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New Method of Curve Number Derivation with Inferential Statistics

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ABSTRACT

The selection of curve number to represent watersheds with similar land use and land cover is often subjective and ambiguous. Watershed with several soil groups further complicates curve number selection process while wrong curve number selection often produces unrealistic runoff estimates. The 1954 simplified Soil Conservation Services (SCS) runoff model over-predicted runoff with significant amount and further magnified runoff prediction error toward higher rainfall depths in this study. The model was statistically insignificant with the rejection of two null hypotheses and paved the way for regional model calibration study. This paper proposes a new direct curve number derivation technique from the given rainfall-runoff conditions under the guide of inferential statistics. The technique offers a swift and economical solution to improve the runoff prediction ability of the SCS runoff model with statistically significant results. A new rainfall-runoff model was developed with calibration according to the regional hydrological conditions. It out-performed the runoff prediction of the simplified SCS runoff model and the asymptotic runoff model. The derived curve number = 89 at alpha = 0.01 level. The technique can be adopted to predict flash flood and forecast urban runoff.

Keywords: Bootstrapping, CN, non-parametric inferential statistics, runoff prediction, SCS

INTRODUCTION

In Malaysia, surface runoff contributed about 97% of total water demand (Department of Irrigation and Drainage (DID), 2000). As a result of rapid urban development and growing anthropogenic activities, frequency of flooding in downstream urban watersheds have increased significantly (Adams & Papa,

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2000). Therefore, a thorough understanding of the rainfall-runoff processes is crucial for the planning and management of water resources (Chan, 2005).

In 1954, the United States Department of Agriculture (USDA) Soil Conservation Services (SCS) proposed a rainfall-runoff prediction model. It even led to the derivation and development of curve number (CN) methodology. Since its inception, the model was incorporated into many official hydro design manuals worldwide and was also adopted by Malaysian agencies. Nevertheless, the major limitation of the model is its inability to predict runoff results accurately where researchers reported inconsistent runoff prediction results throughout the world and casted doubt on the validity of the model (Sharpley & Williams, 1990; Hawkins & Khojeini, 2000; Hawkins et al., 2002; Baltas et al., 2007; Elhakeem & Papanicolaou, 2009; Shi et al., 2009; Shumei & Tingwu, 2011; D'Asaro & Grillone, 2012; Ling & Yusop, 2013; D'Asaro et al., 2014; Yuan et al., 2014). According to the National Engineering Handbook (NEH-4) Soil Conservation Services, Curve Number (SCS-CN) is one of the most popular methods to compute the volume of direct surface runoff amount from a rainfall event (USDA-SCS, 1964, 1972). It is also most frequently used to estimate direct runoff from un-gaged areas. The SCS defined CN as a function of maximum potential retention (S) of a watershed which can also be implied as the water storage ability of different land cover conditions. Tabulated SCS-CN value ranged from 0 to 100 to represent a watershed with infinite infiltration to fully impermeable respectively. In general, observed CN values range from 40 to 98 but forested watersheds may have lower CN values (Van Mullem et al., 2002). The SCS Technical Release 55 (TR-55) tabulated discrete site conditions classification to demarcate CN selection. Forested watersheds faced the utmost challenge in terms of appropriate CN classification and faced huge risk of potential misclassification (Hawkins, 1984) while wrong CN selection often produces unrealistic runoff estimates (Cazier & Hawkins, 1984; Hawkins, 1993).

A common approach for SCS practitioners was to perform "trial and error" CN tweaking with observed data in order to improve the runoff prediction results. However, such practice lacks statistical justification. The practice might produce CN value for a watershed but the "calibrated" CN value might not be able to even represent the same land use and land cover condition again in other watersheds. The CN variation affects direct runoff estimates more than rainfall variability. Several researches concluded CN as a random variable between storm events and varied based on the antecedent runoff condition (ARC) of storm events (Hjelmfelt, 1991; Van Mullem et al., 2002). In situ measurement of site CN becomes difficult while watershed with several soil groups further complicates CN selection process. SCS-CN method almost offers no guidance to account for runoff generation under dry and wet conditions. The SCS practitioners often adopt the model for the sake of its simplicity and rarely explore site specific calibration possibility leading to inconsistent or poor runoff estimate results (Ponce & Hawkins, 1996).

The selection of CN to represent a watershed often becomes subjective, ambiguous and even inconsistent to represent similar land cover area (Hawkins, 1984). As such, there is an imminent need for hydrologists and modellers to improve the modelling approach. The CN values should be determined from rainfall-runoff (*P*-*Q*) dataset in order to reflect the realistic local situations (Hjelmfelt, 1980; Hawkins, 1993; Hawkins & Ward, 1998; Soulis et al., 2009; Soulis & Valiantzas, 2013). In literature, various methods for CN determination from observed *P-Q* data have been reported. The most common and widely used are least-squares method (LSM) (Hawkins et al., 2002) and asymptotic fitting method (AFM) (Hawkins, 1993; Hawkins et al., 2009). This article presents the new approach to derive regional specific CN directly from *P-Q* dataset with the guide from inferential statistics. The base SCS model was proposed in 1954 as below:

$$Q = \frac{(P - I_a)^2}{P - I_a + S} \quad [1]$$

Q = Runoff amount (mm)
P = Rainfall depth (mm)
I_a = the initial abstraction (mm)
S = maximum potential water retention of a watershed (mm)

The initial abstraction is also known as the initial rainfall retention prior to the initiation of runoff process. The SCS also hypothesised that $I_a = \lambda S = 0.20S$. The value of 0.20 was proposed as a constant and referred to as the initial abstraction coefficient ratio (λ) which is a correlation parameter between I_a and S. The substitution of $I_a = 0.20S$ simplifies Eq. [1] into a common and widely adopted simplified SCS runoff prediction model listed below:

$$Q = \frac{(P - 0.2S)^2}{P + 0.8S} \quad [2]$$

Eq. [2] is subjected to a constraint that $P > 0.2S$, else $Q = 0$. However, the increasing evidential study results are leaning against the prediction accuracy of Eq. [2] and the hypothesis that $I_a = 0.20S$. This study performed regional hydrological conditions calibration according to the given *P-Q* dataset instead of blindly adopting Eq. [2]. The proposed CN derivation methodology utilised supervised numerical optimisation algorithm guided by inferential statistics to derive λ and S value for the formulation of a new rainfall-runoff model based on Eq. [1].

METHOD

The present authors are unaware of any previous attempts to perform regional hydrological characteristics calibration with inferential statistics on the SCS base runoff prediction model (Eq. 1) and apply it in urban runoff study in Malaysia until now. This study adopted the rainfall-runoff dataset from a research which was carried out in Melana watershed. It is located in Johor between 1° 30' N to 1° 35' N and 103° 35' E to 103° 39' E (Figure 1). Drained by Melana River which starts in the hilly area of Gunung Pulai in the north, the watershed covers an area of 21.12 km^2. Melana watershed underwent rapid urbanisation whereby in 1993, about 20% of the area in Melana watershed was covered by urbanised area; by 2010, more than 60% of the area was developed as residential area (Majlis Perbandaran Johor Bahru Tengah (MPJBT), 2001). This study derived CN value and formulated a calibrated SCS runoff predictive model for Melana watershed through rainfall-runoff dataset directly.

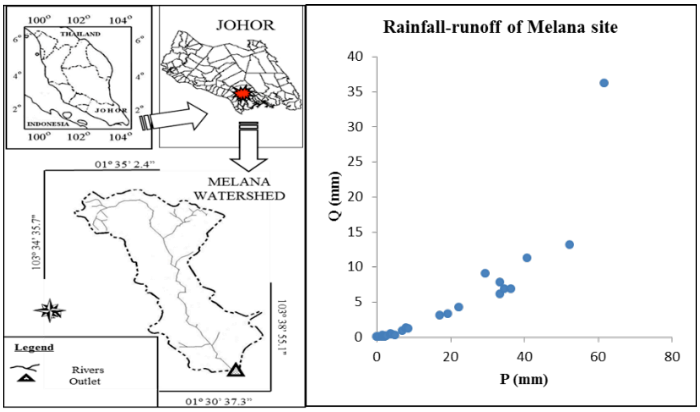

Figure 1. Melana watershed in Johor (Chan, 2005) and its rainfall-runoff graph

A total of 27 rainfall-runoff data pairs were recorded between July and October of 2004 at this site. This study used rainfall-runoff dataset which was collected within a short period in order to minimise the impact of further land use and land cover change. Inferential statistics was conducted by using IBM PASW version 18. Non-parametric Bootstrapping technique, Bias corrected and accelerated (BCa) procedure with 2,000 sampling (Efron & Tibshirani, 1994; Efron, 2010) was conducted at 99% confident interval (CI) for the derivation of key parameters (λ and S) in order to calibrate Eq. [1] (Wright, 1997; Howell, 2007; Rochoxicz, 2011). Bootstrapping BCa statistics was selected for its robustness and the inferential ability through its confident interval (Davison & Hinkley, 1997; Young, 2005; Cox, 2006).

Eq. [1] can be re-arranged to solve for $S = f(P, Q, \lambda)$. Substitute $I_a = \lambda S$ into Eq. [1] and isolate S through completing the square technique will yield the S general formula. Different λ will yield different S value, denotes by S_λ. New derived λ value will have a corresponding S_λ value which is different from $S_{0.2}$ (where $\lambda = 0.2$). Given P-Q data pairs of any storm event, when λ value is known, the general S_λ formula can be used to derive its corresponding S values. When $\lambda = 0.2$, the corresponding $S_{0.2}$ value leads to the derivation of the conventional CN ($CN_{0.2}$) value(s) which has been in use since 1954. Any other λ value will result in S_λ leading to the derivation of CN_λ known as the "Conjugate CN" (Jiang, 2001; Hawkins et al., 2009; Hawkins, 2014). In the event that the calibrated optimum λ value is different from the conventional value where $\lambda = 0.2$, a correlation between S_λ and $S_{0.2}$ must be identified in order to convert the CN_λ back to an equivalent $CN_{0.2}$ with the CN formula ($CN = \frac{25,400}{S+254}$) which was proposed by SCS for CN comparison. The general S_λ formula which we solved is listed below:

$$S_\lambda = \frac{\left[P - \frac{(\lambda-1)Q}{2\lambda}\right] - \sqrt{PQ - P^2 + \left[P - \frac{(\lambda-1)Q}{2\lambda}\right]^2}}{\lambda} \quad [3]$$

Non-parametric inferential statistics were employed for two claim assessments set forth by the 1954 SCS proposal with two null hypotheses (Young, 2005; Cox, 2006). Both hypotheses will assess Eq. [2] on its validity according to the site dataset.

Null Hypothesis 1 (H_{01}): Eq. [2] is applicable globally with the assumption of: $I_a = 0.20S$.

Null Hypothesis 2 (H_{02}): The value of 0.20 is a constant in Eq. [2].

Rejection of H_{01} implies that Eq. [2] is invalid and not applicable to model runoff conditions of Melana watershed, while H_{02} rejection indicates that λ is not a constant as initially proposed by SCS in 1954 but a variable. Rejection of both hypotheses will pave way to derive new regional specific λ value. The *P*-*Q* data pairs from Melana watershed were used to derive *S* and λ values. The difference of rainfall depth (*P*) and initial abstraction (I_a) is the effective rainfall depth (P_e) to initiate runoff (*Q*) thus $P - I_a = P_e$ (Schneider & McCuen, 2005; Hawkins et al., 2009; Hawkins, 2014). If this relationship is expressed as Eq. [1], the model can be re-arranged in order to calculate corresponding *S* and λ value for each *P*-*Q* data pair. Bootstrapping, Bias corrected and accelerated (BCa) procedure was then used to aid numerical optimisation technique in the selection of the optimum λ and *S* value to represent the entire dataset within the BCa confident intervals (Hansen, 1992; Fattorini, 1999). The selection of the optimum λ and *S* value will then formulate a new calibrated SCS runoff prediction model of Melana watershed. Past researchers used AFM to determine the representative CN for the watershed of interest through its *P*-*Q* dataset (Hawkins, 1973; Hjelmfelt, 1980; Zevenbergen, 1985; Sneller, 1985; Hjelmfelt et al., 2001; Van Mullem et al., 2002; Hawkins et al., 2009) and therefore, the asymptotic CN will also be derived for the formulation of another rainfall-runoff model for Melana watershed. This study will assess and benchmark the runoff prediction accuracy of the new calibrated SCS runoff prediction model against Eq. [2] and the Asymptotic CN runoff model.

Runoff Models Assessment

Model's prediction efficiency index (*E* also known as Nash-Sutcliffe index), residual sum of squares (*RSS*) and predictive model *BIAS* are calculated in order to draw further comparison between different runoff model with following formulas:

$$RSS = \sum_{i=1}^{n}\left(Q_{predicted} - Q_{observed}\right)^2 \qquad [4]$$

$$E = 1 - \frac{RSS}{\sum_{i=1}^{n}\left(Q_{predicted} - Q_{mean}\right)^2} \qquad [5]$$

$$BIAS = \frac{\sum_{i=1}^{n}\left(Q_{predicted} - Q_{observed}\right)}{n} \qquad [6]$$

Q = Runoff amount (mm)

n = Total number of data pairs

RSS value indicates the residual spread from a model. Lower *RSS* indicates a better runoff predictive model. Model efficiency index (*E*) ranges from minus to 1.0 where index value = 1.0 indicates a perfect predictive model. When $E < 0$, the predictive model performs worse than using the average to predict the dataset. Predictive model *BIAS* shows the overall model prediction error calculated by the summation of predictive model's residual to indicate the overall model prediction pattern. Zero *BIAS* value indicates a perfect overall runoff model prediction with no error, the negative value indicates the overall model tendency of under-prediction in runoff and vice versa.

RESULTS AND DISCUSSION

Statistics and Null Hypotheses Assessment

Twenty-seven λ values were derived from Melana dataset with the proposed methodology. λ optimization study was conducted via numerical analyses approach based on Eq. [1]. The supervised numerical optimisation algorithm was set to identify an optimum λ value by minimizing the *RSS* between final runoff model's predicted Q and its observed values. λ value was optimised within the BCa CI at alpha = 0.01 level. The descriptive statistics of the data distribution of twenty-seven derived λ values was tabulated in Table 1.

Table 1
Bootstrapping BCa 99% CI results of derived λ values at Melana watershed

Melana dataset	Descriptive Statistics λ	(λ) 99% Lower	BCa Upper	Descriptive Statistics S	(S) 99% Lower	BCa Upper
Mean	0.059	0.009	0.154	58.083	37.191	81.958
Median	0.009	0.004	0.015	42.120	23.600	90.600
Skewness	4.677			0.771		
Kurtosis	22.778			-0.593		
Std. Deviation	0.188	0.013	0.306			

The supervised optimisation study was based on λ variation within the median confident interval [0.004, 0.015] due to the skewed λ dataset (Table 1). The optimised λ value was identified as 0.015. The skewness of S dataset is near to zero which can be considered as normal hence the S optimisation was conducted within [37.191, 81.958]. The best collective representation S value was identified as 81.804 mm for Melana watershed. Since $I_a = \lambda S$ the substitution of λ and S value yields I_a = 1.248 mm. With the substitution of I_a and S back to Eq. [1], the calibrated SCS rainfall-runoff prediction model was formulated as:

$$Q_{0.015} = \frac{(P-1.248)^2}{P+80.555} \quad [7]$$

The formulation of the calibrated SCS runoff prediction model Eq. [7] using the optimum λ and S value will have the same inherent significant level (at alpha = 0.01). BCa results provided CI span for λ at Melana watershed (Table 1) which can also be used to assess Null hypotheses. The span of λ BCa CI was used to assess H_{01} while H_{02} assessment was based on the standard deviation of the derived λ dataset (Ling & Yusop, 2014, 2014b). The standard deviation of λ

dataset is not equal to zero but with high variation percentages to imply the fluctuation nature of λ. Neither the mean nor the median's BCa CI span includes λ value of 0.2 (Table 1) and therefore, $\lambda \neq 0.2$ for this dataset. H_{01} and H_{02} were both rejected at alpha = 0.01 level. As such, Eq. [2] is statistically insignificant and invalid to model runoff.

The Correlation between $S_{0.015}$ and $S_{0.2}$ for Melana Watershed

$S_{0.015}$ and $S_{0.2}$ can be calculated for the *P-Q* dataset using Eq. [3] through the substitution of respective λ = 0.015 and 0.20 corresponding to the same *P-Q* dataset for Melana watershed. A statistical significant correlation between $S_{0.051}$ and $S_{0.2}$ is expressed as:

$$S_{0.2} = 0.366 S_{0.015}{}^{1.013} \qquad [8]$$

$S_{0.051}$ = Total abstraction amount (mm) of $\lambda = 0.051$

$S_{0.2}$ = Total abstraction amount (mm) of $\lambda = 0.2$

Eq. [8] has an adjusted $R^2 = 0.962$, standard error = 0.325 and $p<0.001$. Since the best collective representation $S_{0.051}$ value was calculated as 81.804 mm for Melana watershed, its equivalent value of $S_{0.2}$ can be determined from Eq. (8). Through the substitution of the $S_{0.2}$ parameter in SCS-CN formula ($CN = \frac{25,400}{S_{0.2}+254}$) and derive the CN value of 89 to represent the given runoff condition of Melana watershed. On the other hand, when $\lambda = 0.2$, the best collective $S_{0.2}$ = 23.35 mm for SCS model which led to the CN value of 92. The substitution of $S_{0.2}$ value into Eq. [2] formulated the SCS runoff model to predict runoff conditions at Melana watershed.

The Asymptotic CN of Melana Watershed

Using the Asymptotic CN fitting method, CN_∞ was derived as 81.72 as shown in Figure 2. Rounding to the nearest positive integer, $CN_\infty = CN_{0.2} = 82$ for Melana watershed.

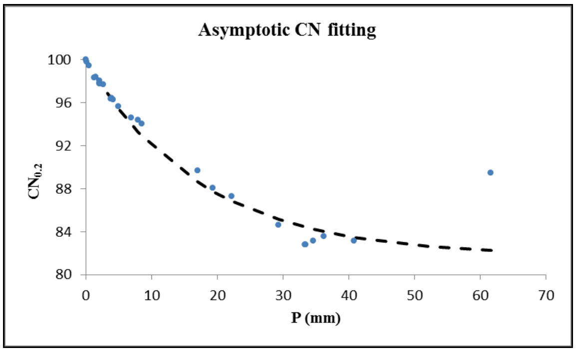

Figure 2. For AFM, standard behaviour pattern, $CN_\infty = 82$

Through SCS-CN formula $(CN = \frac{25,400}{S_{0.2}+254} = 82)$, the $S_{0.2}$ value of the asymptotic CN can be calculated as 56.8 mm and $I_a = 0.20 \times 56.8$ mm = 11.36 mm. These values are used to formulate an Asymptotic runoff model using Eq. [1] and benchmark its runoff prediction accuracy against Eq. [2] and [7]. The assessment and comparison of runoff models' prediction results are shown in Table 2.

Table 2
Descriptive statistics and 99% BCa results of three runoff predictive models

Predictive model	Asymptotic model	Eq. [7]	Eq. [2]
E	0.82	0.87	0.37
RSS	264.70	193.20	910.37
BIAS	-4.63	0.07	3.11
$CN_{0.2}$	82	89	92
Residual Skewness	-2.39	-1.74	1.71
Residual Kurtosis	8.39	9.63	2.55
Median Residual	0.62	-0.10	0.89
Median Residual: 99% BCa CI	[-1.04, 1.66]	[-0.31, -0.01]	[0.00, 3.64]
Model error Standard Deviation	3.19	2.73	4.99
Residual Variance	10.16	7.43	24.98

Eq. [7] has lowest *RSS* with highest E index compared with the other two runoff models. Every model's residual skewness and Kurtosis are greater than 1.0 and hence, the median residual value can be used as the indicator for predictive model's accuracy. Eq. [7] has the median residual value and 99% BCa confident interval range nearest to zero which indicates that the model is capable of achieving near to zero (residual) runoff prediction error ($p<0.01$). On the contrary, Eq. [2] tends to over predict runoff amount as its median residual confident interval range spans within positive figures only. Eq. [7] also has the lowest standard deviation and variance in its model's residual with smaller confident interval ranges than the other two models and therefore, is the most stable and reliable runoff predictive model for the dataset in this study.

CONCLUSION

This study affirmed that the SCS runoff prediction model had to be calibrated according to regional specific characteristics. Inferential statistics assessment rejected both H_{01} and H_{02} at alpha = 0.01 level. Therefore, Equation [2] became obsolete and not applicable to model runoff conditions in this study. Blind adoption of Eq. [2] will commit a type II error.

A new CN derivation approach was presented with supervised numerical optimisation technique under the guide of inferential statistics. The new calibrated runoff predictive model out-performed its counterpart models. It has high model efficiency (*E*), low *BIAS* with 99% BCa confident level and *RSS* to produce the smallest runoff prediction error. As such, the derived CN value of 89 to represent the given runoff conditions of Melana watershed also has the inherent statistical significance at alpha = 0.01 level. This study proved that SCS base runoff predictive model can be calibrated to predict urban runoff conditions accurately.

On average, Eq. [2] over-predicted nearly 150,000 m^3 at rainfall depth scenarios larger than 16 mm in comparison to the Eq. [7] in this study. The over-prediction risk (error) was significant and further magnified by increased rainfall. Rapid urbanisation and landscape change post a challenge to correctly identify CN according to tabulated handbook value. Extreme weather conditions due to global climate change will compound the challenge to induce frequent unexpected flash flood at unseen magnitude. Direct CN derivation from the given rainfall-runoff conditions offers a swift and economical solution to restore the runoff prediction ability of the SCS runoff model and it can be calibrated for a specific region to reflect the latest rainfall-runoff condition.

It is noteworthy to mention that the extrapolation of Eq. [7] to higher rainfall depths will involve unknown uncertainties as the dataset of this study has an upper constraint of 62 mm. However, the authors already calibrated the SCS model to achieve high runoff prediction accuracy with bigger dataset up to 427 mm rainfall depth with this method in Peninsula Malaysia in another study. Design engineers and SCS practitioners are encouraged to conduct regional specific calibration for SCS rainfall-runoff model.

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