Meteorological Administration (http://data.cma.cn/). The land use and rainfall-runoff data used to calculate CN values were obtained from literature and Loess Plateau Data Center, National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China (http://loess.geodata.cn).

2.3 Data Analyses

The two statistical indices used to test the performance of the methods are expressed as follows:

$$NSE = \left[1 - \frac{\sum_{i=1}^{N} \left(Q_i - Q_i^* \right)^2}{\sum_{i=1}^{N} \left(Q_i - \overline{Q}_i \right)^2} \right] \times 100\% \quad (4)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(Q_i - Q_i^* \right)^2} \quad (5)$$

where *NSE* is the Nash–Sutcliffe efficiency , and *RMSE* is the root mean square error; Q_i and Q_i^* are the i^{th} observed and estimated runoff, respectively; $\overline{Q}$ is the mean observed runoff of events, and *N* is the total number of events. Higher *NSE* and lower *RMSE* values indicate that the model exhibits better agreement with the observations.

3 Results

3.1 Comparison of calculated and tabulated CN values

The *CN* values of the 43 study watersheds were calculated based on data for the observed rainfall-runoff events. The calculated CN_2 values were significantly different from the CN_2 values derived from the SCS handbook table *CN* entries (SCS, 1972) of the study area (Fig. 2). The CN_2 value calculated using the observed data has a larger range of 63.7–85.7, whereas the tabulated *CN* value of the study sites varies as 62.5–

75.1. The difference between the calculated and tabulated *CN* values ranges as -9.1–15.9, and only 13 of the 43 study sites (30%) had calculated CN_2 values that were within -5–5% of the tabulated values. This result is consistent with that of Lian et al. (2020), who adjusted *CN* values for 55 study sites in China with available observed rainfall-runoff event data and concluded that only one-third of the study sites could use the SCS handbook table to achieve a satisfactory (±5%) *CN* value.

Comparing the average CN_2 value and error for each study site revealed that the CN_2 value of different watersheds may be very different, which largely ignores the study site characteristics. Moreover, the data for the SCS handbook table developed by the USDA were obtained from a limited watershed observation dataset (Bartlett et al., 2016; Ogden et al., 2017). Thus, some studies questioned the applicability of the existing *CN* look-up table for other areas that differ from the characteristics of the original model, suggesting that *CN* values should be revised using monitored rainfall-runoff data (Lian et al., 2020; Walega et al., 2019). However, the SCS-CN method using the calculated CN_2 value performed poorly as compared to that using the tabulated CN_2 value (Table 2). Figure 3a shows that 76.7 % of the latter points have a lower *RMSE* value than the former. The poor performance can be derived from the large *CN* value variations in each watershed (Fig. 3b). Based on this result, we infer that the performance of the original SCS-CN method cannot be improved by using calculated average *CN* values of monitored rainfall-runoff data instead of the tabulated *CN* values for most of the study sites in the Loess Plateau region. Moreover, other factors that influence runoff prediction should be considered to reflect the large

CN value variations in each watershed.

3.2 Relationships between rainfall depth and CN value

Figure 4a shows the linear rainfall-runoff relationship for 1479 events, with a widely dispersed scatter point distribution. The regression line slope of 0.09 and intercept of 8.11 reflect the runoff coefficient and the minimum rainfall required to produce runoff, respectively. Studies show that the SCS-CN model exhibits better runoff prediction results for study areas with a runoff coefficient greater than 0.5 as compared to those with runoff coefficients less than 0.5 (Peng and You, 2006). However, almost all the data points lie under the $Q = 0.5P$ line for the 43 study sites, indicating that the original SCS-CN performed poorly in the Loess Plateau region.

Figure 4b presents the relationships between runoff and *CN* values at different rainfall depths. According to the SCS-CN method, the same runoff depth can be obtained by the combination of different *CN* values and rainfall, and different *CN* values for the same rainfall event and different rainfall depths for the same *CN* value may generate the same runoff. Therefore, the relationship between thee *CN* value and rainfall should be studied.

The relationship between rainfall and *CN* value was analysed by Hawkins (1993), who developed an asymptotic *CN* method that determines *CN* values for river basins by monitoring rainfall-runoff data. The method shows an asymptotic trend, such that as rainfall increases, the *CN* value decreases and approaches a constant value at large rainfall depths. Our study verified that this relationship is highly correlated with a high coefficient of determination ($R^2 = 0.99$; Fig. 5a). However, the

CN values of the asymptotic *CN* method were identified with the ordered rainfall and runoff depths that were sorted independently in the descending order instead of as measured rainfall and runoff pairs, which may overemphasise the relationship between rainfall and *CN* value and ignore the influence of other factors on *CN*, thus failing to reflect the true relationship between rainfall and runoff. Therefore, a relationship between actual rainfall and *CN* based on measured rainfall-runoff pairs was also developed that still shows a good correlation with a coefficient of determination R^2 of 0.76 (Fig. 5b).

3.3 Relationship between rainfall intensity and the CN value

Figure 6a shows the relationships between the potential maximum retention (S) and the product of rainfall (P) and potential maximum retention of the average moisture condition (S_2) under different rainfall intensities. Storm intensity partially reflects the variation of the relationship between the product of rainfall and the mean potential maximum retention with the S value. Fig. 6a shows that lower rainfall intensity corresponds with higher S, while lower *CN* values under the same rainfall event can generate large runoff. Moreover, as rainfall intensity increases, the trend of the product of P and S_2 increases as S gradually decreases.

An exponential relationship between the product of P and S_2 and the measured S value was developed, and the exponent was further expressed as an exponential function based on rainfall intensity. The comparison of measured *CN* and estimated *CN* based on the abovementioned function are shown in Fig. 6b. The coefficient of determination R^2 between the estimated and measured *CN* value was increased from

0.76 to 0.83 when only accounting for rainfall depth.

3.4 Relationships between AMC and the CN value

Figure 7a presents the comparison of measured and tabulated *CN* values as a function of the 5-day antecedent precipitation. The measured and tabulated *CN* values have no significant relationship with the 5-day AMC, and tabulated *CN* values are almost always lower than measured ones, confirming the runoff underprediction. The SCS-CN method using the tabulated *CN* value with 5-day AMC (M3) has an RMSE value 62.5 % lower than that without the 5-day AMC (M1) (Fig. 7b). However, the SCS-CN method, accounting for the 5-day AMC, improved the prediction accuracy of some watersheds and reduced that of others with the same number of study sites, where the *NSE* value is greater than zero (compared to M1; Fig. 7c). The results indicated that a new indicator of soil moisture condition, such as the actual soil moisture, is more correlated with the *CN* values than antecedent 5-day rainfall when considering *CN* in the calculation (Huang et al., 2007; Shi et al., 2017; Shi and Wang, 2020b).

3.5 Proposed method

A modified SCS-CN method incorporating rainfall depth, rainfall intensity, and soil moisture factors was proposed, and the *S* and *CN* values can be calculated as follows:

$$S = \mu\left[P(S_0 - V_0)\right]^{\omega} \tag{6}$$

$$CN = \frac{25400}{\mu\left[P(\frac{25400}{CN_1} - 254 - V_0)\right]^{\omega} + 254} \quad (7)$$

$$\omega = aI^{b} \quad (8)$$

where P is the amount of observed rainfall (mm); S is the potential maximum retention (mm); V_0 is the antecedent or initial soil moisture (mm); I is the rainfall intensity (mm h^{-1}); S_0 is the potential maximum retention in completely dry conditions (mm); CN_1 is the tabulated CN value corresponding to AMC 1; and μ, ω, a, and b are coefficients (dimensionless).

Because soil moisture data are not easily available for all study sites, three watersheds (Nanyaogou, Jiuyuangou, and Peijiamaogou) with available rainfall, rainfall intensity, and soil water content data were selected to test the applicability of the proposed method. The hydrologic characteristics and the optimised parameters of the three watersheds for the proposed method are listed in Table 3. To simplify the model, only parameter μ was optimised in the proposed method, whereas for parameters a and b, the values obtained from Fig. 6b based on 1479 rainfall-runoff events were adopted. Table 4 presents the performance between the original and proposed SCS-CN methods with statistical indexes.

Using the original SCS-CN and the proposed method, the estimated runoff against the corresponding measured values of the three watersheds are plotted in Fig. 8. The original SCS-CN method consistently under- and over-predicts small storm-runoff events. On the other hand, the proposed method presented a superior performance, yielding a larger *NSE* value of 74.70% and a lower *RMSE* value of 3.08 mm for all the three watersheds, as compared with the original SCS-CN method (Table 4); most data points were quite close to the perfect line (Fig. 8a). Therefore, according to the results of the experimental sites, the proposed method is more suitable for runoff estimation with the SCS-CN method in the Loess Plateau.

3.6. Sensitivity analyses

The above results show that the new method predicts runoff more accurately than the original SCS-CN method. A sensitivity analysis can identify the primary importance parameters that affect model performance. To conduct the sensitivity analysis, the complete dataset of the three tested watersheds was used to calibrate the variables (μ, a, and b), and the effect of the variation of the calibrated parameter on the runoff prediction in terms of *NSE* was observed.

Figure 9 presents the sensitivity of various parameters of the proposed method in terms of runoff prediction. Sensitive variables are those parameters that change significantly in terms of *NSE* when the parameter fluctuates around the calibration value. Figure 9 shows that for parameter a ranging from 110% to 90% of the optimised value, *NSE* decreased dramatically from 81.30% to 31.10%, indicating that parameter a is the most sensitive to variation. However, the initial ratio μ appears to be the least sensitive. Model parameters are ranked by sensitivity as: $a > b > \mu$.

4 Discussion

4.1. Impact factors of the revised CN

4.1.1. Effect of rainfall depth

Rainfall is one of the primary driving forces of runoff generation, and different rainfall characteristics lead to varying runoff generation capacity in the watershed. The dominant behaviour of the *CN* values in response to rainfall depth is of great significance to the runoff calculation (Muche et al., 2019; Soulis et al., 2009). The specific behaviour of the *CN* value calculated from the measured rainfall runoff data systematically varies with rainfall size. A single asymptotic *CN* value at a very high rainfall depth was determined to reflect the runoff response of the watersheds (Hawkins, 1975, 1993; Soulis and Valiantzas, 2012).

However, the *CN* values of the asymptotic *CN* method were identified with the ranking of rainfall depth, and runoff depth was conducted independently in descending order. This may potentially overemphasise the relationship between rainfall and the *CN* value, while ignoring the influence of other factors on the *CN* value and thus, fail to reflect the relationship between measured rainfall and runoff. Therefore, a relationship based on measured rainfall-runoff pairs was developed to reflect the actual rainfall and *CN* value in our study. Although it appears scattered as compared with the asymptotic *CN* method, the new relationship is explained by temporal variability variables, such as rainfall intensity and soil moisture conditions. This conclusion is consistent with that of Soulis and Valiantzas (2012), who stated that the produced effect of the *CN* and rainfall depth relationship should be considered as part of a deterministic analysis, whereas other temporal variables can describe the remaining scatter points on the primary *CN-P* correlation curve.

4.1.2. Effect of rainfall intensity

The SCS-CN method only accounts for the rainfall amount but ignores rainfall intensity. The runoff, predicted by the conventional SCS-CN method, and rainfall intensity increased as the rainfall amount increased; therefore, the measured runoff did not increase monotonously with rainfall amount or negatively affect the performance of the SCS-CN method (Shi and Wang, 2020a). However, when incorporating the rainfall intensity in the *CN* calculation, most of the data points between estimated and measured *CN* values lie close to 1:1, compared to the *CN-P* relationship (Fig. 6b). The better performance indicated that rainfall intensity plays a vital role in runoff production and estimation. Another study also confirmed that rainfall intensity greatly influences runoff generation and prediction, which should be considered to reflect the large variations in the *CN* value for each watershed (Fang et al., 2008; Reaney et al., 2010).

4.1.3. Effect of soil moisture

AMC is one of the primary factors affecting runoff. The conventional SCS-CN method uses the 5-day antecedent precipitation prior to an individual rainfall-runoff event to define AMC at three discrete levels, causing the *CN* value to suddenly shift from one level to another. Our study indicated that the measured *CN* values have no significant relationship with the 5-day AMC and that tabulated *CN* values are almost always lower than measured ones; this confirms the runoff underprediction (Fig. 7). Therefore, the traditional *CN* method using 5-day AMC adopted is unreasonable; this has also been proven by other researchers (Huang et al., 2007; Shi et al., 2017; Shi and Wang, 2020b).

Soil moisture has an important impact on runoff generation. During a certain rainfall period, the runoff capacity increases as the soil water content increases, and the *CN* value of the *CN* method should be increased accordingly (Thorndahl and Willems, 2008). Thus, detailed observations of actual soil moisture are a more reliable alternative to the use of antecedent rainfall—the most important factor defining the initial abstraction of the SCS-CN method and the study sites—for characterising AMC. Strengthening the understanding of antecedent moisture significantly improves the runoff estimation of the *CN* method (Wood, 1976; Michele and Salvadori, 2002). The results of the proposed method incorporating the antecedent soil moisture factor performed better than the standard SCS-CN method, which also indicated that soil moisture is more suitable for AMC determination than the antecedent 5-day rainfall.

4.2. Differences in CN values between the United States and China

The difference between calculated and looked-up *CN* values ranges from -12.2 to 23.6% (Fig. 2). However, the SCS-CN method using the calculated *CN* value performed more poorly than the tabulated *CN* value due to large *CN* value variations in each watershed (Fig. 3b). Based on this result, we infer that the performance of the original SCS-CN method cannot be improved when using calculated average *CN* values of the monitored rainfall-runoff data instead of the tabulated *CN* value for most of the study sites in the Loess Plateau region.

Therefore, the predominant controlling factors that influence the runoff prediction should be considered to reflect the large *CN* value variations in each watershed to improve the applicability of the SCS-CN method. The results show significant spatiotemporal variability in soil moisture content and rainfall characteristics, which are proven to be related to the *CN* value in our study (Ponce and Hawkins, 1996; Tramblay et al., 2010; Wang, 2018; Zeng et al., 2017). Table 4 shows that the proposed method incorporating soil moisture, rainfall depth, and intensity factors with tabulated *CN* value suggests an accurate runoff prediction using the optimised parameter for the three watersheds. The original SCS-CN method did not exhibit good performances for the test watersheds and underestimated multiple rainfall-runoff events.

Moreover, we found that the error between the calculated and tabulated *CN* value of the three watersheds ranged from 6.3% to 15.4%. However, the performance of the original SCS-CN method using the calculated average the *CN* value of each watershed did not improve, whereas the proposed method showed superior performance, indicating that the factors influencing runoff prediction more effectively reflect the large *CN* value variations than the average *CN* value calculated based on the measured dataset in the Loess Plateau region.

4.3. Shortcomings and future perspectives

The largest potential error source of the SCS-CN method is that runoff prediction results are sensitive to *CN* values. Our study found that incorporating factors to reflect the large *CN* value variations is more effective for runoff prediction than the use of the modified CN_2 lookup table based on measured datasets in the Loess Plateau region. However, several issues require further investigation. First, because actual soil moisture is more correlated with the *CN* parameters than with antecedent precipitation in the SCS-CN method, and these data are difficult to obtain in situ, multi-source soil moisture data—including satellite and model derived data—should be introduced to demonstrate applicability to the model. Second, higher resolution *CN* values will result in good runoff predictions, which require long-term and high-resolution monitoring data. High resolution *CN* values are effectively generated by mapping global *CN* values based on moderate resolution imaging Spectroradiometer (MODIS) and normalised Difference vegetation Index (NDVI) datasets (Lin et al., 2017; Zeng et al., 2017). Third, The proposed method provides validation that when the error between the calculated and tabulated *CN* values is within 15%, incorporating factors to reflect the large *CN* value variations is more effective than the use of the revised *CN* value based on measured datasets in the runoff prediction of the model. However, the effectiveness needs to be tested for errors greater than 15%. Moreover, the proposed method can be applied to similar sub-humid, semi-arid, and arid regions with the optimised parameters but may need adjustment for humid regions, because of soil moisture and rainfall characteristics may be different from the test results in this study.

5 Conclusions

In this study, *CN* values calculated using observed rainfall-runoff data from 43 sites in the Loess Plateau region were determined to be considerably different from the CN_2 values obtained from the USDA-SCS handbook table. However, the calculated average *CN* values showed little improvement in terms of runoff estimation using the SCS-CN method because of large *CN* value variation. Therefore, three factors—soil moisture, rainfall depth, and intensity—were identified as influencing the *CN* values under field conditions of the Loess Plateau, and a new *CN* value was developed with the CN_2 value used in the conventional SCS-*CN* method. The proposed method with optimised parameters was used to test the reliability of data from three watersheds on the Loess Plateau. The large *NSE* values and low *RMSE* values of the proposed method indicated that it could accurately predict runoff for the tested watersheds and had greater reliability than the original SCS-CN method. Moreover, the factors incorporated in the proposed method seemed to more effectively reflect the large variations of the *CN* value than the revised CN_2 value based on measured datasets in the Loess Plateau region.

Acknowledgements

This study was supported by the China Postdoctoral Science Foundation (2019M663917XB). We also acknowledge the data support from "Loess Plateau Data Center, National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China. (http://loess.geodata.cn)".

Data Availability Statement

Data supporting the findings of this study are available on request from the corresponding author.

References

Babu, P. S., Mishra, S. K., 2012. Improved SCS-CN–inspired model. Journal of Hydrologic Engineering 17, 1164-1172. https://doi.org/10.1061/(ASCE)HE. 1943-5584.0000435

Baginska, B., Milne-Home, W., Cornish, P. S., 2003. Modelling nutrient transport in Currency Creek, NSW with AnnAGNPS and PEST. Environmental Modelling & Software 18, 801-808. https://doi.org/10.1016/S1364-8152(03)00079-3.

Banasik, K., Woodward, D.E., 2010. Empirical determination of runoff curve number for a small agriculture catchment in Poland. In: 2nd Point Federal Interagency Conference. Las Vegas June 27-July 1, 2010

Bartlett, M.S., Parolari, A.J., McDonnell, J.J., Porporato, A., 2016. Beyond the SCS-CN method: a theoretical framework for spatially lumped rainfall-runoff response. Water Resour. Res. 52 (6), 4608-4627. https://doi.org/10.1002/2015WR018439

Bhuyan, S, J., Mankin, K. R., Koelliker, J. K., 2003. Watershed-scale AMC selection for hydrologic modeling. Transactions of the ASAE 46, 237-244. https:// doi.org/10.1016/S1364-8152(03)00079-3.

Ebrahimian, M., Nuruddin, A.A.B., Soom, M.A., et al., 2012. Runoff estimation in steep slope catchment with standard and slope-adjustment Curve Number Method. Polish Journal of Environmental Studies, 21 (5), 1191-1202.

Fang, H. Y., Cai, Q. G., Chen, H., Li, Q. Y., 2008. Effect of rainfall regime and slope on runoff in a gullied loess region on the Loess Plateau in China. Environmental Management 42, 402-411. https://doi.org/10.1007/s00267-008 -9122-6

Fu, B., Meng, Q., Qiu, Y., Zhao, W., Zhang, Q., Davidson, D., 2004. Effects of land use on soil erosion and nitrogen loss in the hilly area of the Loess Plateau, China. Land Degradation & Development. 15, 87-96. https://doi.org/10.1002/ldr.572

Hawkins, R. H., 1975. The importance of accurate curve numbers in the estimation of storm runoff. Water Resources Bulletin 11, 887-891. https://doi.org/10.1111/ j.1752-1688.1975.tb01810.x.

Hawkins, R, H., 1978. Runoff curve numbers with varying site moisture. Journal Irrigation and Drainage Division 104, 389-398.

Hawkins, R. H., 1993. Asymptotic determination of runoff curve numbers from data. Journal of Irrigation and Drainage Engineering-ASCE 119, 334. https://doi.org/10.1061/(ASCE)0733-9437(1993)119:2(334)

Huang, M., Gallichand, J., Dong, C., Wang, Z., Shao, M., 2007. Use of soil moisture data and curve number method for estimating runoff in the Loess Plateau of China. Hydrological Processes 21, 1471-1481. https://doi.org/10.1002/hyp.6312

Jacobs, J. M., Myers, D. A., Whitfield, B. M., 2003. Improved rainfall/runoff estimates using remotely sensed soil moisture. Journal of the American Water Resources Association 39, 313-324. https://doi.org/10.1111/j.1752-1688.2003.tb04386.x

Jain, M. K., Mishra, S. K., Babu, P. S., Venugopal, K., 2006. On the I_a–S relation of the SCS-CN method. Hydrology Research 37, 261-275. https://doi.org/10.2166/nh.2006.011

Kaffas, K., Hrissanthou, V., 2015. Estimate of continuous sediment graphs in a basin, using a composite mathematical model. Environmatal Processes 2, 361-378. https://doi.org/10.1007/s40710-015-0069-3.

Koelliker, J.K., 1994. User's manual of potential yield model revised (POTYLDR). Kansas State University, Department of Biological and Agricultural Engineering, Manhattan, KS.

Lal, M., Mishra, S.K., Pandey, A., Pandey, R.P., Meena, P.K., Chaudhary, A., Jha, R.K., Shreevastava, A.K., Kumar, Y., 2017. Evaluation of the Soil Conservation Service curve number methodology using data from agricultural plots. Hydrogeology Journal, 25(1), 151-167. https://doi.org/ 10.1007/s10040-016-1460-5

Lal, M., Mishra, S.K., Kumar, M., 2019. Reverification of antecedent moisture condition dependent runoff curve number formulae using experimental data of Indian watersheds. Catena 173, 48-58. https://doi.org/10.1016/j.catena.2018.09.002

Lian, H., Yen, H., Huang, C., Feng, Q., Qin, L., Bashir, M.A., Wu, S., Zhu, A. X., Luo, J., Di, H, 2020. CN-China: Revised runoff curve number by using rainfall-runoff events data in China. Water Research, 115767. https://doi.org/10.1016/j.watres.2020.115767

Lin, W., Yang, F., Zhou, L., Xu, J.G., Zhang, X.Q., 2017. Using modified Soil Conservation Service curve number method to simulate the role of forest in flood control in the upper reach of the Tingjiang River in China. Journal of Mountain Science, 14(1), 1-14. https://doi.org/10.1007/s11629-016-3945-z

Michele, C. D., Salvadori, G., 2002. On the flood frequency distribution: analytical formulation and the influence of antecedent soil moisture condition. Journal of Hydrology 262, 245-258. https://doi.org/10.1016/S0022-1694(02)00025-2.

Mishra, S. K., Pandey, R. P., Jain, M. K., Singh, V. P., 2008. A rain duration and modified AMC-dependent SCS-CN procedure for long duration rainfall-runoff events. Water Resources Management 22, 861-876. https://doi.org/10.1007/s11269-007-9196-6

Muche, M.E., Hutchinson, S.L., Hutchinson, J.M.S., Johnston, J.M., 2019. Phenology-adjusted dynamic curve number for improved hydrologic modeling. Journal of Environmental Management, 235, 403-413. https://doi.org/10.1016/j.jenvman.2018.12.115

Nash, J. E., Sutcliffe, J. E., 1970. River flow forecasting through conceptual models: part I-A discussion of principles. Journal of Hydrology 10, 282-290. https://doi.org/10.1016/0022-1694(70)90255-6.

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2011). Soil and Water Assessment Tool theoretical documentation version 2009. Texas Water Resources Institute Technical Report no. 406. https://doi.org/10.1016/j.scitotenv.2015.11.063

Ogden, F.L., Hawkins, R., Walter, M.T., Goodrich, D.C., 2017. Comment on "Beyond the SCS-CN method: a theoretical framework for spatially lumped rainfall-runoff response. In: Bartlett, M.S. (Ed.), Water Resources Research, 53(7), 6345-6350. https://doi.org/10.1002/2016WR020176

Peng, D., You, J., 2006. Application of modified SCS model into runoff simulation. Journal of Water Resources and Water Engineering, 17, 20-24. https://doi.org/10.3969/j.issn.1672-643X.2006.01.005

Ponce, V. M., Hawkins, R. H., 1996. Runoff curve number: Has it reached maturity? Journal of Hydrologic Engineering, ASCE 1:11-19. https://doi.org/10.1061/(ASCE)1084-0699(1996)1:1(11).

Reaney, S. M., Bracken, L. J., Kirkby, M. J., 2010. Use of the connectivity of runoff model (CRUM) to investigate the influence of storm characteristics on runoff generation and connectivity in semi-arid areas. Hydrological Processes 21, 894-906. https://doi.org/10.1002/hyp.6281

Risse, L. M., Nearing, M. A., Savabi, M. R., 1994. Determining the Green-Ampt effective hydraulic conductivity from rainfall-runoff data for the WEEP model. Transactions of the ASAE 37, 411-418.

Saxton, K. E., 1992. User's manual for SPAW: a soil-plant-atmosphere water model. USDA-ARS: Pullman, WA.

SCS, 1972. National Engineering Handbook, Section 4. Soil Conservation Service USDA, Washington, DC.

Sharpley, A. N., Williams, J. R., 1990. EPIC-erosion/productivity impact calculator: 1. Model documentation. U.S. Department of Agriculture Technical Bulletin No. 1768, U.S. Government Printing Office, Washington, DC.

Shi, W. H., Huang, M. B., Barbour, S. L. (2018a). Storm-based CSLE that incorporates the estimated runoff for soil loss prediction on the Chinese Loess Plateau. Soil and Tillage Research, 180, 137-147. https://doi.org/10.1016/j.still.2018.03.001.

Shi, W. H., Huang, M. B., Gongadze, K., Wu, L. H. (2017). A modified SCS-CN method incorporating storm duration and antecedent soil moisture estimation for runoff prediction. Water Resources Management, 31, 1713-1727. https://doi.org/10.1007/s11269-017-1610-0.

Shi, W. H., Huang, M. B., & Wu, L. H. (2018b). Prediction of storm-based nutrient loss incorporating the estimated runoff and soil loss at a slope scale on the Loess Plateau, China. Land Degradation & Development. https://doi.org/10.1002/ldr.3028.

Shi, W., Wang, N. 2020a. Improved SMA-based SCS-CN method incorporating storm duration for runoff prediction on the Loess Plateau, China. Hydrology Research, 51(3), 443-455. https://doi.org/10.2166/nh.2020.140

Shi, W., Wang, N. 2020b. An Improved SCS-CN Method Incorporating Slope, Soil Moisture, and Storm Duration Factors for Runoff Prediction. Water, 12(5), 1335. https://doi.org/10.3390/w12051335

Soulis, K.X., Valiantzas, J.D., 2012. SCS-CN parameter determination using rainfall runoff data in heterogeneous watersheds–the two-CN system approach. Hydrology and Earth System Sciences, 16(3), 1001-1015. https://doi.org/10.5194/hess-16-1001-2012

Soulis, K.X., Valiantzas, J.D., 2013. Identification of the SCS-CN parameter spatial distribution using rainfall-runoff data in heterogeneous watersheds. Water Resources Management, 27(6), 1737-1749. https://doi.org/ 10.1007/s11269-012-0082-5

Tramblay, Y., Bouvier, C., Martin, C., Didon-Lescot, J.F., Todorovik, D., Domergue, J.M., 2010. Assessment of initial soil moisture conditions for event-based rainfallrunoff modelling. Journal of Hydrology, 387(3-4), 176-187. https://doi.org/10.1016/j.jhydrol.2010.04.006

Thorndahl, S., Willems, P., 2008. Probabilistic modelling of overflow, surcharge and flooding in urban drainage using the first-order reliability method and parameterization of local rain series. Water Research, 42 (1-2), 455-466. https://doi.org/10.1016/j.watres.2007.07.038

Tian, P., Zhai, J., Zhao, G., Mu, X., 2016. Dynamics of runoff and suspended sediment transport in a highly erodible catchment on the Chinese Loess Plateau. Land Degradation & Development, 27, 839-850. https://doi.org/10.1002/ldr.2373

Walega, A., Salata, T., 2019. Influence of land cover data sources on estimation of direct runoff according to SCS-CN and modified SME methods. Catena 172, 232-242. https://doi.org/10.1016/j.catena.2018.08.032

Walega, A., Amatya, D. M., Caldwell, P., Marion, D., Panda, S., 2019. Assessment of storm direct runoff and peak flow rates using improved SCS-CN models for selected forested watersheds in the southeastern United States. Journal of Hydrology: Regional Studies, 27, 100645 https://doi.org/10.1016/j.ejrh.2019.100645

Wang, D.B., 2018. A new probability density function for spatial distribution of soil water storage capacity leads to the SCS curve number method. Hydrology and Earth System Sciences, 22 (12), 6567-6578. https://doi.org/10.5194/hess-22-6567-2018

Wood, E. F., 1976. An analysis of the effects of parameter uncertainty in deterministic hydrologic models. Water Resources Research 12, 925-932. https://doi.org/ 10.1029/WR012i005p00925

Zeng, Z.Y., Tang, G.Q., Hong, Y., Zeng, C., Yang, Y., 2017. Development of an NRCS curve number global dataset using the latest geospatial remote sensing data for worldwide hydrologic applications. Remote Sensing Letters, 8(6), 528-536.

https://doi.org/10.1080/2150704X.2017.1297544
Zhang, X.C., Liu, W.Z., 2005. Simulating potential response of hydrology, soil erosion, and crop productivity to climate change in Changwu tableland region on the Loess Plateau of China. Agricultural and Forest Meteorology. 131, 127-142. https://doi.org/10.1016/j.agrformet.2005.05.005

Table 1

Main characteristics of all the 43 study watersheds.

ID	Watershed	Area (km^2)	Observed period	Events	Land use (%)					Lon	Lat
					Cropland	Forest	Pasture	Wasteland	Others		
1	Liudaogou	6.89	2004–2009	17	12.8	28.3	26.6	25.5	6.9	38°48′	110°22′
2	Xiangtagou	0.45	1958–1961	11	75.5	3.5	0.0	6.0	6.3	37°33′	110°16′
3	Donggou	13.50	1958–1959	24	64.9	4.5	1.3	27.5	2.0	35°02'	107°30'
4	Nanyaogou	0.73	1954–1961	72	80.2	6.6	11.3	1.9	0.0	37°21′	110°17′
5	Yangdaogou	0.21	1956–1970	97	58.0	0.0	0.0	42.0	0.0	37°33'	111°09'
6	Yangyagou	1.88	1960–1961	15	34.4	32.5	0.0	22.4	10.7	38°51′	110°30′
7	Peijiamaogou	41.50	1959–1969	111	68.8	12.5	0.0	16.7	2.0	37°29′	110°17′
8	Wangdonggou	8.30	1996–1997	7	42.5	29.7	14.2	6.8	6.8	35° 14'	107°41'
9	Qingcaogou	0.37	1958–1959	10	54.2	14.0	28.8	3.1	0.0	38°08′	109°51′
10	Yujiaguagou	19.17	1960–1961	11	19.3	31.7	0.0	32.9	15.9	37°34′	108°47′
11	Mengjiagou	2.03	1959–1961	25	28.5	9.4	17.0	45.2	0.0	38°51′	110°30′
12	Gangou	20.10	1959–1960	22	40.0	2.5	4.5	43.2	9.8	36°03'	107°05'
13	Sigou	4.37	1959–1967	82	2.7	67.7	0.0	28.7	0.9	35°44′	109°34′
14	Caijiachuan	37.57	2004–2006	19	6.1	78.1	0.0	14.7	1.2	36°16'	110°43'
15	Xiaoyanggou	0.47	1958–1960	12	25.2	0.6	0.0	64.2	10.0	36°40'	107°11'
16	Tiaogou	0.86	1959–1961	18	42.6	2.2	4.6	40.9	9.7	38°11′	109°47′
17	Beilougou	0.33	1959–1961	14	66.4	27.1	0.0	6.5	0.0	35°11′	109°55′
18	Wangjiagou1	0.43	1959–1960	25	79.4	0.0	3.7	17.0	0.0	38°08′	109°51′
1	Tuanyuango	0.49	1958–	18	79.2	8.5	0.0	6.0	6.3	37°33′	110°16′

9	u		1961								
20	Chacaizhugou	0.19	1956–1970	80	65.2	0.0	0.0	34.8	0.0	37°33'	111°09'
21	Jiuyuangou	70.10	1956–1976	169	49.5	7.2	0.0	33.1	11.7	37°33′	110°16′
22	Yangwangou	0.90	1959–1961	8	21.5	28.5	2.0	43.3	4.8	37°34′	108°47′
23	Mingyuchigou	3.83	1958–1964	50	49.0	35.9	0.0	8.4	6.7	35°01′	108°06′
24	Xiaobiangou	4.05	1961–1967	69	48.2	0.0	0.0	41.8	10.0	36°36′	109°26′
25	Lvergou	12.01	1964–1980	13	23.3	26.3	0.0	32.8	17.7	34°34'	105°43'
26	Erdaogou	0.41	1959–1961	10	45.3	12.0	0.0	25.7	17.0	34°41′	108°08′
27	Yuanguzhuang	2.82	1959–1960	5	69.7	5.0	0.0	24.6	0.7	34°00′	109°08′
28	Nangou	5.11	1964–1967	39	18.4	2.7	0.0	76.1	2.8	35°44′	109°34′
29	Dabiangou	3.70	1959–1967	59	45.4	9.7	0.0	31.2	13.7	36°35′	109°27′
30	Dicungou	4.40	1960–1961	26	86.6	3.2	0.0	7.3	3.0	34°11′	109°8′
31	lijiazhai	5.45	1962–1963	15	57.3	0.3	0.0	15.2	27.2	37°33′	110°16′
32	Wangjiagou2	9.10	1955–1980	107	60.0	0.0	0.0	40.0	0.0	37°33'	111°09'
33	Yanwachuan	329.00	1976–1980	26	54.0	4.5	1.3	27.5	13.0	35°35'	107°52'
34	Wangmaogou	5.97	1960–1965	22	45.9	2.6	0.0	32.1	19.5	37°33′	110°16′
35	Guanzhuanggou	3.39	1959–1960	6	69.0	10.3	0.0	18.9	1.8	34°00′	109°08′
36	Beiyazhigou	145.79	1959–1961	6	5.3	64.4	0.0	30.3	0.0	35°44′	109°34′
37	Fengyugou	1.18	1958–1960	36	61.9	1.8	5.1	10.5	20.7	35°01′	108°06′
38	Lijiagou	0.87	1959–1961	13	50.7	6.0	3.7	29.9	9.8	38°11′	109°47′
39	Xingshugou	0.52	1958–1959	9	80.2	0.0	0.0	19.8	0.0	35°11′	109°55′
40	Buzigou	2.86	1957–1962	21	27.2	46.6	0.0	26.2	0.0	36°04'	108°17'
4	Nanxiaohego	36.3	1965–	57	49.7	4.5	1.3	27.5	17.0	35°42	107°37'

1	u	0	1980							'	
42	Qiaozixigou	1.09	1988–2006	12	57.1	0.0	5.9	30.5	6.5	34°34'	105°43'
43	Yaojiagou	7.82	1960–1961	11	80.8	2.3	0.0	4.3	12.5	34°11′	109°50′

Table 2

Performance statistics of the SCS-CN method used different CN values for the 43 studied watersheds

ID	Watershed	CN value		*RMSE* (mm)				*SD* (mm)
		Calculated	Tabulated	M1	M2	M3	M4	
1	Liudaogou	83.6	67.7	6.0	7.7	-	-	4.8
2	Xiangtagou	80.7	68.3	4.2	4.2	6.3	5.5	5.2
3	Donggou	85.7	73.4	4.9	5.4	6.9	4.9	6.2
4	Nanyaogou	80.7	70.0	4.1	6.0	6.1	3.9	3.9
5	Yangdaogou	84.2	73.1	4.7	8.0	8.6	11.0	8.0
6	Yangyagou	79.1	69.0	6.2	11.2	2.1	4.1	1.3
7	Peijiamaogou	83.3	72.8	8.8	12.9	6.9	10.0	4.1
8	Wangdonggou	78.7	69.6	1.9	1.4	-	-	1.5
9	Qingcaogou	80.2	71.5	1.9	4.7	5.0	7.6	3.6
10	Yujiaguagou	76.1	68.1	2.3	4.6	0.3	0.7	0.2
11	Mengjiagou	78.4	70.1	9.6	14.9	2.3	6.2	5.6
12	Gangou	80.3	72.1	1.7	4.1	1.6	0.9	0.5
13	Sigou	70.0	63.1	9.0	11.8	3.6	6.2	0.6
14	Caijiachuan	69.1	62.5	3.6	6.2	0.5	0.7	0.3
15	Xiaoyanggou	78.5	71.2	4.0	6.0	2.5	2.6	3.5
16	Tiaogou	79.4	72.3	4.4	6.9	2.3	3.0	2.7
17	Beilougou	77.9	71.2	1.4	3.4	2.5	1.9	2.1
18	Wangjiagou[1]	81.3	74.6	4.3	6.3	1.4	2.9	4.5
19	Tuanyuangou	80.7	74.1	5.6	9.8	11.5	13.6	5.5
20	Chacaizhugou	80.1	73.6	5.6	9.8	11.5	13.6	4.2
21	Jiuyuangou	79.8	73.5	7.7	10.3	5.9	5.9	10.2
22	Yangwangou	73.9	68.2	4.8	7.8	2.0	1.3	2.1
23	Mingyuchigou	74.9	69.5	6.5	8.8	7.8	9.0	0.3
24	Xiaobiangou	78.3	72.9	5.4	7.4	7.5	9.1	2.5
25	Lvergou	74.1	69.2	5.0	16.9	11.7	17.1	7.5
26	Erdaogou	77.0	71.9	5.5	7.2	7.1	6.2	2.5
27	Yuanguzhuanggou	78.0	73.5	0.7	0.8	0.9	0.9	0.7
28	Nangou	74.3	70.2	2.8	4.2	2.0	2.6	1.0
29	Dabiangou	75.5	72.0	6.0	7.6	6.0	6.9	3.2
30	Dicungou	78.4	74.9	2.7	2.4	4.2	3.7	0.1
31	lijiazhai	77.6	74.3	4.6	5.9	0.6	1.0	0.8
32	Wangjiagou[2]	76.1	73.2	6.4	7.7	4.3	4.8	7.0
33	Yanwachuangou	75.2	73.2	18.0	19.7	7.6	8.9	2.2
34	Wangmaogou	73.3	73.0	12.3	12.5	3.9	4.1	7.9
35	Guanzhuanggou	73.2	73.0	0.9	0.9	0.9	0.9	0.9

36	Beiyazhigou	63.7	63.6	3.2	3.3	0.2	0.2	0.5
37	Fengyugou	72.6	74.2	10.9	9.8	2.4	1.9	0.8
38	Lijiagou	70.5	72.5	7.6	8.7	2.7	3.0	2.5
39	Xingshugou	72.3	74.6	3.4	2.7	0.3	0.4	0.3
40	Buzigou	64.4	66.7	7.5	6.4	9.1	8.5	0.1
41	Nanxiaohegou	69.7	72.9	10.6	8.9	9.0	7.9	1.1
42	Qiaozixigou	68.6	73.3	2.1	2.0	-	-	9.4
43	Yaojiagou	65.9	75.1	6.6	2.7	1.7	0.8	0.1

Note: M1: Original SCS-CN method using tabulated CN_2 values;
M2: Original SCS-CN method using calculated CN_2 values;
M3: Original SCS-CN method using tabulated CN values and accounting for AMC with 5-day antecedent precipitation;
M4: Original SCS-CN method using calculated CN values and accounting for AMC with 5-day antecedent precipitation;
RMSE: root mean square error; *SD*: standard deviation.

Table 3

Hydrologic characteristics and optimised parameters of the proposed method in Nanyaogou, Jiuyuangou, and Peijiamaogou watersheds.

Watershed		Nanyaogou	Jiuyuangou	Peijiamaogou	All
Precipitation (mm)		20.33±15.15	25.25±26.79	20.69±19.65	22.16±21.15
Rainfall intensity (mm h^{-1})		8.72±9.01	6.03±5.85	4.87±5.04	6.33±6.73
Soil moisture (cm^3 cm^{-3})		23.27±6.73	19.29±7.25	18.35±6.34	20.03±6.97
Runoff depth (mm)		1.68±3.96	2.80±9.15	1.86±3.98	2.13±6.14
Measured CN value		80.74±10.73	80.82±11.64	83.25±11.20	81.72±11.38
Tabulated CN value		69.97	73.50	72.80	-
	μ	0.053	0.052	0.056	0.054
Parameter	a	0.876	0.876	0.876	0.876
	b	-0.043	-0.043	-0.043	-0.043

Table 4

Performance of the original SCS-CN and proposed method for the three tested watersheds

Method	Variable	Watershed			
		Nanyaogou	Jiuyuangou	Peijiamaogou	All
SCS-CN method	Slope	0.87	0.47	0.45	0.51
	Interception	1.30	0.41	1.92	1.33
	R^2	0.25	0.57	0.16	0.32
	NSE (%)	-142.32	53.69	33.70	19.26
	RMSE (mm)	6.12	5.94	2.82	5.51
Proposed method	Slope	0.55	0.67	0.85	0.67
	Interception	0.91	1.40	0.06	0.83
	R^2	0.68	0.77	0.82	0.82
	NSE (%)	65.23	75.00	85.14	74.70
	RMSE (mm)	2.32	4.55	1.47	3.08

R^2: coefficient of determination; *NSE*: model efficiency; *RMSE*: root mean square error.

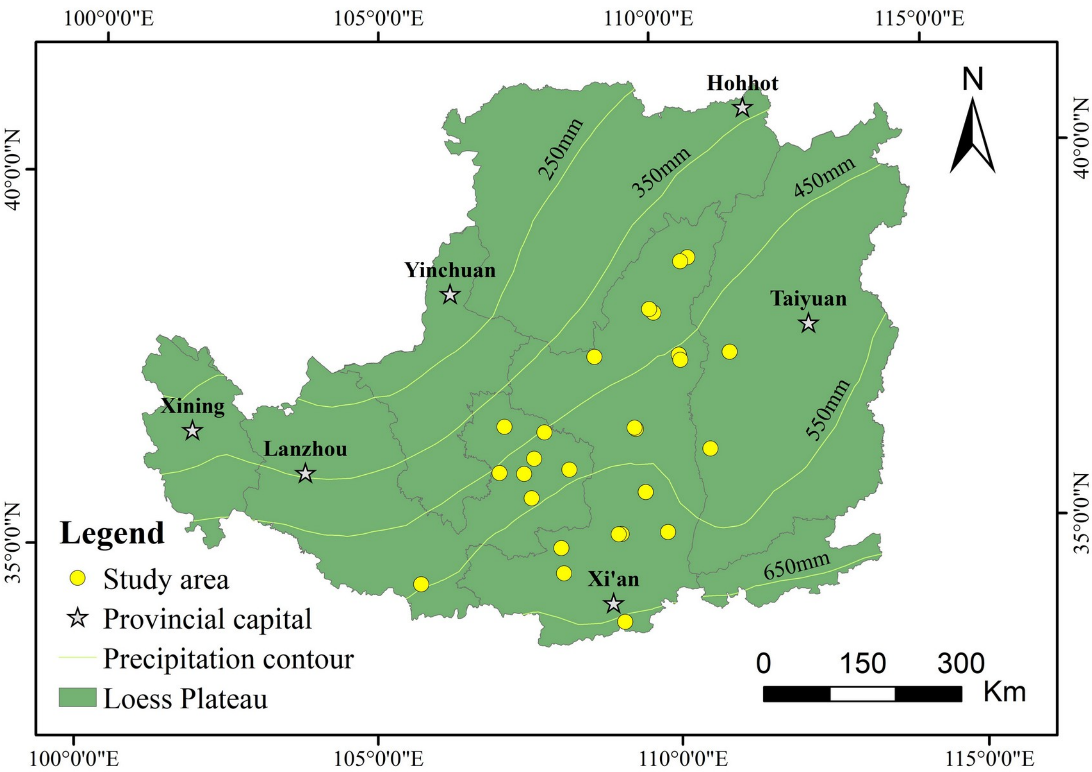


Fig. 1. Location of monitoring sites for rainfall and runoff.

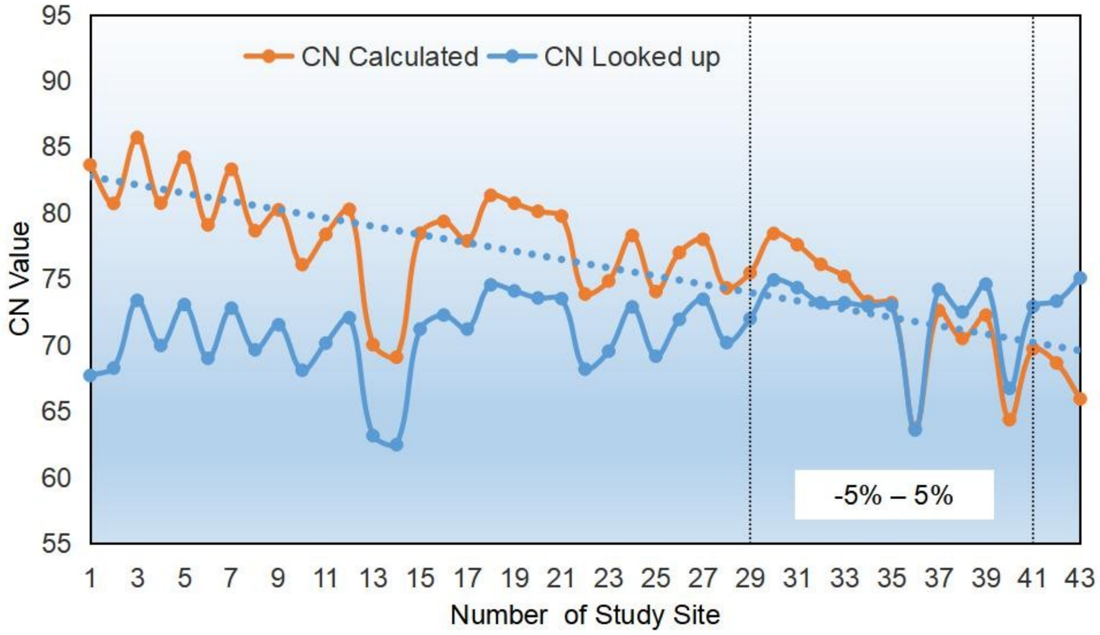
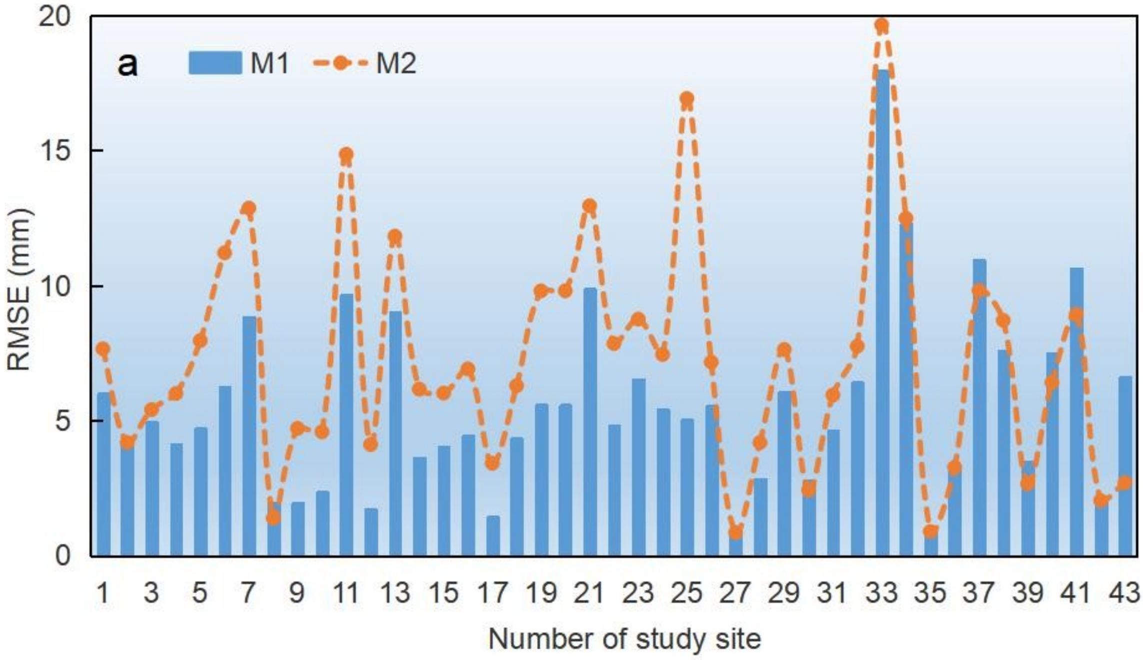


Fig. 2. Calculated CN value and looked-up CN value for 43 study sites.



a
M1
M2
RMSE (mm)
20
15
10
5
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43
Number of study site

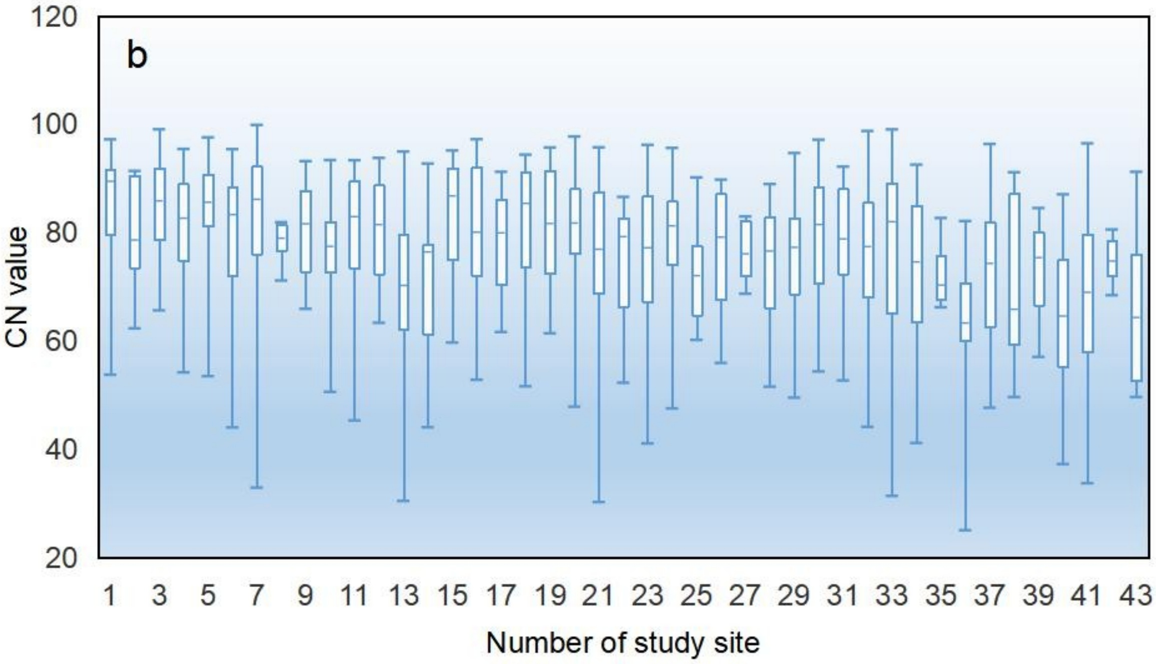
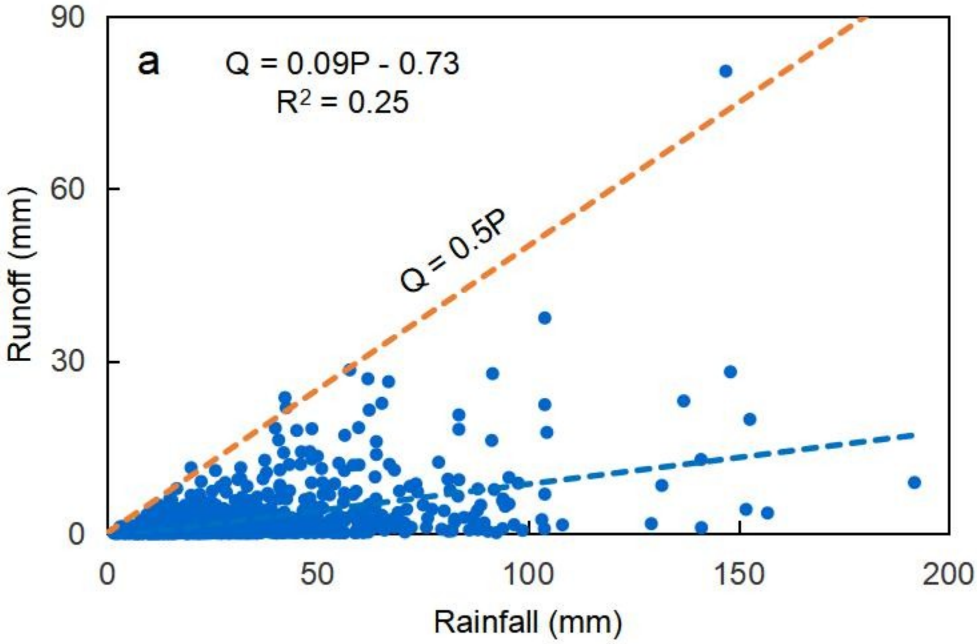


Fig. 3. (a) Comparison of M1 and M2 with the root mean square error (*RMSE*)and (b) variation of the measured CN values for the 43 study sites. M1: The original SCS-CN method using tabulated CN_2 values; M2: the original SCS-CN method using calculated CN_2 values.



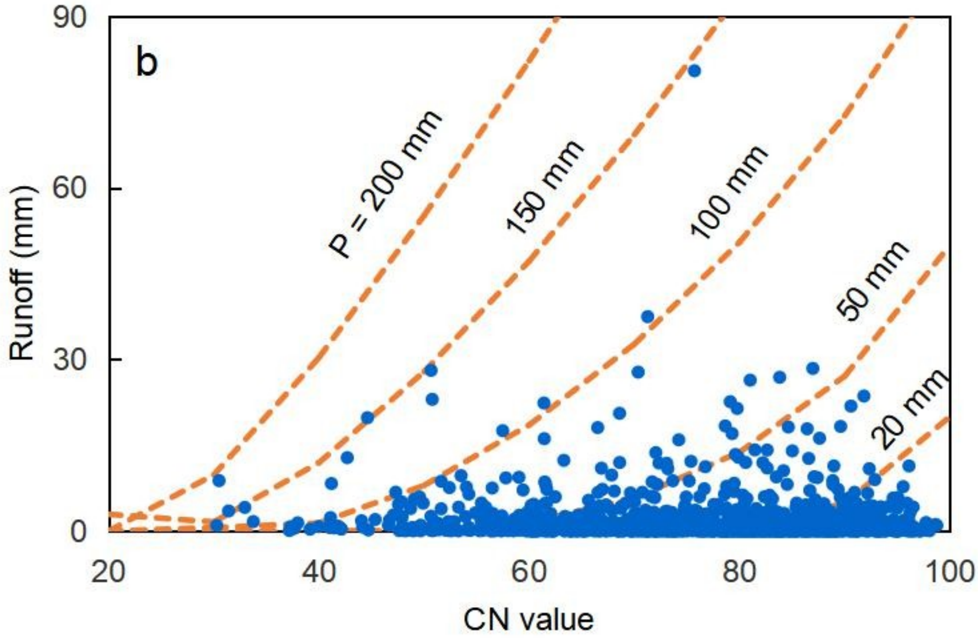
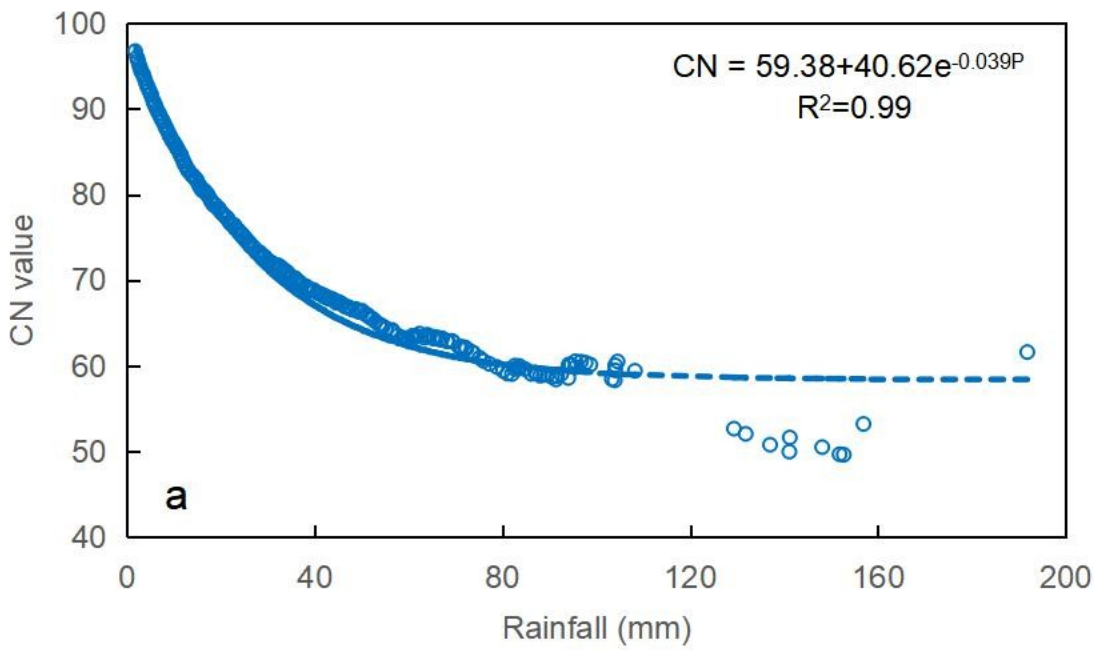


Fig. 4. Runoff versus (a) rainfall (*P*) and (b) CN values under different rainfall depths at all monitoring sites. A total of 1479 rainfall events were considered across the Loess Plateau region.



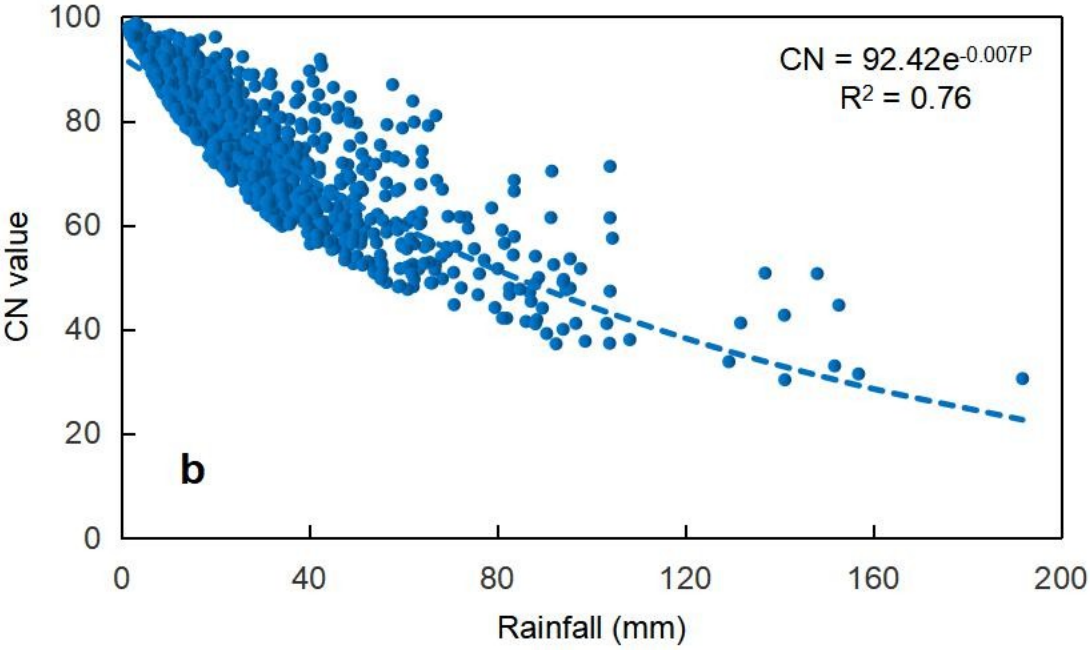
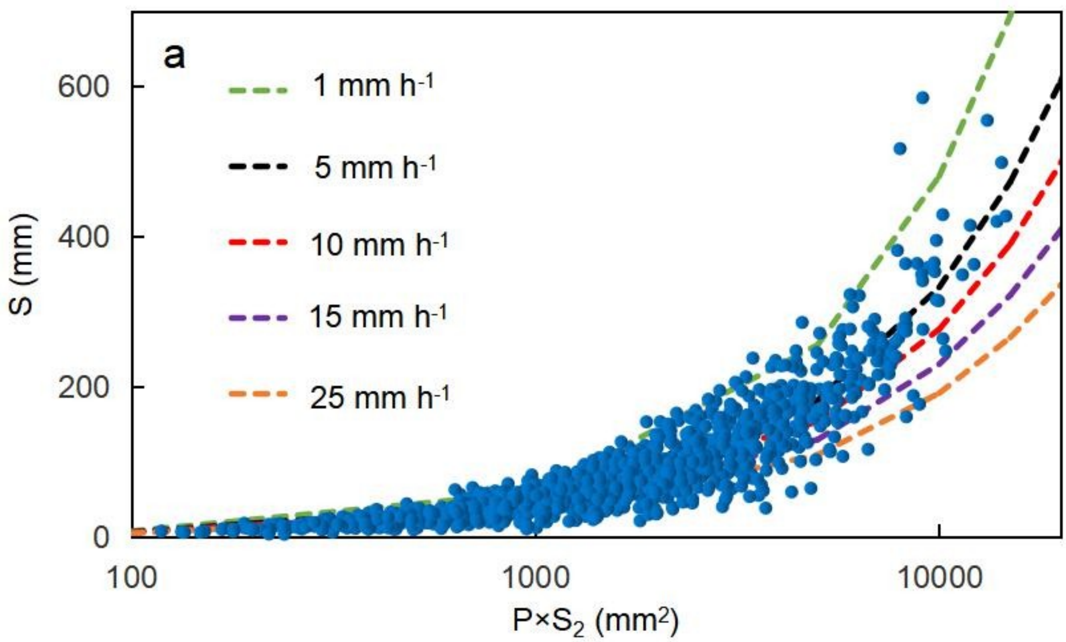


Fig. 5. The relationship between (a) rainfall (*P*) and CN value for the ordered rainfall and runoff pairs and (b) rainfall (*P*) and observed CN value for a total of 1479 rainfall events.



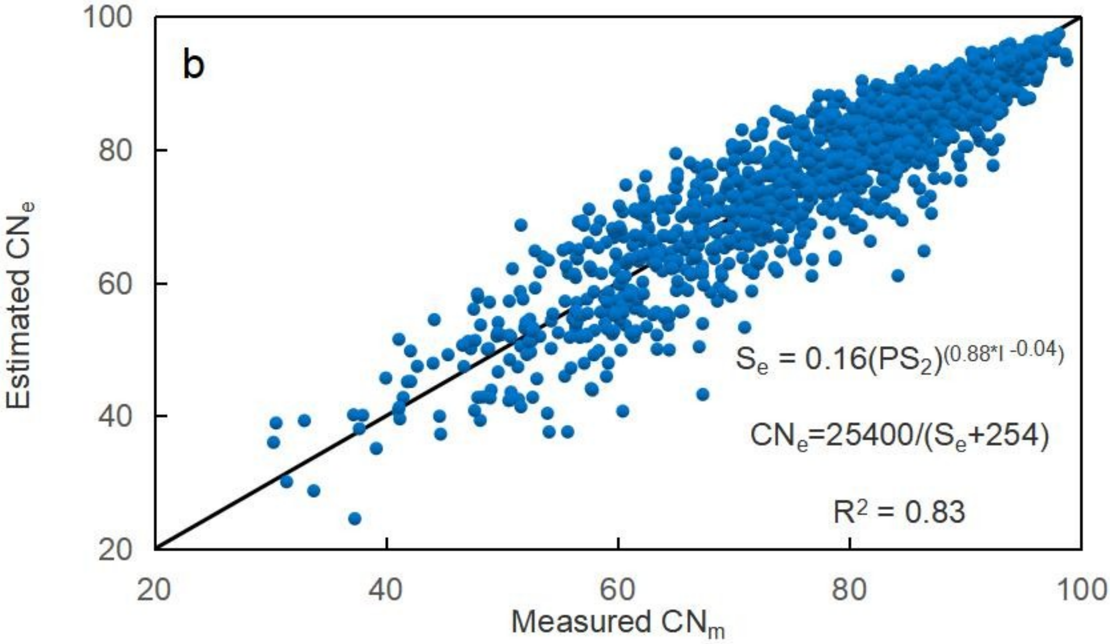
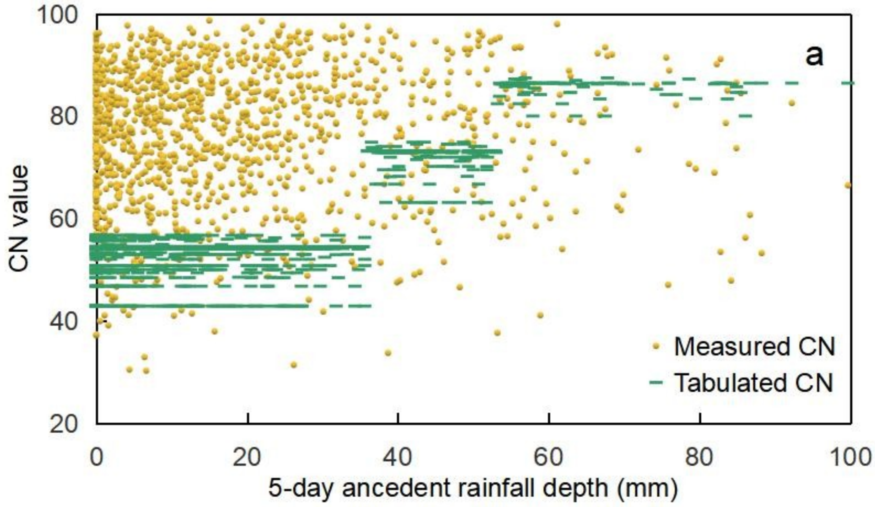


Fig. 6. The relationship between (a) the product of rainfall (*P*) and average potential maximum retention (S_2) and measured potential maximum retention (*S*), and (b) measured versus estimated CN values under different rainfall intensities for a total of 1479 rainfall events. S_e and CN_e denote the calculated *S* and *CN* values, respectively.



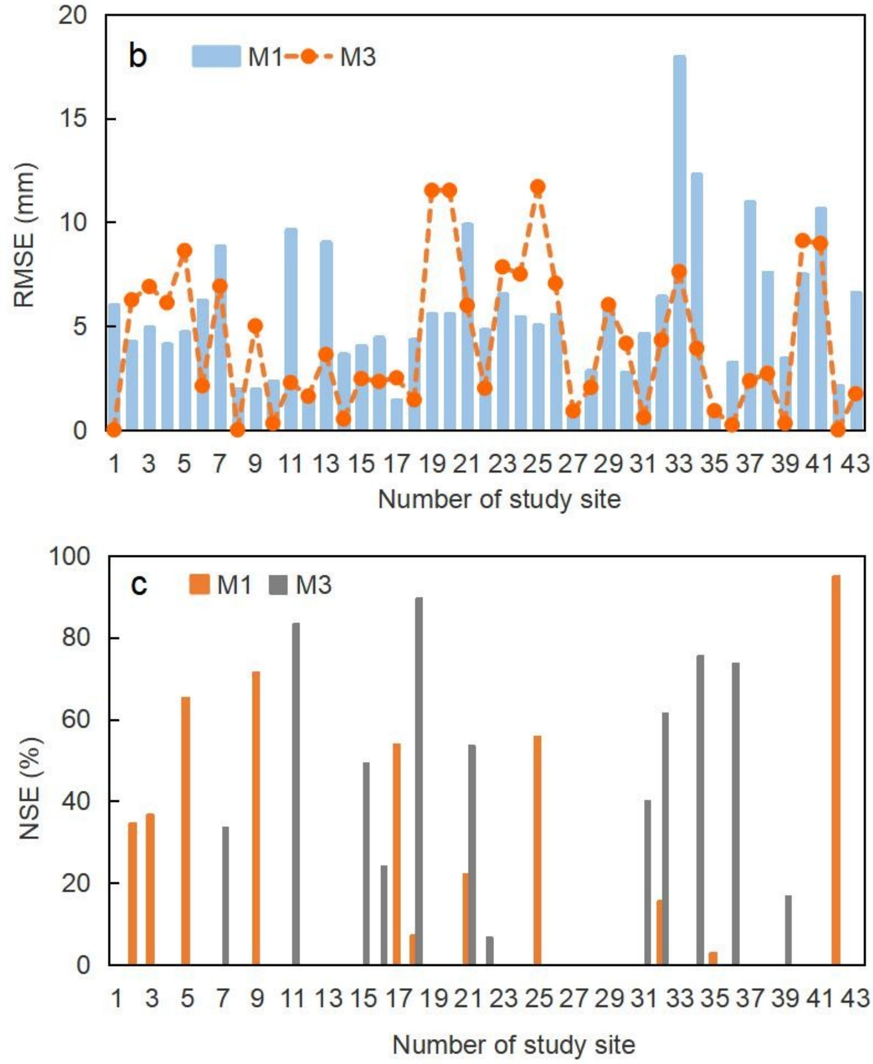


Fig. 7. (a) Measured and tabulated CNs versus 5-day AMC and comparison of the SCS-CN method with (M3) and without 5-day AMC (M1) using the (b) root mean square error (*RMSE*) and (c) Nash–Sutcliffe efficiency (*NSE*)

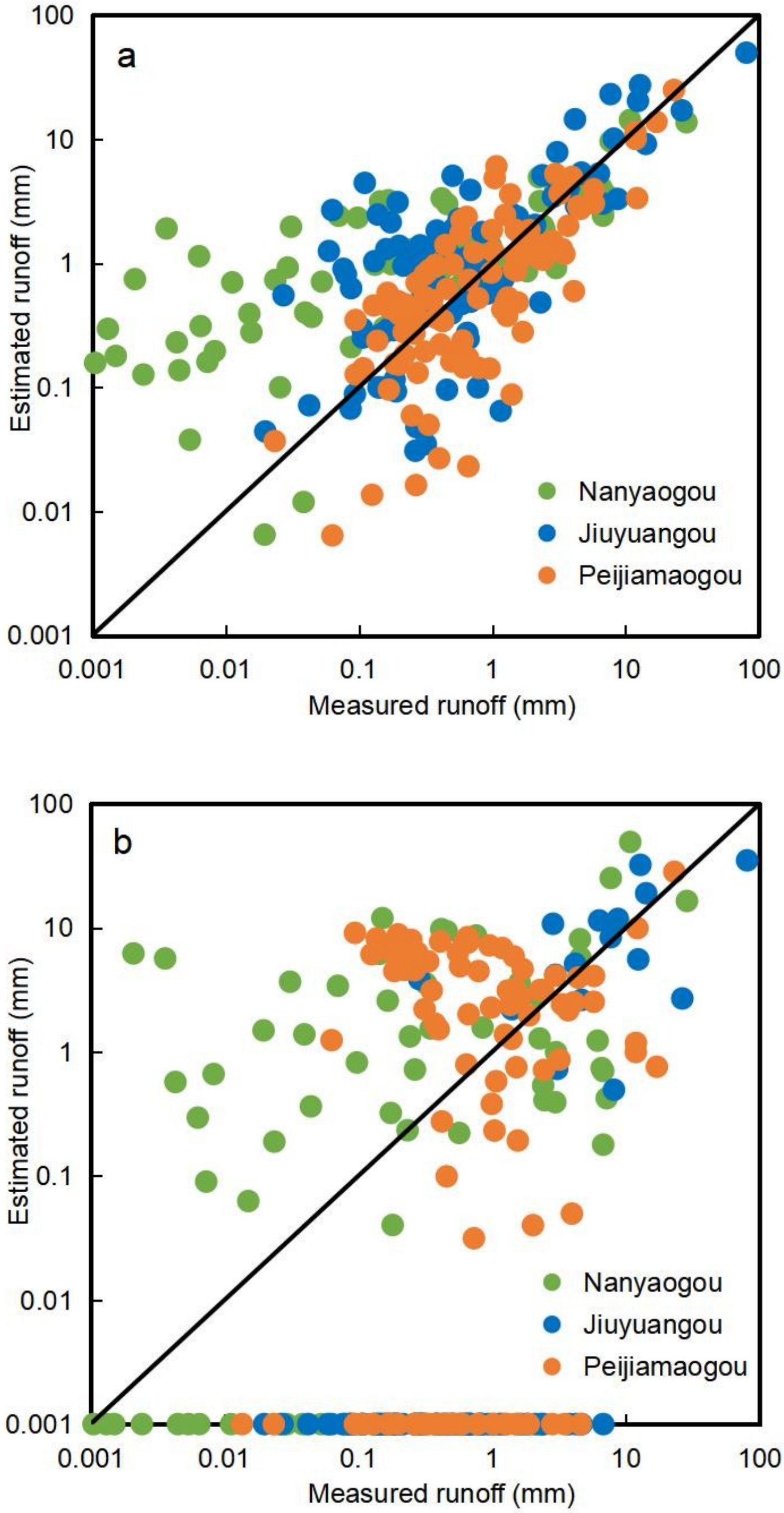


Fig. 8. Measured versus estimated runoff depths for (a) the proposed method and (b) the original SCS-CN method in the three tested watersheds.

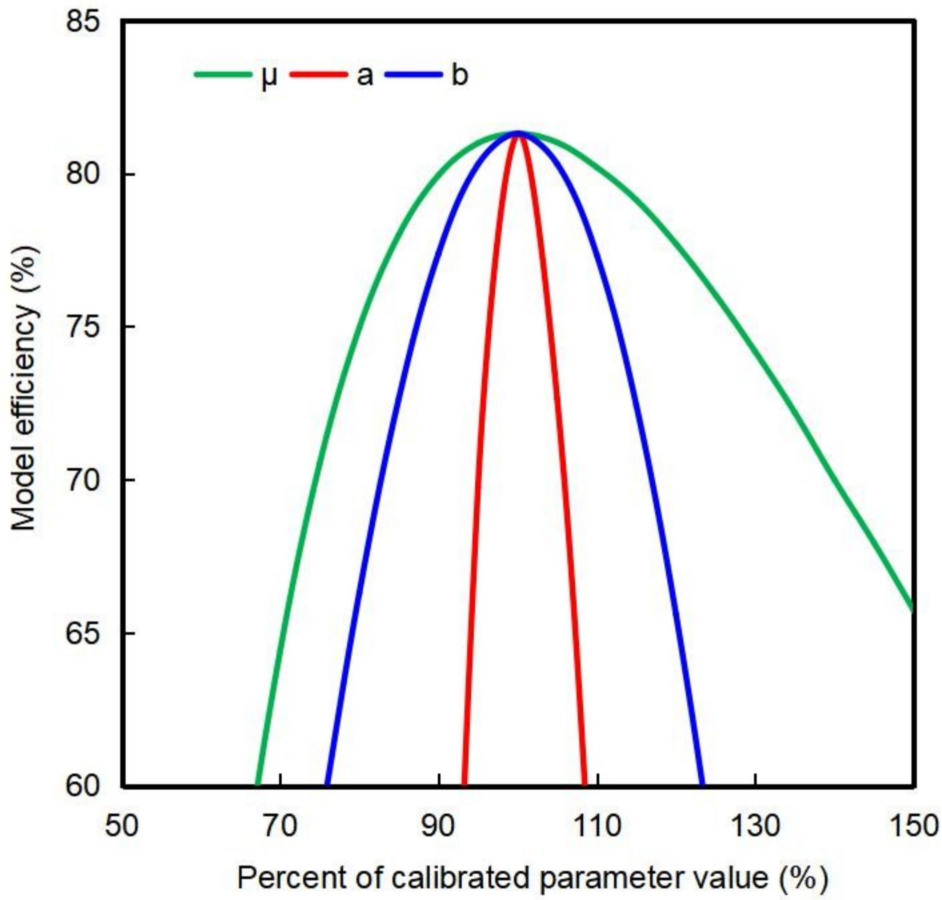


Fig. 9. Sensitivity analysis of the three proposed model parameters.