Is the Curve Number (CN) Method Climate-Ready? Implications for Future Rainfall–Runoff Prediction

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Abstract. The Soil Conservation Service Curve Number (SCS-CN) method remains one of the most widely used rainfall–runoff models due to its simplicity and low data requirements. However, increasing hydro-climatic non-stationarity, intensified rainfall extremes, and climate change raise critical questions regarding the climate readiness of the conventional Curve Number (CN) formulation. This study critically examines the suitability of the conventional CN methodology for future rainfall–runoff prediction, with particular emphasis on its underlying mathematical derivation and embedded assumptions. The analysis reveals fundamental limitations in the conventional CN framework, notably its fixed key parameter, which inadequately represents evolving rainfall–runoff dynamics under altered climatic conditions. As a result, the conventional approach exhibits systematic bias and reduced robustness when applied to non-stationary rainfall regimes. To address these deficiencies, this study adopts a data-driven non-parametric calibration strategy to optimise key model parameters of the conventional model framework. The study demonstrates that new approach substantially improves runoff estimation accuracy, reduce prediction bias, and enhance adaptability across varying rainfall conditions. The findings indicate that although the conventional Curve Number method is not inherently climate ready, its predictive performance can be significantly strengthened through targeted recalibration, offering important implications for climate resilient hydrological modelling and flood risk assessment.

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1 Introduction

Floods and related hydrological disasters arise primarily from excessive surface runoff that exceeds the land's infiltration capacity. Populations residing in low-lying areas are particularly vulnerable to inundation, economic damage, and loss of life. With rapid urbanisation occurring globally, the frequency and severity of flash flood events have increased markedly due to the expansion of impervious surfaces and altered hydrological responses. Between 1900 and 2025, flood events worldwide resulted in approximately 68,000 fatalities, corresponding to an average of nearly eight deaths per day, alongside cumulative economic losses exceeding USD 5.1 trillion, equivalent to an estimated USD 1,300 losses per second [1]. These figures highlight the pressing need for robust rainfall–runoff analysis to accurately quantify runoff generation from rainfall. Reliable rainfall–runoff relationships are fundamental to effective water resources management, flood forecasting, and disaster risk reduction. Although numerous rainfall–runoff models have been developed for runoff estimation, this study focuses on evaluating the widely adopted Soil Conservation Service (SCS) rainfall–runoff model developed by the United States Department of Agriculture (USDA). Specifically, the runoff prediction performance of the conventional SCS model for flash flood applications is assessed and benchmarked against two parsimonious alternative models that similarly rely on only two governing parameters.

1.1 The Conventional Curve Number Rainfall-Runoff Model

Originated from the Small Watershed and Flood Control Act of 1954, the Curve Number (CN) runoff model was introduced by the SCS [2] as:

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

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

where Q is the runoff depth (mm), P is the rainfall depth (mm), I_a is the initial abstraction (mm), and S is the potential maximum retention (mm). SCS defined $I_a = \lambda S$, and proposed λ (initial abstraction ratio) = 0.20 to simplify Equation (1). Therefore, Equation (2) was introduced as the conventional CN runoff predictive model, with S as the only parameter. SCS also introduced a correlation between CN value and S through the equation below:

$$CN = \frac{25{,}400}{254+S} \tag{3}$$

where CN is the unitless value pending upon the land use and land cover (LULC) condition of a watershed. The SCS released CN handbook values as the primary reference for Curve Number (CN) practitioners, enabling them to map the closest LULC conditions to the handbook classifications and select the corresponding CN values. The selected (mapped) CN value is then substituted into Equation (3) to compute the storage parameter (S), which is subsequently substituted into Equation (2) to estimate the watershed runoff depth (Q). Fixing the λ value at 0.20 became a global constant for all watersheds, while matching land use and land cover (LULC) conditions to select a "suitable" CN value from handbook tables ignores geological conditions differences and assumes that the published handbook values are universally applicable to those watersheds with similar LULC conditions. The conventional Curve Number (CN) model (Equation 2) became one of the most widely used methods for runoff prediction and has been extensively taught in colleges and universities worldwide. It has also been integrated into numerous software platforms, despite many researchers reporting inaccuracies in runoff estimation and unstable model performance across different rainfall ranges [3-5].

2 Methods

To preserve the original SCS CN runoff predictive framework, two approaches were explored in our studies. No extra parameters are added to Equation (1) to retain the parsimonious nature of its initial framework.

2.1 Non-Parametric inferential statistical optimisation technique

First approach was to substitute $I_a = \lambda S$ (as proposed by then SCS) into Equation (1) to obtain Equation (4) as:

$$Q = \frac{(P-\lambda S)^2}{(P-\lambda S+S)} \quad (4)$$

where Q, P, λ and S are as previously defined. Instead of adopting the SCS approach of referencing Curve Number (CN) handbook tables to match the land use and land cover (LULC) conditions of a watershed, this approach employs non-parametric inferential statistical techniques to optimise the λ and S parameters directly using observed rainfall–runoff datasets collected from a watershed. This optimisation framework formulates a watershed-specific runoff predictive model. The proposed approach does not rely on CN values input or Equation (3). The derived λ and S parameters are watershed-specific and explicitly reflect local rainfall–runoff characteristics. During the λ and S parameters optimisation process, Equation (4) was constrained to achieve an overall model bias close to zero in order to minimise overfitting and underfitting. Details of the optimisation technique and a comprehensive implementation guide for this approach can be found in two of our published journal articles [3,4]. The first approach was initially evaluated using official datasets provided by the Malaysian Department of Irrigation and Drainage (DID), specifically the rainfall–runoff data from published Hydrological Procedure No. 27 (DID HP 27) [3]. Subsequently, a Malaysian urban watershed dataset was employed to develop an urban flash flood predictive model with this approach also [4].

2.2 SCS Model rederivation with power function

In the subsequent phase of the study, the research focus shifted following a closer examination of historical SCS archives and official documents from the Natural Resources Conservation Service (NRCS). Agency records from 1954 to the present showed that I_a and S correlation were actually plotted on log-log scale graphs (Fig.1). There was no explanation as to why the linear correlation form of $I_a = \lambda S$ or $I_a = 0.2S$ was adopted directly to simplify Equation (1) while the anti-log form of $I_a = S^{\lambda}$ should be used instead.

It is possible that the SCS agency either overlooked this issue or was constrained by the limited computational capability available at the time, as adopting the antilogarithmic form of: $I_a = S^{\lambda}$ to simplify Equation (1) posed significant challenges in 1954. It is also difficult to simplify Equation (1) with $I_a = S^{\lambda}$ by hand. However, with the introduction of numerical analysis techniques and the increasing affordability and accessibility of desktop and laptop computing power, it is now feasible to explore the adoption of the antilogarithmic form of $I_a = S^{\lambda}$ to simplify Equation (1).

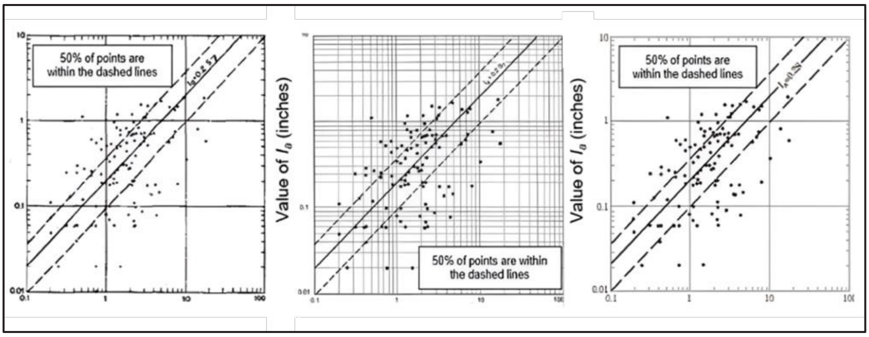

Fig. 1. Three different sources [6-8].

As such, the second approach was to substitute the $I_a = S^\lambda$ into Equation (1), and numerical analysis techniques were employed to examine the feasibility of the rederived SCS runoff predictive model. To distinguish this model reformulation approach from the conventional use of the λ parameter, our study used the L parameter and substitute $I_a = S^L$ into Equation (1) to obtain below equation:

$$Q = \frac{\left(P - S^L\right)^2}{\left(P - S^L + S\right)} \tag{5}$$

Consistent with the initial intent to preserve the parsimonious form of the original SCS CN runoff framework, Equation (5) remains with two parameters only (S and L). Similar to the section 2.1 Non-Parametric Inferential Statistical Optimisation Technique, Equation 5 model optimisation process of S and L parameters are also based on the rainfall-runoff dataset collected from a watershed. The second approach also bypassed the conventional way to source for the CN value according to the LULC conditions and rely on Equation (3) to calculate the S value. A detailed description of the optimisation technique of the second approach and a comprehensive guide to its implementation are provided in one of our published journal articles [5]. The second approach was applied to a previously studied Malaysian urban watershed to benchmark its feasibility and robustness in runoff estimation.

3 Results and discussion

The first approach was developed to address limitations faced by CN practitioners in Malaysia, particularly the reliance on Curve Number handbooks developed for different geographical contexts. Matching land use and land cover (LULC) conditions to handbook classifications has been shown in numerous studies worldwide to introduce uncertainty, often requiring ad hoc adjustment of selected CN values to improve runoff estimates. Such practices indicate that the Curve Number (CN) mapping and selection process is subjective and inherently ambiguous. This study therefore adopts a data-driven framework to recalibrate the original SCS runoff predictive model (Equation 1) through a systematic inferential statistical approach, enabling direct optimisation of the λ and S parameters. The optimisation process of the SCS model in this approach is based on rainfall–runoff datasets collected from the watershed, resulting in a watershed-specific rainfall–runoff model. In our previous studies [3,4], watershed-specific Curve Number (CN) value ranges were successfully derived together with corresponding confidence intervals. Unlike the conventional SCS approach, which selects CN values as model inputs based on land use and land cover (LULC) conditions, this framework derives CN values as statistically significant model outputs that more accurately reflect watershed-specific rainfall–runoff characteristics.

Using the DID HP 27 dataset, our study demonstrated that the conventional SCS runoff model (Equation 2) is statistically invalid for runoff modelling at the significance level of $\alpha = 0.01$ and therefore requires model calibration. Applying the first approach, the calibrated parameter value was $\lambda = 0.051$, with a 99% confidence interval ranging from 0.034 to 0.051, and the derived Curve Number (CN) was 72.58, with a 99% confidence interval ranch of 67 to 76 for Peninsular Malaysia. The uncalibrated conventional SCS model was found to underpredict runoff when storm rainfall depths were below approximately 70–85 mm, while model overprediction tendency increased for larger storm events. These findings raise concerns that infrastructure projects relying on the uncalibrated SCS model and rainfall return periods below 70 mm may be under-designed, whereas projects associated with storm depths exceeding 85 mm may face over-design risks in Peninsular Malaysia [3].

For smaller urban watersheds, the conventional SCS model has also been reported as unsuitable for runoff prediction. The study identified a novel phenomenon: as the urban watershed became increasingly saturated, the watershed CN value increased even though the land use and land cover (LULC) remained unchanged throughout the study period. This outcome highlights a fundamental limitation of the SCS practice of selecting CN values based solely on LULC conditions [4].

The second approach was developed following a re-examination of historical SCS archives, which raised the question of why the antilogarithmic form of: $I_a = \lambda S$ was not employed to simplify Equation (1), despite the primary SCS data relating I_a and S being originally plotted on log–log scales. From a mathematical standpoint, once a linear relationship between I_a and S is established in log–log space, the corresponding relationship should be expressed in an antilogarithmic form to facilitate simplification of Equation (1). A feasibility analysis exploring the use of the antilogarithmic formulation of $I_a = \lambda S$ subsequently led to the development of the second approach. Consistent with the philosophy of the first approach, this method avoids the conventional SCS practice of matching and selecting Curve Number (CN) values from handbook tables. Instead, the second approach also derives watershed-specific CN values as statistically robust outputs directly from observed rainfall–runoff datasets.

In the study applying the second approach to a Malaysian urban watershed, the CN value was also observed to vary according to watershed saturation condition. The findings indicated that single CN value and the conventional SCS runoff model is statistically invalid for modelling runoff in this context. In contrast, the newly formulated runoff model, optimised using Equation (5), significantly improved runoff estimation even as the urban watershed became increasingly saturated. This outcome facilitated the development of an urban flash flood predictive model [5]. The second approach was also benchmarked using datasets from three published studies by other researchers [9–11]. This demonstrates that the newly formulated SCS model under the second approach can be applied successfully to foreign watersheds for runoff estimation.

4 Conclusion

Two approaches were developed to restore the runoff estimation accuracy of the conventional SCS model. The first approach, described in Section 2.1, returns to the fundamental SCS runoff framework (Equation (1)) to perform parameter calibration. The second approach, described in Section 2.2, establishes a procedure to re-derive the SCS runoff model by addressing the underlying mathematical concerns. The key highlights are summarised below:

1. It is possible to derive watershed-specific CN values directly from collected rainfall–runoff datasets, offering an alternative to the conventional practice of estimating CN values based on watershed LULC conditions. CN practitioners are encouraged to adopt either the first or second approach rather than relying solely on CN handbook

values developed from different countries. In the context of climate change resilience, the two alternative approaches presented in this article offer CN practitioners an improved pathway to collect latest watershed-specific rainfall–runoff datasets and to formulate statistically significant runoff predictive models.

2. The observed phenomenon whereby the watershed CN value increased as the urban watershed became increasingly saturated, despite unchanged land use and land cover (LULC) raises further concerns about the conventional SCS practice and the combined use of Equations (2) and (3). Practitioners using GIS-based methods should exercise caution when deriving watershed CN values solely from LULC information. Selecting and using a single CN value as an input for runoff modelling might not adequately reflect the dynamic saturation conditions of a watershed, thereby introducing risks of over design or under design in hydraulic structures.
3. $I_a = 0.2S$ might not be applicable globally and to the watershed of study interest. The conventional SCS runoff predictive model was simplified with: $I_a = 0.2S$ ($I_a = \lambda S$ and λ was fixed = 0.2) which failed the NULL hypothesis test that $\lambda = 0.2$ is statistically valid for the rainfall-runoff datasets in studies of this research. Therefore, CN practitioners are encouraged to perform the same test using local rainfall–runoff datasets before applying Equation (2). Otherwise, the conventional SCS model should be calibrated or reformulated as proposed in this article.
4. The SCS runoff framework has two fitting parameters: λ and S. The SCS proposal to fix λ at 0.2 further limits the model, leaving only one parameter (S) to achieve runoff estimation accuracy. From a changing climate perspective, this constraint can further reduce model performance. Both the first and second approaches returned to the original dual-parameter SCS runoff framework and demonstrated that the SCS runoff predictive model performs better when both fitting parameters (λ and S, or L and S) are calibrated. Both approaches presented in this article break away from the conventional practice of selecting and using a CN value as an input. The data-driven framework enables CN practitioners to utilise rainfall–runoff datasets from any watershed, thereby improving model adaptability under hydro-climatic non-stationarity, intensified rainfall extremes, and evolving climate change conditions.
5. The conventional CN model was found to exhibit both runoff underprediction and overprediction across different rainfall depths within the same study. Pairing an uncalibrated conventional CN model with return period–based rainfall information introduces inherent design risks, of which CN practitioners should be aware. Moreover, extrapolating runoff estimates using the conventional CN model is also risky, as the magnitude and direction of potential underprediction or overprediction remain unknown.
6. In the interest of parsimonious modelling, the two developed approaches preserve the fundamental SCS rainfall–runoff framework without introducing a third parameter into Equation (1). Both approaches have demonstrated promising results in improving runoff prediction performance compared with the conventional SCS CN model (Equation (2)). In addition, each approach incorporates built-in procedures to assess the statistical validity of Equation (2) using collected rainfall–runoff datasets. Therefore, SCS practitioners are strongly encouraged not to adopt Equation (2) without prior validation. At present, it remains unclear which of the two approaches will outperform the other, as additional datasets are required for further testing and comparison. Both approaches are grounded in inferential statistics and are therefore subject to the minimum requirement of collecting at least 25 rainfall–runoff datasets prior to model development, in order to ensure meaningful statistical interpretation of the formulated model. This requirement must not be violated. Modellers adopting these two approaches should be cautioned that, although the

formulated model may be statistically significant, it remains constrained by the range of rainfall–runoff data collected. Excessive extrapolation beyond the maximum observed data range is not recommended, particularly when addressing climate change–related challenges and uncertainties.

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