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Urban Flood Depth Estimate with a New Calibrated Curve Number Runoff Prediction Model

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ABSTRACT The 1954 Soil Conservation Services (SCS) runoff predictive model was adopted in engineering designs throughout the world. However, its runoff prediction reliability was under scrutiny by recent studies. The conventional curve number (CN) selection methodology is often very subjective and lacks scientific justification while nested soil group catchments complicate the issue with the risk of inappropriate curve number selection which produces unreliable runoff results. The SCS CN model was statistically invalid ($\alpha = 0.01$ level) and over predicted runoff volume as much as 21% at the Sungai Kerayong catchment in Kuala Lumpur, Malaysia. Blind adoption of the model will commit a type II error. As such, this study presented a new method to calibrate and formulate an urban runoff model with inferential statistics and residual modelling technique to correct the runoff prediction results from the SCS CN model with a corrected equation. The new model out-performed the Asymptotic runoff model and SCS CN runoff model with low predictive model bias, reduced sum of squared errors by 32% and achieved high Nash-Sutcliffe efficiency value of 0.96. The derived urban curve number is 98.0 with 99% confidence interval ranging from 97.8 to 99.5 for Sungai Kerayong catchment. Twenty-five storms generated almost 29 million m^3 runoff (11,548 Olympic size swimming pools) from the Sungai Kerayong catchment in this study. 75%-94% of the rain water became runoff from those storms and lost through the catchment, without efficient drainage infrastructure in place, the averaged flood depth reached 6.5 cm while the actual flood depth will be deeper at the flood ponding area near to the catchment outlet.

INDEX TERMS Bootstrap, Curve Number, Rainfall-Runoff Model

I. INTRODUCTION

FLOOD is a natural disaster whereby excessive volumes of water accumulate in a region, submerging dry land. On the other hand, flash flood takes place within a short duration of time and is most often caused by incredibly heavy rainfall from thunderstorms. Flood prone areas are usually low in elevation, near to the outlet of a watershed or on a flat terrain. When a ground is saturated, even low intensities of rainfall can induce a flood. As the ground can no longer absorb the rainfall, the excessive body of water becomes runoff which does not permeate into the ground and instead flows across the land surface. The percentage ratio of the runoff amount (Q) over the rainfall amount (P) is known as the runoff coefficient. The coefficient percentage (ranges from zero to 100%) value tends to be larger for regions with low infiltration as well as high runoff and vice versa. It also indicates the likelihood of runoff generation. If the percentage value of the runoff coefficient is high, it implies that a catchment is highly saturated. In case as such, a flood will occur.

Runoff volume from rainfall is nearly 97% of the Malaysian water demands [1]. Unclaimed water loss through runoff also causes flooding and financial losses at the downstream of urban catchments [2] and therefore, it is crucial to be able to model the rainfall-runoff behaviour of a catchment in order to manage the water resources effectively. The study surrounding the topic of floods is significant to better understand its paleohydrologic and geomorphic aspects, why it

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occurs, and how to overcome the negative effects of flooding. An emphasis has been put on this field because it creates a great deal of damage to homes and causes many casualties each year.

Reports regarding the destructive aftermath of flash floods have also been observed worldwide [3], [4]. According to the International Disaster Database, over 1.4 billion people were affected and about 100,000 people were killed by floods in the last decade of the 20^{th} century [5]. Flood related disasters affected nearly 770 million people worldwide in the past 10 years and caused over 53 thousands casualties, injured more than 75 thousands with reported total losses around 374 billion dollars [6]. Natural hazards are still one of the major causes of casualties amongst the human population reported in the latest annual disaster statistical review from 2019 [4], [5]. Floods also disrupt daily lives and businesses, cause damage in the field of agriculture and damages infrastructure such as roads, sewer systems, and buildings. In cases as such, a rapid approximation of inundated regions is important to effectively plan response operations. Global demand for research regarding natural disasters has increased immensely over the years as an effort to reduce these disastrous events, the near real time (NRT) detection of a flood event and flood mapping studies were conducted with different technologies [7]–[10].

Although the soil profiling method has been in use to predict and model subsurface storm flow response, the method is expensive and comes with a certain degree of ambiguity to assume uniform geological formation between bore sites. Many deterministic runoff predictive models require extensive data collection and input which is tedious and costly to set up and update. The fast pace of urban development outdated many studies and modelling results as those models can no longer represent the latest condition of the catchment of interest and therefore, it is imminent to develop a feasible rainfall-runoff modelling technique to produce swift yet statistically significant runoff prediction results especially for an urban catchment which undergoes development at a fast pace.

In 1954, the Soil Conservation Services (SCS) from the United States of America introduced a runoff predictive model which used curve number (CN) to represent an overall land cover condition. The model was adopted by government agencies and became popular worldwide for runoff prediction. It is also part of every Hydrology text book. Nevertheless, many researchers expressed the concern of unreliable runoff estimates and scrutinised the validity of the model in recent years [11] - [17]. The SCS CN method has been used to predict and compute the runoff volume of a storm event [18], [19]. Technical Release 55 (TR-55) of SCS classified site conditions into different CN values. However, a US researcher reported that forested catchments had the highest CN classification mistake. The wrong CN choice often produces unrealistic runoff estimates [20]. Some researchers reported that practical CN values only spanned from 40 to 98 in their field studies [21]. Instead of relying on the conventional SCS procedure and handbook, many researchers started to utilise advance technologies to classify land use, detect soil moisture, monitor rainfall characteristics and to model hydrologic conditions in their studies [22]–[28].

The selection of CN is highly subjective to its practitioners and therefore, hydrologists and modellers must improve this modelling approach [20], [33]. Many researchers also concluded that rainfall-runoff ($P - Q$) dataset should be used to derive CN values in order to reflect catchment runoff characteristics [20], [29]– [33]. SCS practitioners often tweak the CN value to gain better results but such unscientific practice does not have any justification. In-situ CN measurement can be difficult while nested soil group catchments further complicate CN selection process. SCS practitioners often adopt the model and almost never explore site specific calibration possibility [33] while the least-squares method (LSM) [33] and the asymptotic fitting method (AFM) [20] are the most commonly used techniques with SCS CN model.

The aim of this study is to develop a methodology to formulate a statistically significant rainfall-runoff model to reflect runoff characteristics under highly saturated ground conditions in order to address urban flooding issue. With the guide from inferential statistics, this study used a new methodology to derive CN through $P-Q$ dataset and formulate a catchment specific runoff predictive model according to the $P-Q$ conditions under high catchment saturation state in order to estimate flood depth for the Sungai Kerayong urban catchment in Malaysia.

II. STUDY SITE AND METHODOLOGY

This study was carried out in the Sungai Kerayong catchment which is located in the capital city Kuala Lumpur of Malaysia. The Sungai Kerayong river is one of the major tributaries of the Klang River in Malaysia. The total area of the catchment is about 48.3 km^2 (Fig. 1). The study area is highly urbanized with 77.5 % of imperviousness. Low residential area formed the largest fraction of the impervious surfaces covering 24.0% of the catchment [34].

In 1954, SCS proposed the following equation:

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

where P is the depth of a rainfall event (mm), Q is the runoff depth from a rainfall event (mm), S is the water retention depth of a catchment (mm) and I_a is the initial retention or abstraction depth (mm).

The initial abstraction is defined as the initial retention amount before the beginning of runoff process. SCS also proposed that $I_a = 0.20S$. The initial abstraction coefficient ratio(λ) was proposed as a constant (0.20). It is a parameter which correlates I_a and S. $I_a = 0.20S$ simplified Eq. (1) into:

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

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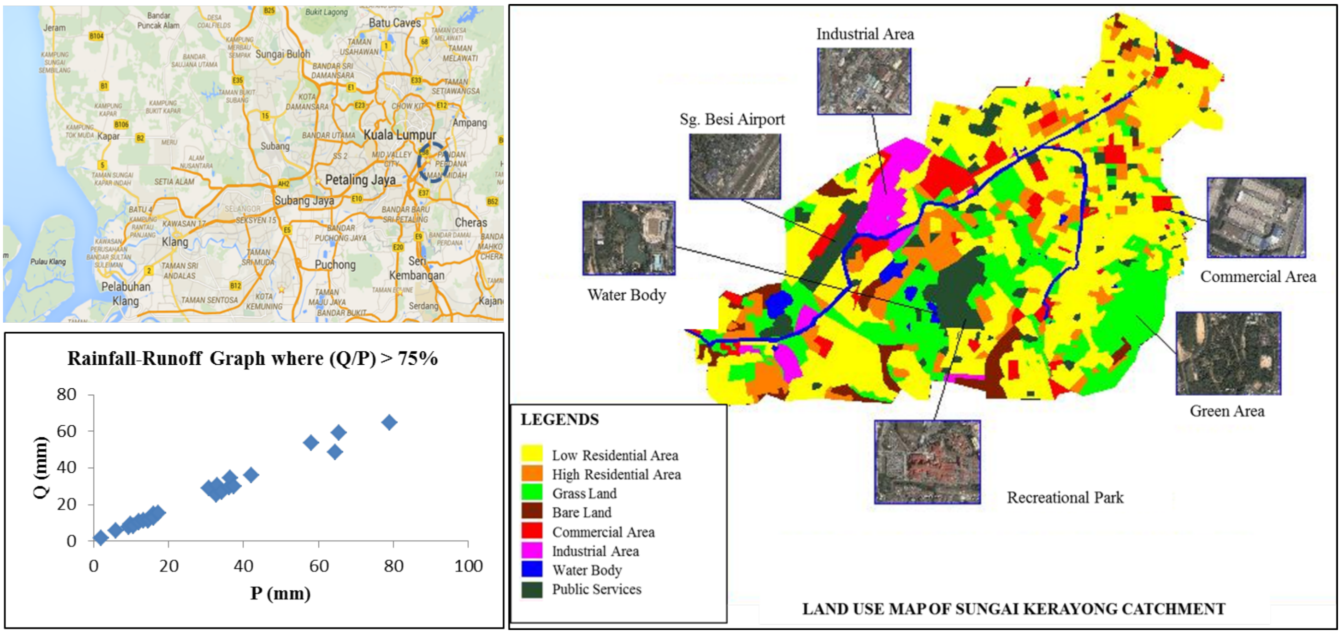

FIGURE 1. Sungai Kerayong catchment and its rainfall-runoff graph (with runoff coefficient larger than 75%). Modified from [34].

In Eq. (2) if $P < 0.2S$, there will be no runoff. According to the literature review study of [15] and [33] many studies questioned the hypothesis of $I_a = 0.20S$ and challenged the runoff prediction accuracy of Eq. (2) in recent decades.

Twenty-five rainfall-runoff data pairs with runoff coefficient larger than 75% were selected from a seventy-two $P–Q$ dataset collected from 1998 to 2003 at this site in order to formulate a runoff predictive model to reflect the catchment's runoff characteristics near to a flood prone saturation state at the Sungai Kerayong catchment (remaining data pairs with low runoff coefficient were discarded as they do not reflect the saturated catchment condition that will cause flooding).

Previous researchers presented the methodology that Eq. (1) can be rearranged to find S and λ values according to $P - Q$ data pairs [33], [35]. This study took extra steps to conduct inferential statistics with IBM statistic software, SPSS (version 18) after deriving S and λ values. Non-parametric Bootstrapping, Bias corrected and accelerated (BCa) technique (2,000 random sampling with replacement) [36]– [41] was conducted at 99% confidence interval (CI) in order to find the optimum λ and S value to calibrate Eq. (1) and perform hypotheses assessment [38], [40]. Unlike previous research studies, the optimum λ and S value was derived according to inferential statistics instead of choosing between the mean and the median of the λ and S value from its derived dataset. The proposed new CN derivation and model calibration methodology utilised inferential statistics and supervised non-linear genetic optimisation algorithm (Evolutionary Solver in Excel) to optimise λ and S value. Evolutionary Solver optimisation algorithm created a population size of 2,000 and 2,000 random seed with mutation rate of 0.075 to converge toward an optimal solution within BCa 99% CI at small error of 0.001 mm for the formulation of the Sungai Kerayong runoff prediction model at alpha = 0.01 level [38], [40]. The proposed SCS model calibration of this study consists of the following steps:

1) Given that: $P_e = P - I_a$ and $I_a = \lambda S$; rearrange SCS Eq. (1) into following:
$$Q = \frac{P_e^2}{P_e + S}$$
$$S = \frac{P_e^2}{Q} - P_e$$
$$\lambda = \frac{I_a}{S}$$
2) Calculate the runoff coefficient $(Q/P)\%$ of each $P - Q$ datapair and select the $P - Q$ event pairs whereby the percentage of the runoff coefficient is larger than or equal to 75%.
3) For each $P - Q$ event pair calculate λ and S value.
4) Conduct Bootstrap, BCa (at α = 0.01 level) inferential statistical analyses (2,000 samples) for λ and S dataset in SPSS and generate CI for λ and S dataset.
5) Test Null Hypotheses by referring to the λ CI span and its standard Deviation.
6) Find the optimum λ and S value from BCa CI and calculate I_a.
7) Formulate the new calibrated SCS model by substituting I_a and S into Eq. (1).
8) According to a group of researchers [33], when λ value other than 0.20 was detected at a catchment, its corresponsing S values (denoted by S_λ) must be correlated to the $S_{0.2}$ values for CN calculation. As

such, correlate S_λ and $S_{0.2}$ with the S general formula derived by past research [41].

9) Lastly, substitute the correlation equation into:
$$CN = \frac{25,400}{S_{0.2} + 254}$$
to determine the CN.

A. RESIDUAL MODELLING TO ADJUST SCS CN MODEL

Although it is difficult to model the residual pattern of scattered data, it is easier to model differences between two similar prediction models which are derivative of the same framework. Two models will eventually converge toward unification through the adjustment of a statistically significant equation which models the difference between them. In the event that H_{01} can be rejected at $\alpha = 0.01$ confidence interval level, Eq. (2) will become invalid. As such, it is imperative to be able to produce an adjusted equation to correct the SCS CN model according to the catchment specific characteristics because the model has gained popularity in many sectors. The calibrated runoff prediction model and the SCS CN model or Eq. (2) are derivative from Eq. (1) thus runoff prediction differences (Q_v) between two models can be modelled according to P values in order to adjust the runoff prediction results from Eq. (2). An adjustment equation can be produced and amended to runoff prediction results from the conventional SCS CN model in order to aid SCS practitioners to calibrate runoff prediction results and improve runoff prediction accuracy. The effective adjustment to SCS CN model will restore its statistical significance as well.

The following two null hypotheses were set up under this study to assess Eq. (2).

- Null Hypothesis 1 (H_{01}): Eq. (2) is applicable to Sungai Kerayong catchment.
- Null Hypothesis 2 (H_{02}): The value of $\lambda = 0.20$ is a constant.

In the event that H_{01} was rejected, Eq. (2) becomes invalid and cannot be used to predict the runoff of the Sungai Kerayong catchment while H_{02} rejection proves that λ is not as suggested by SCS as a fixed value of 0.20 which will pave the way for model calibration by varying λ value. AFM was used by past researchers to derive the CN of a catchment by using the catchment $P - Q$ dataset [32], [33], [35], [40] and therefore, this study will benchmark the new Sungai Kerayong catchment runoff prediction model against Eq. (2) and the AFM runoff model.

B. RUNOFF MODELS COMPARISON AND ASSESSMENT

Residual sum of squares (RSS), Nash-Sutcliffe efficiency index (E) and model $BIAS$ are calculated to assess different runoff models. Better runoff predictive model will have a lower RSS value and a higher Nash-Sutcliffe efficiency index (E) value. E value of 1.0 indicates a perfect model while the mean value of the observed dataset outperforms the model when $E < 0$. The model $BIAS$ shows the overall model's ability to predict accurately. Negative $BIAS$ value indicates a model's under-prediction tendency and vice versa.

C. CRONBACH'S ALPHA RELIABILITY TEST

Cronbach's Alpha has been in use to assess the reliability and internal consistency of a survey or questionnaire. The calculation of alpha value refers to the variances between different entities within a test group. This study adopted the ability of Cronbach's Alpha reliability test to detect differences from a specific measurement or model in order to demarcate or isolate predictive model(s) that has (have) different or inconsistent runoff prediction characteristics when compared to other benchmarked model(s) [42]–[45]. Runoff prediction of the conventional SCS CN rainfall-runoff model, new calibrated SCS runoff predictive model and the adjusted (corrected) SCS runoff predictive model were analysed simultaneously as a test group according to the Cronbach's Alpha reliability test procedure in SPSS through the following steps: Analyze/Scale/Reliability. Analysis/Select to include all runoff predictions models under "Items"/Model: select Alpha option. Under the statistics option; select "Scale" and "Scale if item deleted" option in order to detect and isolate runoff predictive model(s) that is (are) different from other benchmarked model(s)/Continue/Click OK to run the Cronbach's Alpha reliability test.

D. RECEIVER OPERATING CHARACTERISTIC CURVE ANALYSES

The receiver operating characteristic curve (ROCC) was used in world war two for radar operators to assess the validity of the received radar signals. ROCC was adopted by the medical field in 1970 to assess the effectiveness of an administered test with dichotomous outcomes. The concept of the confusion matrix which consists of a true positive, true negative, false positive and false negative test results were summarized and represented through the ROCC graph where the y-axis represents sensitivity and x-axis represents 1-specificity of a test. After plotting the ROCC, the area under the ROCC (AUROCC) was calculated to classify a test on the scale from zero to 1.0 where the value of 1.0 is considered as a perfect test result. AUROCC value > 0.9 is considered as an excellent test, AUROCC value between 0.8 and 0.9 indicates a good test result, a value between 0.7 and 0.8 indicates an acceptable test result while value less than 0.5 indicates an unreliable test with its achieved effectiveness by chance only. The diagonal line on the ROCC graph represents the AUROCC value of 0.5. In the event that AUROCC value is around 0.5, ROCC will fluctuate along the diagonal line [46]–[48].

The study requires a runoff predictive model that can predict runoff conditions of a catchment of interest under high rainfall intensities. As such, any runoff predictions within a ±10% error margin were classified with the value of "1.0" to indicate a true positive runoff prediction while all other predictions with an error margin larger than 10% were classified with the value of "0.0" to indicate true negative pre-

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diction results. The runoff predictions from the conventional SCS CN runoff predictive model and the newly calibrated SCS runoff predictive model were classified according to the dichotomous outcomes classification rule with respective rainfall depths for ROCC analyses in order to determine which rainfall-runoff predictive model is capable of predicting runoff amount within ±10% error margin at high rainfall intensity range. The ROCC analyses were conducted in SPSS through the following steps: Analyse/ROC Curve/Select the rainfall depths data to "Test Variable"/ Select dichotomous outcomes of the models to "State Variable"/ Enter "1.0" (as positive outcome) to "Value of State Variable"/Check the "ROC Curve", "with diagonal reference line", "standard error and confidence interval" and "Coordinate points of the ROC Curve"/Click OK to proceed.

III. RESULTS AND DISCUSSION

A. STATISTICS AND NULL HYPOTHESES ASSESSMENT

This study derived twenty-five λ values from the rainfall-runoff dataset of Sungai Kerayong catchment. Descriptive statistics was tabulated in Table 1.

The supervised non-linear genetic optimization referred to the λ median confidence interval [0.036, 0.129] while S optimisation was also conducted within the median confidence interval [1.690, 7.060] because both λ and S dataset are skewed (Table 1).

TABLE 1. Bootstrapping BCa results of λ and S values at Sungai Kerayong catchment

Statistics	BCa 99% Confident Interval					
	λ	Lower	Upper	S	Lower	Upper
Mean	0.167	0.077	0.276	4.844	2.527	8.315
Median	0.089	0.036	0.129	2.680	1.690	7.060
Skewness	2.408			1.818		
Kurtosis	5.363			3.314		
Std. Dev.	0.234	0.059	0.334	5.139	2.397	7.298

The optimised λ value was 0.036 and the optimised S value was 6.29 mm to represent the dataset of Sungai Kerayong catchment thus I_a = 0.23 mm was calculated. The substitution of I_a and S into Eq. (1) will form a Sungai Kerayong catchment runoff prediction model as:

$$Q_{0.036} = \frac{(P-0.23)^2}{P+6.06} \tag{3}$$

The standard deviation of λ dataset is not equal to zero which proves that λ cannot be a constant. The median's BCa CI spans from 0.036 to 0.129, it does not include the λ value of 0.2. As such, λ value cannot be 0.2 for this site (Table 1) and therefore, H_{01} and H_{02} were both rejected. Eq. (2) becomes invalid to predict runoff at Sungai Kerayong catchment (at α = 0.01 level).

B. CORRELATION BETWEEN $S_{0.036}$ AND $S_{0.2}$ FOR SUNGAI KERAYONG CATCHMENT

$S_{0.036}$ and $S_{0.2}$ can be calculated for the $P-Q$ dataset using the S general formula [41] through the substitution of λ = 0.036 and 0.20 corresponding to the same $P-Q$ dataset for Sungai Kerayong catchment. The correlation between $S_{0.036}$ and $S_{0.2}$ was identified with SPSS as:

$$S_{0.2} = 0.838\ S_{0.036}{}^{0.991} \tag{4}$$

where $S_{0.036}$ is total abstraction amount (mm) when λ = 0.036 and $S_{0.2}$ is total abstraction amount (mm) when λ = 0.2.

The adjusted R^2 of Eq. (4) is 0.99 with low standard error of 0.02 while its p value is less than 0.001. The substitution of the $S_{0.2}$ into SCS CN formula (CN = $\frac{25,400}{S_{0.2}+254}$) will calculate the CN value of 98 to predict runoff conditions at Sungai Kerayong catchment.

C. THE ASYMPTOTIC CN OF SUNGAI KERAYONG CATCHMENT

The "complacent behaviour" was detected through AFM where CN values reduce with increasing rainfall depths and do not approach to any stable CN_∞ value. CN was undefined for Sungai Kerayong catchment (as shown in Fig. 2) as CN_∞ failed to approach a stable state and kept declining [20]. As such, a CN value cannot be identified with this method.

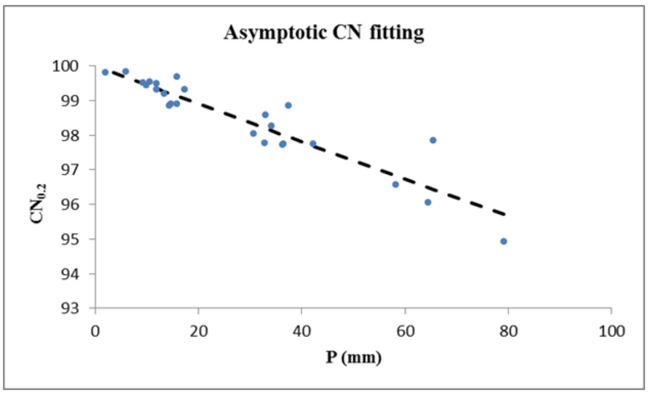

FIGURE 2. CN value cannot be identified for complacent behaviour pattern with AFM.

D. RESIDUAL MODELLING AND THE CORRECTED EQUATION

Runoff prediction differences (Q_v) between Eq. (3) and (2) were mapped with several non-linear regression models according to P values using SPSS. The best correction equation was identified as:

$$Q_v = -0.292 + 0.857LN(P) \tag{5}$$

where Q_v is the runoff prediction difference (mm) between two models and P is the rainfall depth (mm).

This equation was proposed as an amendment for SCS CN model or Eq. (2) to correct its runoff over prediction error as below:

$$Q = \frac{(P-0.2S)^2}{P+0.8S} + 0.292 - 0.857LN(P) \tag{6}$$

if $P < 0.2S$, $Q = 0$ where P, Q and S are the same parameters as stated in previous section. Eq. (5) modelled runoff prediction differences between two models with the low standard error of the estimate and high adjusted R square (0.092, 0.985, $p < 0.001$). Eq. (6) adjusted SCS model into a runoff model very similar to Eq. (3).

E. RUNOFF MODELS ASSESSMENT

The assessment of all runoff models in this study were tabulated in Table 2.

Eq. (6) has proximate RSS, $BIAS$ and E index as Eq. (3). Both Eq. (3) and (6) has the bias value near to zero which indicates that both models are capable of producing similar and accurate runoff prediction results. On the other hand, Eq. (2) tends to over predict runoff amount as its model's $BIAS$ is the highest (1.68 mm).

TABLE 2. Descriptive statistics and 99% BCa results of four runoff predictive models

Predictive model	Asymptotic mode	Eq. (3)	Eq. (2)	Eq. (6)
λ	n/a	0.04	0.20	0.20
λ ($\alpha = 0.01$)	n/a	significant	insignificant	adjusted
E	n/a	0.96	0.94	0.96
RSS	n/a	292.87	427.89	286.27
$BIAS$	n/a	-0.62	1.68	-0.63
$CN_{0.2}$	Undefined	98	99	98

The rejection of H_{01} and H_{02} inferred that the SCS CN model which was represented by Eq. (2) is invalid and not statistically significant. On the other hand, SCS CN model also over predicted runoff of all rainfall scenarios in this study. Runoff residual modelling can be conducted between Eq. (2) and Eq. (3) to produce a corrected equation for Eq. (2). The amendment of Eq. (5) adjusted the runoff prediction results and corrected RSS of Eq. (2) by almost 33% to achieve proximate runoff prediction results as Eq. (3). Un-calibrated SCS CN model or Eq. (2) over-predicted runoff amount by 111,626 m^3 (on average) under different rainfall scenarios from the 48.3 km^2 Sungai Kerayong catchment in this study when compared to the newly calibrated model or Eq. (3). The runoff over prediction risk is significant and worsen toward higher rainfall intensities from the un-calibrated SCS CN model or Eq. (2). SCS CN rainfall-runoff model was statistically in-significant ($\alpha = 0.01$ level) and over predicted urban runoff as much as 21% at Sungai Kerayong catchment in Kuala Lumpur, Malaysia.

Drainage systems were overdesigned by USD$2 billion per year in the United States [49], climate change will post another challenge in future hydro structure designs and projects in Malaysia. Without Eq. (6), SCS CN model or Eq. (2) will over predict runoff at a significant and substantial runoff volume leading to over-design issues at this catchment.

It is noteworthy to mention that although rainfall depth of this study is only up to 80 mm but the runoff coefficient (Q/P) ranges from 75% to 94%. $P - Q$ dataset of this study was selected to model the runoff condition at Sungai Kerayong catchment near to saturation state in order to formulate a rainfall-runoff model for urban flood forecast. Eq. (3) and (6) model the runoff up to 94% saturation condition (at $\alpha = 0.01$ level) with high accuracy.

For social science related studies, the Cronbach's Alpha reliability test was often used to remove or discard survey question(s) from a survey or questionnaire which require(s) modification or further consideration. The removal of those survey question(s) will increase the overall Cronbach Alpha value of a survey or questionnaire. This study utilised the reliability test to differentiate predictive runoff model(s) which is (are) different from other models within the test group. The Cronbach's Alpha reliability test results of the aforementioned test group were tabulated in Table 3.

TABLE 3. Cronbach's Alpha reliability test

Overall Testgroup's Alpha (0.995)	Alpha if item deleted	% Change
New Calibrated Model	0.9897	Dropped 0.53%
SCS CN Model	0.9998	Increased 0.4%
Adj. SCS Model	0.9897	Dropped 0.53%

The overall Cronbach's Alpha reliability test value of the test group was 0.995, if the conventional SCS CN runoff predictive model's runoff predictions were deleted from the test group, the overall reliability value increased by 0.4% from 0.995 to 0.999. On the contrary, if either the newly calibrated SCS runoff predictive model or the adjusted (corrected) SCS runoff predictive model was removed from the test group, the overall reliability value for the test group would reduce by 0.53% from 0.995 to 0.989. As such, runoff predictions from the conventional SCS CN runoff predictive model are considered to have inconsistent or different characteristics when compared to the other two models.

For the newly calibrated SCS runoff model, the AUROCC value is 0.893 and statistically significant ($p = 0.014$) with the asymptotic 95% confidence interval range [0.643, 1.0] which indicates that the model can effectively predict runoff amount within ±10% error margin to fulfil the aim and objective of this study. On the other hand, AUROCC value for the conventional SCS CN runoff predictive model showed low value of 0.483 and statistically insignificant ($p = 0.890$) results. ROCC of the model also fluctuated along the diagonal line (Figure 3) to show that the SCS CN model or Eq. (2) is not capable to predict runoff amount effectively within the ±10% error margin across different rainfall classes. AUROCC analyses outcomes were tabulated below in Table 4:

TABLE 4. Area Under the ROC Curve

Model	Area	p value	95% Lower	CI Upper
New Calibrated Model	0.893	0.014	0.643	1.000
SCS CN Model	0.483	0.890	-	-

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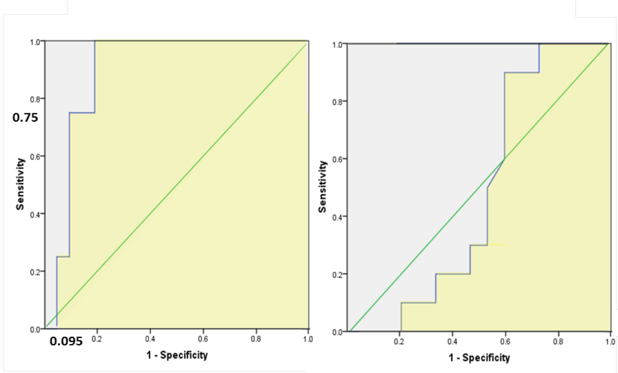

FIGURE 3. ROCC of the newly calibrated runoff model (left) and SCS CN model (right). Modified from SPSS output.

IV. CONCLUSION

This study presented a new method to calibrate the SCS CN runoff model according to the catchment specific $P-Q$ dataset with inferential statistics. H_{01} and H_{02} were rejected at α = 0.01 confidence interval level. Therefore, the SCS CN model cannot be used to predict runoff conditions of Sungai Kerayong catchment. Blind adoption of this model will commit the type II error.

The supervised non-linear genetic optimisation technique has proven to be able to calibrate the conventional SCS CN runoff model with the help from inferential statistics. When compared to other models, newly calibrated runoff model or Eq. (3) out-performed against all other models with high E index value, low $BIAS$ and low RSS with the smallest runoff prediction error. The derived CN value is 98 with 99% CI from 97.8 to 99.5 to represent the high ground saturation runoff conditions of the Sungai Kerayong catchment. This study proved that the conventional SCS CN runoff predictive model or Eq. (2) can be calibrated according to the catchment specific rainfall and runoff conditions to predict urban runoff accurately. This new methodology is capable to develop a feasible and statistically significant rainfall-runoff model swiftly using catchment specific $P-Q$ dataset.

Cronbach's Alpha reliability test concluded that the runoff predictions of the conventional SCS CN runoff predictive model or Eq. (2) are different from the newly calibrated SCS runoff predictive model or Eq. (3) and the adjusted (corrected) SCS runoff predictive model or Eq. (6). ROCC analyses were used to determine if a runoff predictive model is capable of achieving high true positive result to predict runoff amount within ±10% error margin. The ROCC analysis showed that the newly calibrated SCS runoff predictive model and the adjusted (corrected) SCS runoff predictive model were capable to predict runoff amount effectively at different rainfall depths which is an important criteria to meet under this study. In the top two quartiles of rainfall depths (P > 30 mm), both newly calibrated SCS runoff predictive model and the adjusted (corrected) SCS runoff predictive model were capable to predict nine out of twelve runoff events within ±10% error margin. Contrary, SCS CN model only predicted six out of twelve events within ±10% error margin.

Sungai Kerayong catchment has 12 rainfall events with rainfall depths greater than 30 mm which generated 23 million m^3 of runoff volume and the averaged runoff coefficient of those events was at 85% saturated ground condition. This study showed that the proposed newly calibrated SCS runoff prediction model was capable to predict high runoff volume with significantly improved accuracy when compared to the conventional SCS CN model.

Twenty-five storms generated almost 29 million m^3 of runoff (11,548 Olympic size swimming pools) from the Sungai Kerayong catchment in this study. 75%-94% of the rain water became runoff from these storms and was lost through the catchment, without efficient drainage infrastructure in place, the average flood depth reached 6.5 cm in this catchment while the actual flood depth will be deeper at the low flood ponding area near to the outlet of the catchment. It is recommended to review the water resource management policies, flood prevention and mitigation plans for Sungai Kerayong catchment.

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