The Seybold Report
ISSN 1533-9211
DOI: 10.5281/zenodo.10276725

REASSESSMENT OF SCS-CN INITIAL ABSTRACTION RATIO BASED ON RAINFALL-RUNOFF EVENT ANALYSIS AND SLOPE-ADJUSTED CN IN A SEMIARID CLIMATE OF HALABJA GOVERNORATE

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Abstract

In the SCS-CN model, the initial abstraction ratio (λ) is fixed and assumed to be equal to 0.2, but it was revealed that the estimation of runoff is very sensitive to changes in this ratio and is regionally specific. As there are limited investigations on this ratio, the current study was initiated with the main objective of improving the performance of this model by adjusting λ and making adjustments for the curve number (CN). To target the above objective, the database was collected from three watersheds situated to the northeast of Iraq within Halabja governorate. The study included analyzing rainfall and actual runoff data, as well as describing the watersheds with reference to land cover and land use, hydrologic soil groups, and morphometric characteristics. Linear least squares and iterative (optimization) methods were used for adjusting the initial abstraction ratio with and without CN adjustment for slope. A host of performance indicators, along with leave-one-out cross-validation, were used for testing the performance of these methods. The results indicated that the analysis of individual rainfall indicated that λ varied from event to event, and more than 92% of the values were below 0.2 in each watershed. The λ value tended to decrease insignificantly ($P < 0.05$) with an increase in rainfall depth. The correlation analysis also revealed that most land use type and watershed characteristics were positively correlated withλ. CN adjustment led to a reduction in mean absolute error in the range of 5–11% upon applying the traditional SCS-CN method to estimate runoff. It was also noticed that reassessment of λ by using least squares and optimization techniques offered a more accurate estimation before CN adjustment compared with reevaluation after CN adjustment. The least squares and optimization techniques provided close results, but the latter outperformed the least squares and traditional methods on a watershed scale. The mean absolute percentage error of rainfall estimation dropped from 80% under the traditional SCS-CN method to 51% due to the reassessment of λ by the optimization technique.

Keywords: SCS-method, runoff estimation, reassessment of initial abstraction ratio, CN adjustment for slope, Halabja.

1. INTRODUCTION

Precipitation is the key component of the hydrologic cycle and is the main source of runoff (Beven, 2001).The determination of runoff produced from rainfall is one of the key factors in the analysis of hydrologic problems and in the management of water resources (Dalavi et al., 2018). Runoff assessment in a given catchment is a prerequisite for the design of soil erosion control measures, hydraulic structures, and reservoir operation (Tiwari et al., 2014). Among the most commonly used methods for estimating runoff from individual storms are the Soil Conservation Service, Justin, Lacy, the Indian Council of Agricultural Research, and the World

ISSN 1533-9211
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Meteorological Organization (Khosravi et al., 2013). A new name, Natural Resources Conservation Services (NRCS) was given to the SCS-CN in 1994 (Alagha et al., 2016). One of the demerits of this method is that a host of factors like land use, surface condition, soil type, etc. are represented by a single factor (Ibrahim et al., 2022).

The approval of the SCS-CN method is attributable to its simplicity, appropriateness, widespread acceptance, and application to ungauged catchments, besides the need for only the CN parameter (Bhuyan et al., 2003). On the other hand, this method does not consider the effect of land slope. Further, it has some other limitations, such as discounting the storm duration and a lack of guidance on moisture conditions prior to the storm event (Babu, 2012). (Soulis et al., 2009) reported that the estimated runoff is imprecise where catchment retention is a big fraction of precipitation, as in semiarid catchments situated in the southeastern part of Arizona.

Many researchers reassessed the l-value due to ambiguity (Baltas et al., 2007b; Hawkins et al., 2002; Jiang, 2001; Woodward et al., 2003). For instance, (Woodward et al., 2003) concluded from rainfall and runoff analysis for more than 300 catchments located in different parts of the USA that the initial abstraction ratio gave accurate results for a value of $\lambda = 0.05$. Furthermore, it was noticed that the initial abstraction ratio varies from storm to storm and from catchment to catchment (Jiang, 2001).(Liu et al., 2021) revealed that the standard initial abstraction ratio is the most ambiguous assumption and requires dedicated adjustments in runoff prediction. (Fu et al., 2011) indicated that the standard SCS-CN method (with a constant value of $\lambda= 0.2$) offered poor performance in runoff estimation. (Baltas et al., 2007a) observed that the λ-values were 0.014 and 0.037 for a whole watershed and a sub-watershed, respectively. (Gao et al., 2012) highlighted that an initial abstraction ratio of 0.05 offered the best model performance. (Ponce & Hawkins, 1996) elucidated that the initial abstraction ratio is mainly climatic condition-dependent and should be regarded as a regional factor.

(Plummer & Woodward, 1998) revealed that imprecision in direct-runoff modeling is mostly linked with the initial abstraction. Originally, an initial value of 0.2 was suggested forλ, but it was objected to by many researchers (USDA-SCS, 1972). (Fan et al., 2013) demonstrated that many studies based on multifactor analysis indicated that the λ values were related to rainfall storms and landscape features. (Krajewski et al., 2020) reported that the value of the initial abstraction ratio is storm event-dependent and much lower than 0.20. It varied from 0.002 to 0.18 for urbanized areas, while it varied from 0.001 to 0.512 for agroforested catchments. In a recent study by (Kohnová et al., 2020) a regionally based approach was proposed and assessed for estimating curve number (CN) values along with different initial abstraction ratio (λ) values. The optimal value of λ was determined to be 0.15 based on their analysis. On the other hand, (Satheeshkumar et al., 2017) indicated that this parameter should be considered a regional parameter reflecting geographical variability. Numerous researchers (Lal et al., 2015; Shi et al., 2009; Woodward et al., 2003) demonstrated that using reduced l gave rise to much more accurate results. With an increase in slope, each of the initial abstraction, infiltration, and overland recession times tends to decrease. This will give rise to a smaller opportunity for infiltration and more chances of runoff as compared with a catchment on a lower slope (Shi & Wang, 2020). Additionally, they demonstrated that the CN values in the USDA-NRCS

ISSN 1533-9211
DOI: 10.5281/zenodo.10276725

handbook table are derived from lands with a 5% slope. Therefore, the CN should be modified and adjusted according to the actual slope. Many researchers have studied the effect of slope on CN. For instance, (Sharpley & Williams, 1990) adjusted the CN based on the slope factors. (Huang et al., 2006) derived an equation for adjusting CN based on collected data from experimental plots with slopes in the range of 14% to 140%.

The tabulated CN values have been used to estimate runoff from many catchments in the area under investigation by several researchers, but the power of prediction of the SCS-CN model was not examined from the analysis of measured rainfall and runoff. Further, the effect of slope correction was not studied on the performance of the SCS-CN method. Accordingly, the current study was initiated to target the following objectives: 1) to improve the predictability of the SCS-CN to estimate runoff through adjusting or reassessing the initial abstraction ratio; and 2) to study the effect of incorporating land slope into the estimate of CN on the performance of the SCS-CN empirical model.

2. MATERIALS AND METHODS

2.1. Description of Study area

The database for this study was obtained from three small watersheds located in the Halabja governorate in the northeast of Iraq, namely, Darashish (WS1), Gulp (WS2), and Xargillan (WS3). Fig. 1 shows the location map of the study area after delineating the watersheds. The covered areas of these watersheds are 20.30, 37.76, and 13.85 km2, respectively. Administratively, they are in Halabja governorate and situated about 78 km from Sulaimani city. They lie between parallels of 35º 10′ N and 35º 20′ N and meridians of 46º 00′ E and 46º 10′ E. As a whole, the elevation ranges from a minimum of 656 m to a maximum of 2522 m amsl, with average slopes of 40%, 46%, and 22% for the WS1, WS2, and WS3 watersheds, respectively. The lengths of the main channels are estimated at 7.884 km for WS1, 5.102 km for WS2, and 4.22 km for WS3 (Table 1). Based on the elongation ratio and according to the scheme proposed by Stahler (1964), all the study watersheds fall into the elongated class ($0.50 < Re < 0.70$). Furthermore, the drainage system in the watershed is dendritic. The mean bifurcations are 1.739, 1.830, and 1.664 for the WS1, WS2, and WS3 watersheds, respectively, indicating that the extent of branching is not high.

ISSN 1533-9211
DOI: 10.5281/zenodo.10276725

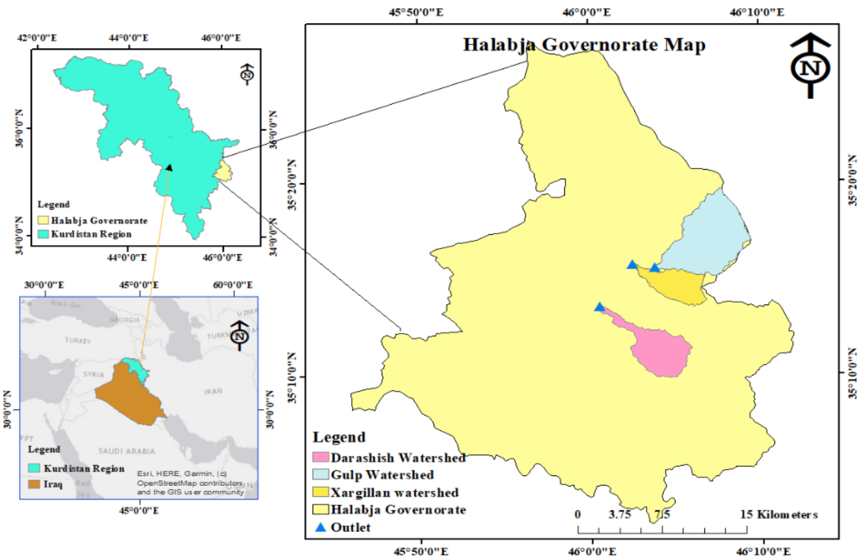

Fig 1: Location map showing the distribution of the study watersheds within the administrative borders of Halabja governorate

Table1: Some selected characteristics of the watersheds under study

Variable	Symbol	Unit	Average values		
			WS1	WS2	WS3
Area	A	km^2	20.30	37.76	13.85
Perimeter	Pe	km	21.36	28.63	19.37
The maximum basin length (axial length)	L_b	km	7.27	9.195	7.36
Length of the main channel	L_c	km	7.885	5.103	4.220
Minimum elevation	E_{min}	m	753	726	656
Maximum elevation	E_{max}	m	1761	2522	1507
Basin relief	ΔH	m	1008	1796	851
Bifurcation ratio	Rb	(-)	1.739	1.830	1.664
Slope	S	%	39.967	45.909	21.570
Elongation ratio	Re	(-)	0.534	0.752	0.571
Circularity ratio	Rc	(-)	0.559	0.579	0.464
Drainage density	Dd	Km^{-1}	2.238	2.617	2.688

According to the classification scheme proposed by Koppen, all three watersheds fall within the **Csa** class. This type of climate prevails in the countries surrounding the Mediterranean Sea and implies that the summer season is hot and dry, while the winter season is normal. Based on rainfall historical data for a time span of 23 years (2001–2023) recorded at Halabja meteorological station, the average annual rainfall for the study area is estimated at 623.6 mm, occurring mainly between October and May. There is also snowfall at the high elevations of the watershed, and the mountains remain covered with snow for about three to four months, from mid-December to mid-April. The land cover, or land use, is composed mainly of grazing lands (more than 50%), followed by croplands and orchards. The dominant soil hydrologic group is B, followed by C and D, and group A is absent. Table 2 exhibits the area occupied by

The Seybold REPORT
ISSN 1533-9211
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different land uses and by different soil hydrologic groups. Fig. 2 displays the maps for each drainage pattern, land use, distribution of different soil hydrologic groups, and curve number over the study watersheds.

Table 2: Land use, hydrologic soil group, area fraction and tabulated curve number values for the watersheds under study

Land Cover/Land Use	Hydrologic Soil Group	Tabulated CN	WS1		WS2		WS3	
			Area (Km^2)	Percent of the total area	Area (Km^2)	Percent of the total area	Area (Km^2)	Percent of the total area
Orchard	*B	65	0.760	3.74	3.719	9.85	3.685	3.73
Bare soil	B	86	0.065	0.32	0.183	0.48	0.420	1.19
Grassland	B	79	17.55	86.46	21.620	57.26	20.402	48.50
Urban	B	85	0.043	0.21	0.062	0.16	0.191	0.62
Cropland	B	71	0.071	0.35	2.513	6.66	0.622	19.19
Bare soil	**C	91	0.085	0.42	0.013	0.03	0.006	0.47
Grassland	C	86	0.744	3.67	0.511	1.35	0.317	0.86
Orchard	C	78	0.120	0.59	0.018	0.05	0.017	0.06
Cropland	C	78	0.843	4.15	1.265	3.35	0.895	25.06
Urban	C	90	0.013	0.06	0.007	0.02	0.005	0.32
Grassland	***D	89	-		7.558	20.02	-	
Bare soil	D	94	-		0.217	0.57	-	
Cropland	D	82	-		0.062	0.16	-	
Agriculture	D	81	-		0.009	0.02	-	

*B (Silt loam or Loam), **C (Sandy clay loam), ***D (Silty clay loam, Clay loam, Silty clay, Sandy clay OR Clay); (FAO Map Catalog, n.d.; Harmonized World Soil Database v1.2).

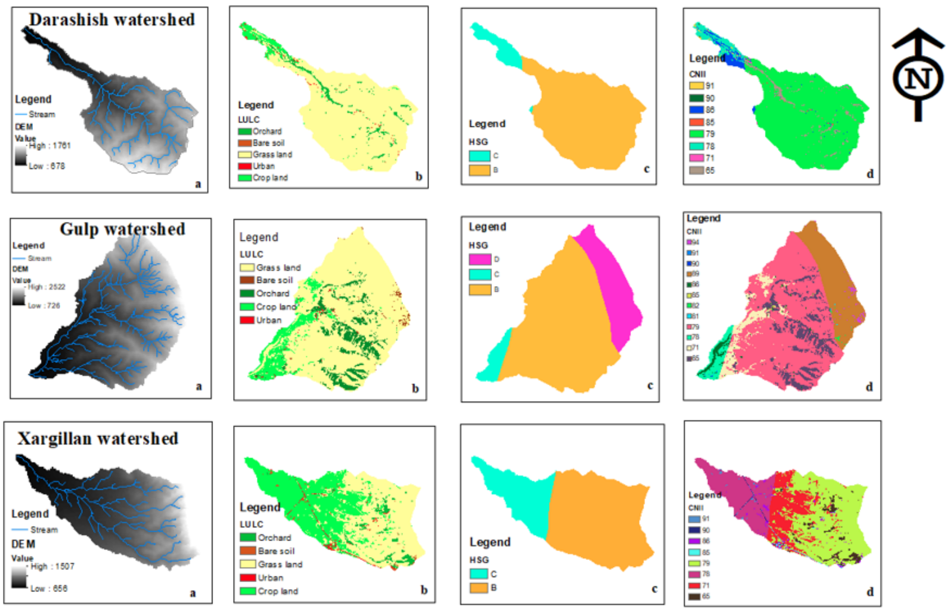

Fig 2: Drainage pattern (a), land use/ land cover (b), hydrologic soil group(c) and curve number (d) generated in GIS environment for the study area

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2.2. Determination of Weighted Curve Number of the Watersheds

The Global Land Cover dataset with a 10-meter resolution was utilized to develop the land use land cover (Venter et al., 2022). After combining land use and land cover with the FAO soil map at a scale of 1500.000 (Asia, 1992), specific tabulated CN values were assigned to different polygons. A weighted curve number was determined for each watershed by summing the product of the curve numbers and its fraction of the total area of the watershed, or:

$$\text{Weighted CN} = \frac{\text{CN}_1 \text{ x } \text{a}_1 + \text{CN}_2 \text{ x } \text{a}_2 + \ldots \text{CN}_\text{n} \text{ x } a_n}{a_1 + a_2 + \ldots + a_n} \quad [1]$$

Where: $a_1, a_2, \ldots a_n$ are the area of the polygons and CN_1, CN_2…and CN_n are the curve number of the polygons respectively

The obtained weighted curve number is for condition II. It was adjusted for other soil moisture conditions (I and III) according to (Mishra et al., 2008):

$$CN_I = \frac{\sum CN_{IIi}}{2.2754 - 0.012754\, CN_{II}} \quad [2]$$

$$CN_{III} = \frac{\sum CN_{IIi}}{0.430 + 0.0059\, CN_{II}} \quad [3]$$

2.3. Measurement of Direct Runoff

At the outlet of each watershed, a suitable section was selected and subdivided into vertical strips of equal width. The depth of flow was measured at the boundary of each strip with a graduated metal rod, while the water velocity for each strip was measured with a digital current meter or a floating body. The discharge of each strip was obtained by multiplying the strip area by the mean velocity of flow. The section discharge was obtained by summing up the discharge of the strips. This procedure was repeated at different time intervals during the runoff period. The total volume of runoff was obtained for each storm after plotting discharge versus time and determining the area under the plotted hydrograph. The runoff volume was converted to runoff depth in mm by dividing the runoff volume in cubic meters by the watershed area in square meters. A rating curve was also prepared for each watershed to measure the runoff from subsequent storms. (Table 3) presents the rainfall events that induced runoff in the period of the study, besides the pre-event conditions and measured runoff.

2.4. The Variability of Initial Abstraction Ratio from the Analysis of Individual Rainfall Events and Measured Runoff

A trial was also made to generate a database for studying the distribution of the initial abstract ratio (λ) and for making comparisons between the estimated values of λ with a constant value of 0.2, besides exploring the relationship between P andλ. This was done by solving the quadratic form of the SCS-CN formula (Eq. 5) and neglecting the negative value forλ.

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2.5. Selection of the Optimum Value for Initial Abstraction

2.5.1. Least Squares Method

The proposed equation for estimating runoff (Q) from precipitation (P) according to SCS-CN method is:

$$Q = \frac{(P - \lambda S)^2}{P + (1-\lambda)\, S} \qquad [4]$$

Where

λ: Initial abstraction ratio.

S: potential maximum retention (mm)

From rearrangement of equation [4], the following form can be obtained

$$S^2\lambda^2 - (2PS - QS)\lambda - (QP + QS - P^2) = 0 \qquad [5]$$

Putting $\lambda^2 = a^2$, $\lambda = a$, $S^2 = X_1$, $-(2PS - QS) = X_2$ and $QP + QS - P^2 = y$ leads to a multiple linear equation with two independent variables (x_1 and x_2) and a dependent variable (y) or

$$y = a^2 X_1 + a X_2 \qquad [6]$$

From measurements of actual runoff, recorded rainfall storms, and estimated S from the estimated weighted CN, a set of data for **X1, X2,** and **Y** can be obtained. The best fitting values for $\mathbf{a^2}$ and **a** can be determined using the principle of least squares. The parameter $\mathbf{a^2}$ should be the square of **a**. Sometimes small deviations were found and tackled by taking the average of **a** and $\mathbf{a^2}$ after taking the square root of $\mathbf{a^2}$.

2.5.2. Optimization Technique (Iteration Method)

This technique was in the form of an iterative procedure. Values between 0 and 1.0 with an interval of 0.01 were selected forλ. The best value for λ was the value that gave the minimum absolute error for estimated runoff values when compared with the measured runoff values.

2.6. Slope Adjusted Curve Number

The curve number was adjusted for slope according to the formula suggested by (Huang et al., 2006):

$$CN_2 adj = CN_2 \text{ x } K \qquad [7]$$

$$K = \frac{322.79 + 15.63\,\alpha}{\alpha + 323.52} \qquad [8]$$

Where CN_2 =the curve number under normal condition

CN2adj = the curve number under normal condition and corrected of slope

The above formula was suggested for slope adjustment for land slopes varying in the range of 14% to 140%.

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2.7. Efficiency Criteria for Assessing the Performance of the Models

Several statistical indices were used to evaluate the predictability of the applied models during this study. The employed indicators encompassed (Anees et al., 2016; Bozdogan, 1987; Mello et al., 2013):

$$1)\quad MBE=\frac{1}{N}\sum_{i=1}^{N}(O_i-P_i) \qquad [9]$$

$$2)\quad MAE=\frac{1}{N}\sum_{i=1}^{N}\left|O_i-P_i\right| \qquad [10]$$

$$3)\quad MAPE=\frac{1}{N}\sum_{i=1}^{N}\left|\frac{O_i \quad P_i}{O_i}\right| x100 \qquad [11]$$

$$4)\quad d=1-\frac{\sum_{i=1}^{N}\left(P_i-O_i\right)^2}{\sum_{i=1}^{N}\left(\left|O_i-\bar{O}\right|+\left|P_i-\bar{O}\right|\right)^2} \qquad [12]$$

$$5)\quad NSE=1-\frac{\sum_{i=1}^{n}\left(O_i-P_i\right)^2}{\sum_{i=1}^{n}\left(O_i-\bar{O}_i\right)^2} \qquad [13]$$

Where: N = number of data points, Oi= Observed values, P_i =predicted values, O^{-}= mean of observed values; MBE= mean biased error, MAE= mean absolute error, MAPE= mean absolute percentage error, d=Coefficient of Agreement and NSE= Nash-Sutcliffe efficiency.

2.8. Cross Validation

Leave-one-out cross-validation (LOOCV) (Chiles & Delfiner, 2012)was used to estimate the performance of the investigated models for assessing the initial abstraction ratio. According to this method, one sample was removed from the dataset as the test data, and the remaining samples were treated as the training set for building the model. This procedure was repeated **n** times, where **n** is the whole sample size. The mean square error was used as an indicator for determining the degree of disparity between the observed value and the predicted value from the test model.

3. RESULTS AND DISCUSSION

3.1. Distribution of Initial Abstraction Ratio

Before going into depth analysis, the variations of the initial abstraction ratio were studied for the individual rainfall events that produced runoff in the three watersheds by solving the quadratic form of the SCS-CN method. These procedures were implemented before and after

ISSN 1533-9211
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adjusting the curve number for slope steepness, and the results are displayed in (Table 3). It is apparent from Table 4 that this parameter is characterized by high variability. It ranged from as low as 0.004 to as high as 0.379 in WS1 before CN adjustment and from a minimum of 0.01 to 0.040 after CN adjustments for slope. In the watershed with code WS2, the computed value of the initial abstraction ratio varied from a minimum of 0.005 to a maximum of 0.375 before adjustment for slope and from 0.016 to 0.405 in WS2 after adjustment for slope. Additionally, it was observed that the value of this parameter varied from as low as 0.011 to as high as 0.360 in WS3 before CN adjustment for slope and from 0.013 to 0.372 in WS3 after adjustment. In a similar study by (Krajewski et al., 2020), it was noticed that the postulated λ values varied from season to season and from storm to storm, and most of them were below 0.2. The median values for these parameters were 0.083, 0.093, and 0.096 for the watersheds WS1, WS2, and WS3, respectively, without adjustment, and 0.097, 0.117, and 0.102 when the curve number was adjusted for slope. It is evident from these results that the adjustment gave rise to a slight increase in the median values of the initial abstraction ratio.

It can also be observed that more than 92% of the obtained values were less than 0.2, indicating that taking the initial abstraction ratio as a constant value of 0.2 will offer poor performance for runoff estimation in the watersheds under study (Shi et al., 2009).

Close inspection of the box whisker plots for the distribution of the initial abstraction ratio in Fig. 3 revealed that the WS3 watershed without adjustment for CN and WS2 after adjustment offered the shortest and longest boxes, respectively, indicating that the data obtained from WS3 with no adjustment has the smallest dispersion. The reverse may be true for the second case.

The fact that the median line is not located at the center of most of the boxes and the whiskers on the sides of a given box are not equal in length is indicative of a deviation of the initial abstraction ratio from a normal distribution. As the median line of the box for WS2 after adjustment is situated above the median lines of the other boxes, it reflects that this treatment offered the highest value for the average for λ in terms of median value.

Additionally, it can be observed from box plots that a single data point is located outside of each box fence. This means that these data are highly different from the remaining data, i.e., they are outliers.

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Table 3: Determination of initial abstraction ratio for the individual rainfall events with and without adjusted curve number for slope

Watershed	Storm No.	Rainfall depth (mm) P	Runoff depth (mm) Q	Antecedent Moisture condition	Without slope correction			With slope correction		
					CN	S	λ	CN	S	λ
WS1	1	24.80	3.26	I	62.09	155.06	0.004	63.88	143.64	0.010
	2	13.10	0.56	I	62.09	155.06	0.023	63.88	143.64	0.027
	3	16.30	1.39	II	78.75	68.54	0.085	79.99	63.53	0.097
	4	13.20	2.92	II	78.75	68.54	0.379	79.99	63.53	0.400
	5	17.80	1.63	II	78.75	68.54	0.093	79.99	63.53	0.107
	6	19.10	1.23	II	78.75	68.54	0.135	79.99	63.53	0.151
	7	34.60	5.48	II	78.75	68.54	0.179	79.99	63.53	0.205
	8	16.80	0.61	I	62.09	155.06	0.044	63.88	143.64	0.050
	9	17.60	1.00	I	62.09	155.06	0.030	63.88	143.64	0.036
	10	21.70	2.42	II	78.75	68.54	0.110	79.99	63.53	0.126
	11	34.60	4.23	I	62.09	155.06	0.044	63.88	143.64	0.054
	12	59.80	11.46	I	62.09	155.06	0.074	63.88	143.64	0.091
	13	48.70	6.70	I	62.09	155.06	0.083	63.88	143.64	0.098
WS2	1	25.20	3.39	I	62.73	150.93	0.005	65.55	133.49	0.016
	2	13.70	0.70	I	62.73	150.93	0.020	65.55	133.49	0.028
	3	18.10	1.43	II	79.29	66.33	0.115	80.76	60.52	0.133
	4	12.30	3.09	II	79.29	66.33	0.375	80.76	60.52	0.405
	5	18.40	1.78	II	79.29	66.33	0.100	80.76	60.52	0.117
	6	19.70	1.27	II	79.29	66.33	0.149	80.76	60.52	0.170
	7	36.50	5.71	II	79.29	66.33	0.211	80.76	60.52	0.245
	8	17.70	0.77	I	62.73	150.93	0.043	65.55	133.49	0.054
	9	18.00	1.04	I	62.73	150.93	0.033	65.55	133.49	0.043
	10	22.60	2.47	II	79.29	66.33	0.128	80.76	60.52	0.150
	11	35.40	4.53	I	62.73	150.93	0.046	65.55	133.49	0.063
	12	61.20	13.65	I	62.73	150.93	0.056	65.55	133.49	0.084
	13	51.20	7.32	I	62.73	150.93	0.093	65.55	133.49	0.120
WS3	1	26.10	3.01	I	59.72	171.30	0.011	60.52	165.71	0.013
	2	14.30	0.47	I	59.72	171.30	0.030	60.52	165.71	0.032
	3	18.60	1.38	II	76.96	76.02	0.101	77.54	73.57	0.106
	4	14.30	2.81	II	76.96	76.02	0.363	77.54	73.57	0.372
	5	19.20	1.58	II	76.96	76.02	0.098	77.54	73.57	0.103
	6	20.40	1.19	II	76.96	76.02	0.135	77.54	73.57	0.142
	7	36.10	5.70	II	76.96	76.02	0.161	77.54	73.57	0.171
	8	18.20	0.56	I	59.72	171.30	0.047	60.52	165.71	0.050
	9	19.30	0.95	I	59.72	171.30	0.035	60.52	165.71	0.038
	10	21.70	2.29	II	76.96	76.02	0.096	77.54	73.57	0.102
	11	37.60	4.38	I	59.72	171.30	0.046	60.52	165.71	0.051
	12	62.40	8.82	I	59.72	171.30	0.110	60.52	165.71	0.118
	13	50.30	6.57	I	59.72	171.30	0.078	60.52	165.71	0.084

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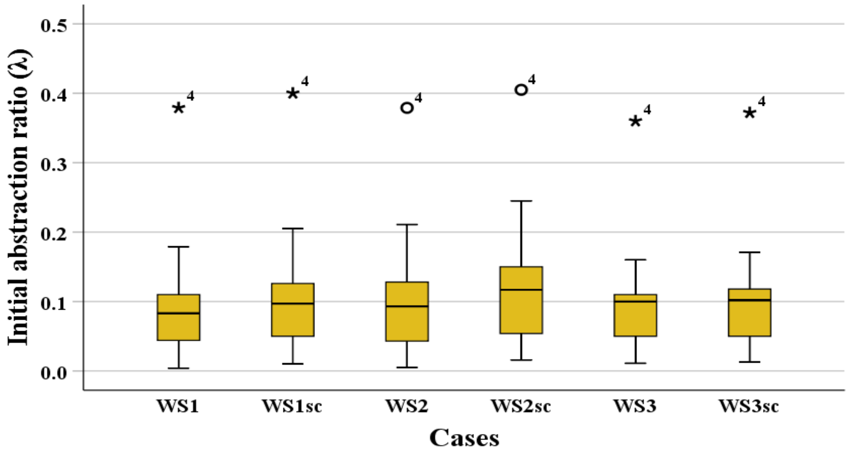

WS: Watershed without slope correct. WSsc: watershed with slope correct.

Fig 3: Box whisker plot showing the distribution of initial abstraction ratio obtained from the analysis of individual in rainfall storms before (WS) and after (WSsc) CN adjustment for slope

3.2. Relation of Initial Abstraction Ratio with Rainfall and Watershed Characteristics

3.2.1. Relation of Initial Abstraction Ratio with Rainfall

The analysis of correlation between λ and P showed that λ is negatively correlated with P in all watersheds before and after CN adjustment for slope. The results indicated also that Pearson's correlation coefficient (r) ranged from -0.111 in WS3 without adjustment to -0.188 in WS2 without adjustment (Table 4). Albeit the value of λ tended to decrease with an increase in rainfall depth, the decrease in λ was not significant at ($P \le 0.05$). The poor relationship between P and λ may due to increased water retention in the catchments due to the dominance of dense grasslands, the fractured nature of the geologic formations, and the low ratio of barren lands to the total area of the catchments. The finding of (Baltas et al., 2007b) from a watershed in Greece also revealed that the initial abstraction ratio was poorly related to rainfall depth, and most of the obtained values were close to 0.01. It is also obvious from the data in Table 5 that CN adjustment for slope has a minor effect on the values of (r) in the study watersheds.

Table 4: Relationship between rainfall and initial abstraction ratio obtained from individual rainfall -actual runoff analysis with and without CN adjustment for slope

Method	WS1	WS2	WS3
Traditional SCS-CN	-0.147	-0.188	-0.111
SCS-CN with CN adjusted Slope	-0.119	-0.135	-0.099

3.2.2. Relation of Initial abstraction ratio with Some Selected Watershed Characteristics

It can also be noticed from Table 5, with exceptions, that the initial abstract ratio was positively correlated with the factors that are in favor of abstraction, such as area covered by grassland (r = 0.69), crop land (r = 0.33), orchards (r = 0.93), and watershed characteristics like elongation

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ISSN 1533-9211

DOI: 10.5281/zenodo.10276725

ratio (r = 0.99). Conversely, it is also assumed to be negatively correlated with factors that encourage runoff, like urban areas (r = -0.08). Some factors deviated from this rule, like the watershed slope. This may be due to the limited size of the data used for correlation analysis. The reliability of these findings can be improved upon expanding the database by analyzing the data belonging to a reasonable number of watersheds with different land cover and land use and different morphometric characteristics.

Table 5: Correlation between initial abstraction ratio using optimization method with each of land use type and some selected watershed characteristics

CN adjusted for Slope	Type of land use					Watershed characteristics	
	Grassland	Urban	Bare land	Cropland	Orchard	Re	Slope
Without slope adjustment	0.692	-0.078	0.999	0.334	0.928	0.992	0.515
Raftering adjusting for slope	0.978	-0.623	0.817	-0.252	0.977	0.891	0.907

3.3. Improvement of Runoff estimation on Watershed Scale

3.3.1. Effect of Adjusted CN for Slope on Improving Runoff Estimation

For this study, the rainfall events that yielded runoff during the years 2021–2022 and 2022–2023 were considered. The effect of CN adjustment on the runoff estimation from the SCC-CN method was examined using five performance indicators, and the results of this analysis are displayed in Table 6. It is evident from Table 6 that adjusting CN for slope without reassessment for λ gave rise to a reasonable improvement in runoff estimation. For instance, CN adjustment in the traditional SCS-CN method resulted in a decrease in mean absolute error by 10, 11, and 5% in WS1, WS2, and WS3, respectively. Additionally, CN adjustment led to a higher coefficient of agreement and a higher Nash-Sutcliffe efficiency compared with the traditional SCS-CN method without CN adjustment. This result is in concordance with the finding of (Ajmal et al., 2020), who observed that slope-adjusted CN gave rise to a lower root RMSE and a larger NSE during the estimation of runoff from watersheds situated on the peninsula of Korea. With an increase in land slope, both infiltration and initial abstraction decrease and, consequently, give rise to a smaller chance for infiltration and higher runoff compared with a nearly level surface(Shi et al., 2023).

3.3.2. Effect of Reassessment of initial abstraction Ratio on Improving Runoff Estimation without Adjustment for CN

It can also be noticed from Table 6 that the MAE value dropped from 2.318 under the traditional SCS-CN method to 1.335 under the least square method and to 1.047 under the optimization method in WS1 due to the reassessment ofλ, but without CN adjustment. Similar drops can be observed under WS2 and WS3. Similarly, significant drops in RMSE and MBE can be observed upon reevaluation of λ only. Furthermore, it can be observed that the mean absolute percent error (MAPE) in WS1 dropped from 81% under SCS-CN to 52% under the least square method and to 49% under the optimization method. Nearly similar drops can be observed in WS2 and WS2. On the other hand, the results indicated that NSE increased from 0.362 under the SCS-CN method to 0.804 under the least square method and to 0.862 under the optimization method

ISSN 1533-9211
DOI: 10.5281/zenodo.10276725

in WS1. Similarly, WS2 and WS3 exhibited the same behavior. Like NSE, the coefficient of agreement (d) increased significantly upon reevaluation of λ without slope adjustment. For instance, in WS1, the (d) values were 0.669, 0.940, and 0.967 upon applying traditional SCS-CN, least squares, and optimization methods, respectively.

Table 6: Test of performance of different methods for estimating runoff in the investigated watersheds after reassessing the initial abstraction ratio with and without adjusted CN for slope

Watershed	Case	Reevaluation Method	λ	Performance Indicators					
				MBE	MAE	RMSE	MAPE	NSE	d
WS1	Without adjustment for slope	SCS-method	0.2	-2.318	2.318	3.011	81.207	0.362	0.669
		Least Square method	0.114	-0.961	1.335	1.667	52.417	0.804	0.94
		Optimization method (Iteration Method)	0.08	-0.218	1.047	1.4	49.063	0.862	0.967
	With adjustment for slope	SCS-method	0.2	-2.068	2.088	2.713	75.533	0.482	0.764
		Least Square method	0.13	-0.975	1.371	1.703	55.161	0.796	0.939
		Optimization method (Iteration Method)	0.098	-0.292	1.07	1.462	50.097	0.85	0.963
WS2	Without adjustment for slope	SCS-method	0.2	-2.36	2.408	3.284	76.361	0.42	0.709
		Least Square method	0.111	-0.844	1.504	1.932	53.658	0.799	0.94
		Optimization method (Iteration Method)	0.09	-0.362	1.388	1.762	55.353	0.833	0.956
	With adjustment for slope	SCS-method	0.2	-1.938	2.137	2.767	69.719	0.588	0.829
		Least Square method	0.139	-0.921	1.519	1.951	54.701	0.795	0.939
		Optimization method (Iteration Method)	0.118	-0.467	1.371	1.789	54.346	0.828	0.955
WS3	Without adjustment for slope	SCS-method	0.2	-2.206	2.206	2.726	83.121	0.311	0.648
		Least Square method	0.129	-1.141	1.32	1.668	56.616	0.742	0.918
		Optimization method (Iteration Method)	0.1	-0.537	1.054	1.374	48.86	0.825	0.956
	With adjustment for slope	SCS-method	0.2	-2.106	2.106	2.608	80.601	0.369	0.696
		Least Square method	0.136	-1.135	1.326	1.676	56.844	0.739	0.918
		Optimization method (Iteration Method)	0.103	-0.46	1.066	1.386	49.049	0.822	0.957

ISSN 1533-9211
DOI: 10.5281/zenodo.10276725

3.3.3. Effect of the combined effect of Slope-Adjusted CN and Initial Abstraction Ratio Reassessment in SCS-CN-Method

The results displayed in Table 6 also revealed that performing CN adjustment and reevaluating of λ together brought significant changes in performance indicators compared with traditional SCS-CN method. As can be seen in Table 6, no significant improvement was obtained in runoff estimation upon reevaluation of λ after doing adjustment of CN. The slight increase in MBE, MAE and RMSE and a slight decrease in NSE and d were not expected.

3.4. Comparison of the Study Methods for Estimating Runoff

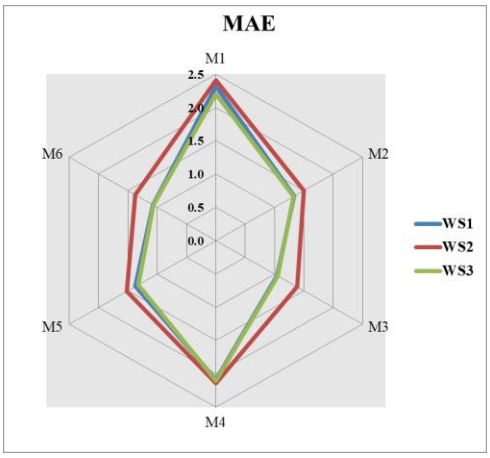
It is also obvious from Table 6 that the optimization method exhibited the lowest value for λ compared to other methods in all the study watersheds. In the meantime, the results displayed in Table 6 or in Fig. 4 indicated that the optimization method without CN adjustment for slope offered the highest precision in estimating runoff compared to other methods, followed by the least square method.

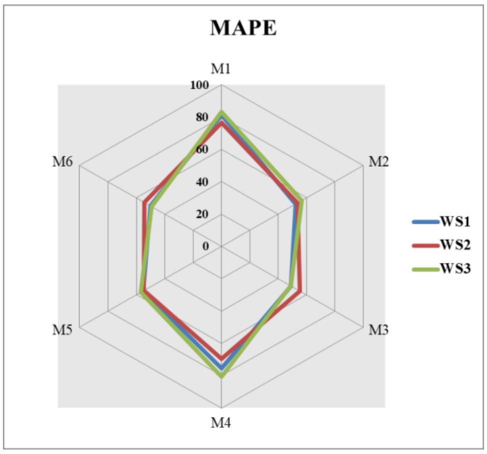
The lowest MAE (or RMSE or MBE) and the highest NSE (or d) were recorded under the optimization technique before adjustment in WS1, while the opposite of these results was noticed under traditional SCS-CN.

The percentage of mean absolute percent error (MAPE) for the optimization technique without adjustment for slope was 49%, 55%, and 49% in WS1, WS2, and WS3, respectively. On the other hand, the values of this indicator for the same watersheds were 81.2%, 76.3%, and 83.1% when the traditional SCS-CN method was used.

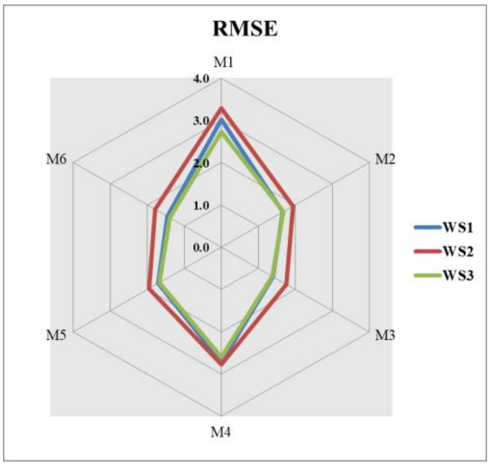
Overall, these three methods can be ranked in the three watersheds with and without adjustment in terms of preference or precession as follows:

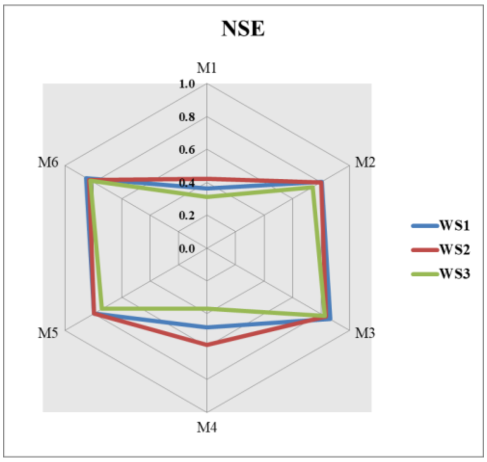
Optimization > Least Square > Traditional SCS-CN in all the watersheds and Traditional SCS-CN with adjusted CN > Traditional SCS-CN without CN adjustment for slope





ISSN 1533-9211
DOI: 10.5281/zenodo.10276725





M1: SCS-method without slope correction. **M2**: Least square method without slope correction. **M3**: Optimization Technique (Iteration Method) without slope correction. **M4**: SCS-method with slope correction. **M5**: Least square method with slope correction. **M6**: Optimization Technique (Iteration Method) with slope correction

Fig 4: Radar chart showing the performance indicators for evaluating the predictability of the methods for estimating runoff with and without CN adjustment for slope in the study watersheds

The leave-one-out cross validation as an additional test to examine the reliability of the prediction of the optimization technique indicated the mean square error is less than 2.5 in most cases and optimized λ is in the range of 0.079 to 0.117 (Table 7).

It is interesting to note that reassessment of λ by using least squares and optimization methods offered a more accurate estimation before CN adjustment compared with reassessment after CN adjustment. On the other hand, it is noteworthy to state that although the optimization method outperformed the least squares method, the results of these methods were close together. The overall results from this study also indicated that the method or case that offered the lowest value for λ resulted in a better fit between the measured and estimated runoff. This result supports the finding of (Mishra et al., 2004), who observed that as initial abstraction ratio decreases, predictability power increases.

Table 7: Summary of cross validation for the optimization method for estimating runoff following Leave-one-out cross validation technique

Watershed	Correction	Optimum λ	MSE
WS1	With slope correction	0.096	2.171
	Without slope correction	0.079	2.204
WS2	With slope correction	0.117	3.533
	Without slope correction	0.087	4.435
WS3	With slope correction	0.110	2.462
	Without slope correction	0.097	2.232

ISSN 1533-9211
DOI: 10.5281/zenodo.10276725

4. CONCLUSIONS

Flexibility in the initial abstraction ratio (λ) rather than taking a constant value of 0.20 led to an improvement in the estimation of runoff from watersheds in the area under study. With one exception, individual rainfall analyses offered values for (λ) below 0.2 in each watershed. The optimization method followed by least squares methods is a suitable method for reevaluating (λ) in the area under study. The parameter (λ) was negatively and insignificantly correlated with rainfall depth. Furthermore, CN adjustment alone in the traditional SCS-CN gave rise to a moderate improvement in rainfall estimation, but it did not cause further improvement in runoff prediction when (λ) revaluation was carried out after adjusting CN for slope.

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