CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

There are numerous approaches to estimate runoff for ungauged watersheds. One approach utilizes precipitation data in conjunction with topographic, soil, and vegetative conditions within catchment to arrive at an estimate of the likely runoff. One of the models falling within this group is SCS-CN model. This is frequently used for rainstorm events in ungauged basins (Muttharam et al 1997). The model was developed in 1954 by the U.S. Department of Agriculture (USDA) Soil Conservation Service (SCS), and is described in the Soil Conservation Service (SCS) National Engineering Handbook Section 4: Hydrology (NEH-4) (SCS 1985). In 1994, SCS became Natural Resources Conservation Service (NRCS), and therefore, the SCS-CN model is renamed as NRCS-CN model in the current literature.

This NRCS-CN (or SCS-CN) model is the product of more than 20 years of studies of rainfall–runoff relationships from small rural watersheds. Based on annual flood data collected at a number of study watersheds with drainage areas of 1 sq. miles (2.6 sq. km) or less and with a uniform basin hydrologic soil–cover complex, the SCS developed the CN tables (Bales and Betson 1981). It is a simple procedure for estimating streamflow volume (exclusive of base flow) generated by large rainstorms. Further, this SCS-CN model is basically empirical, and provided a consistent basis for estimating the amount of runoff under varying land use and soil types.
To the origin of the SCS-CN methodology, Sherman (1942, 1949) was the first to propose the plotting of direct runoff against storm rainfall. Later, Mockus (1949) proposed that the estimates of surface runoff for ungauged watersheds could be based on soil, landuse, antecedent rainfall, storm duration, and average annual temperature. He combined these factors into an empirical parameter ‘b’ characterizing the relationship between rainfall depth $P$ and runoff depth $Q$ (Rallison and Miller 1981) as:

$$Q = P (1-10^{-bp})$$

(2.1)

According to Mishra and Singh (1999b, 2003c), Equation (2.1) forms the basis of the development of the SCS-CN concept. In a separate attempt, Andrews (unpublished report, 1954) developed a graphical procedure for estimating runoff from rainfall utilizing infiltrometer data, and consequently, graphs were developed for several combinations of soil texture, type and amount of cover, and conservation practices, combined together referred as ‘soil–cover complex’. Mockus empirical rainfall–runoff ($P$–$Q$) relationship and Andrew’s soil–cover complex formed the basis of the conceptual rainfall–runoff relationship incorporated in NEH-4 (Ponce and Hawkins 1996).

In the past three decades, the SCS-CN methodology has been used by a number of researchers for runoff estimation worldwide and, in turn, has attracted intensive and extensive exploration into its formation, rationality, applicability and extendibility, pros and cons aspects, physical significance, etc. Accordingly, based on the reviews available on its applicability to field data (Hjelmfelt et al 2001), the NEH-4 was significantly revised several times, and more recently in 1993 (SCS 1993).
Since its inception, the SCS-CN model has been improved, extended and modified in various aspects. Therefore, this chapter aims at critically reviewing the SCS-CN model, particularly to discuss the following in detail: the theoretical (analytical) justifications, importance of CN and development of representative CN for a watershed, low rainfall–high CN bias, AMC and its developments, initial abstraction relation with potential maximum retention, effect of storm duration, source-area concept, applications, long-term hydrologic simulation, distributed modelling, use of Remote Sensing (RS) data and Geographical Information System (GIS), advantages and limitations of the model. Finally at the end, the chapter provides an overview of specific issues still to be addressed based on the insights from literature review.

2.2 THEORETICAL JUSTIFICATION

The SCS-CN model is based on the water balance equation and two fundamental hypotheses. The first hypothesis equates the ratio of the actual amount of direct surface runoff (Q) to the total rainfall (P) (or maximum potential surface runoff) to the ratio of the amount of actual infiltration (F) (or cumulative infiltration) to the amount of the potential maximum retention (S). The second hypothesis relates the initial abstraction (I_a) to the potential maximum retention (S). These are expressed, respectively, as

\( P = I_a + F + Q \)  

(a) Water Balance Equation

\( \frac{Q}{P - I_a} = \frac{F}{S} \)

(b) Proportionality Hypothesis
(c) I_a–S Hypothesis

\[ I_a = \lambda S \]  \hspace{1cm} (2.4)

where \( P = \) total rainfall, \( I_a = \) initial abstraction, \( F = \) cumulative infiltration, \( Q = \) direct surface runoff, \( S = \) potential maximum retention, and \( \lambda = \) initial abstraction ratio. A complete derivation of SCS-CN equation is described in Appendix 1.

Mockus (1949) suggested that the model produced rainfall–runoff curves of the type found on natural watersheds. The concepts (assumptions) of SCS-CN model are purely empirical, and therefore, a brief review of the justifications available in literature is in order. The Handbook of Hydrology (Maidment 1993) states that the assumption of proportionality (Equation (2.3)) seems to be quite arbitrary and has no theoretical or empirical justification (Pilgrim and Cordery 1993). Based on this proportionality, Mishra and Singh (2003c) described it in terms of \( C = S_r \) concept, where \( C \) is the runoff coefficient and \( S_r \) is the degree of saturation, and presented several SCS-CN-inspired models.

According to Chen (1981) and Mishra and Singh (2004a,b), the SCS-CN model is an alternative expression of the infiltration decay curve, and in practice, it can be used as one of the parametric infiltration models, or modified forms thereof, to formulate the standard infiltration capacity curve for a given soil–cover–moisture complex. Yu (1998) derived SCS-CN model theoretically (analytically) assuming exponential distribution for the spatial variation of infiltration capacity and the temporal variation of rainfall rate. Under these assumptions, runoff will be produced anywhere on a catchment where the time-varying rainfall rate exceeds the spatially variable but time-constant infiltration capacity (making no allowance for any runon process) (Beven 2002). Mishra and Singh (1999b) derived the SCS-CN model
analytically with its basis in the Mockus (1949) method. Later on, the constrained region for the validity of the Mockus (1949) method, and the existence of watersheds with CN < 50 was pointed out. Further, the underlying assumption on the spatial variability of rainfall employed by the SCS-CN and Mockus (1949) methods were critically discussed (Mishra and Singh 2001).

Of late, Mishra and Singh (2002a, 2003b) revisited the existing SCS-CN model from an analytical perspective and explored the fundamental proportionality concept (Equation (2.3)). Mishra and Singh (2002a) described F (Equation (2.3)) as the dynamic portion of infiltration ($F_d$) and distinguished it from the static or gravitational infiltration ($F_c$), while Mishra and Singh (2003b) derived Equation (2.3) using the first-order linear hypothesis for the variation of S with rainfall. Further, Mishra and Singh (2003a) explained the physical significance of S using the diffusion term of the linear Fokker–Planck equation for infiltration (Philip 1974), which relates S to the storage and transmission properties of the soil.

### 2.3 DEVELOPMENT OF REPRESENTATIVE CN

The basic parameter-CN of SCS-CN model requires the watershed characteristics such as land use and treatment classes (Agricultural, Range, Forest, and more recently, Urban (SCS 1986)), AMC, Hydrologic Soil Group (HSG) information (A, B, C, and D), and Hydrologic surface condition (Poor, Fair, and Good) of a watershed. From the error analysis, Hawkins (1975) pointed out that the errors in CN may have much more serious consequences than errors of similar magnitude in P, but for a considerable precipitation range (up to about 9 in.). Chen (1981) pointed out that smaller the values of CN, the larger are the effects of the variation of initial abstraction and rainfall on runoff. Further, Bales and Betson (1981) emphasized that CN is
significantly related to storm hydrograph model parameters, such as the peak flow. Especially, in low runoff and low rainfall situations, errors in runoff calculation near its threshold are severe. According to Knisel and Davis (2000), CN is a sensitive parameter in the simulation of runoff volume in GLEAMS and found that the runoff estimates for small changes in high CNs are more sensitive than equivalent small changes in low CNs. Therefore, it is clearly understood that the accurate CN estimation is very important for storm runoff calculation. Due to this, there are numerous approaches practiced elsewhere to estimate the ‘runoff CN’ or ‘representative CN’ for a watershed. They were categorized based on their CN estimation procedure (Figure 2.1):

![Classification of CN estimation methods](image)

**Figure 2.1 Classification of CN estimation methods**

2.3.1 CNs from field data

2.3.1.1 Asymptotic approach

This approach is based on ‘frequency matching’, which was first pointed out by Hjelmfelt (1980) in the SCS-CN model. It uses an ‘Ordered’ data, that is, P and Q data are arranged in descending order, in which a
Q-value corresponding to a particular P may not necessarily represent the actual runoff due to this rainfall. The ‘Natural’ data, however, retain the actual P–Q dataset. Therefore, this approach preserves the return-period matching between rainfall and runoff. Hawkins (1993) found out that a secondary relationship almost emerges between the CN and the storm rainfall depth from ordered P–Q dataset.

The secondary relationship leads to the description of three types of CN-P behaviour, namely, complacent, standard, and violent, as shown in Figure 2.2 (where \( CN_0 = \frac{100}{1+P/2} \); \( CN_{\text{ordered}} = \) CN from ‘Ordered’ P–Q dataset; Hawkins 1993). The standard and violent relations yield a constant CN with increasing storm rainfall, but the complacent one does not yield a stable CN-value. Several options were prescribed to arrive at a CN value by Hawkins (1993, 2005) for this most troublesome pattern – ‘Complacent’. Few researchers (Hawkins 1993; Hawkins and Ward 1998; Price 1998; Hjelmfelt et al 2001; Van Mullem et al 2002) have applied this asymptotic method of ordered data. Rietz and Hawkins (2000) also used the asymptotic approach for CN estimation for each landuse on each watershed at three scales – local, regional and national. Hawkins (2005) states that the approach has the following advantages, such as (1) it is a more efficient use of data resources; (2) it negates the absolute need for rainfall data directly on-site; (3) it avoids CN biasing with high CNs for low P; (4) from experience, the results seem more consistent with external factors such as seasonal issues and adjacent watershed findings; (5) CN solutions with it are less sensitive to occasional outlier P and Q values, and give more consistent results; (6) results are similar to those done with natural data; (7) it is trendy.
The earlier approach is however valid only in frequency matching sense, and therefore, applied to return-period cases. Its use for other than the above cases is questionable and debatable. Furthermore, some of the statistical uneasiness exist in the procedure such as (Hawkins 2005): (1) built-in bias in all P:Q fitting insofar as 0≤Q≤P. That is, all points must fit into the octant below the 1:1 line and above Q=0. Mere random generation of Q≤P for given P will lead to a series of points displaying an unnaturally high coefficient of determination, r². This is exacerbated with the CN situation where all points must fit in the reality space of CN,0≤CN(P,Q)≤100, and also
due to the CN which is already a function of P; (2) sampled watersheds are assumed to be truly valid samples of what they are taken to represent; (3) data points used are end-of-storm total P and Q, and the array of many of these does not necessarily define the relationship with time for an individual event. That is, Q and P are assumed to be Q(t) and P(t) respectively.

2.3.1.2 Least squares approach

This approach adopted the least squares function fitting of the P, Q data to the basic CN equation (Equation (A.1.13)). Before that, the ‘smaller’ storms must be excluded, to avoid low rainfall–high CN bias found in essentially every dataset. If this is the case, then the least squares fitted CN (or S) should be very similar to the asymptotic values (especially for the ordered data), insofar as they both use the same data, and both are taken to be free of the rainfall depth influence. This suggests that little is gained by least squares fitting, except for the natural data case. Therefore, least squares CNs may be an unnecessary refinement.

2.3.1.3 NEH-4 procedure

This NEH-4 procedure consists of graphical approach and median (or mean) CN approach. The graphical approach is a simple procedure, prescribed by NEH-4 (SCS 1972), in which the data set (annual flood P:Q data) is superimposed on the NEH4 P:Q:CN plot, and the CN is selected by visual interpretation. But it consists of the following drawbacks:

1. It uses only one piece of data (the annual flood event) from each year of measurement, which is an inefficient and expensive way to use data.
2. It does not assure freedom from the P:CN bias. Many annual datasets contain the P influence, including the NEH-4 graphical example.

3. In dry years, some small watersheds may not have flow.

4. Many applications of the CN method go well beyond only annual event circumstances.

Due to these drawbacks, this graphical approach is generally not practiced and also it became obsolete. Instead of that, a simple average (mean) or median CN from a number of storms is practiced. From the observed rainfall–runoff data, the CN is determined for each P–Q pair. From these arrays of CNs, either ‘median’ or ‘mean’ CN is selected as a representative CN for a watershed. Here, the occurrence of low P–high CN bias is judiciously considered. This is a common method adopted elsewhere, for example, Rallison and Cronshey (1979); Hawkins et al (1985); Hjelmfelt (1991); Hawkins et al (2002); Mishra et al (2004a); Schneider and McCuen (2005); Mishra et al (2005a,b) were considered the ‘median’ CN of large storms. In addition to that, the NEH-4 (SCS 1985) example divides the P–Q plot into two equal numbers of P–Q points for deriving the median CN corresponding to average antecedent moisture condition (AMC II). According to Hawkins (2005), either median or mean CN of large storms is appropriate, if the bias in dataset is removed. The median is more appropriate for small samples for it reduces the effect of outliers (Schneider and McCuen 2005) and is useful in operational setting (Hjelmfelt 1991). This approach can be applied to both ‘ordered’ and ‘natural’ datasets, and thus differs from asymptotic approach. Since the asymptotic method considers the ‘ordered’ dataset and, in turn, shifts the values to another position, but within the conditional distribution function of Q for the measured P (Schneider and McCuen 2005), its accuracy in the estimated CN is affected. In a comparative study among
asymptotic method, median CN method, and least square method, Simanton et al (1996) found them to yield similar results, and sensed the existence of CN – drainage area relationship. Traditionally, these ‘median’ or ‘mean’ CN value is represented as \( CN_{II} \), describes the ‘average condition’ of the watershed in terms of wetness, and is considered as representative CN for the watershed.

### 2.3.2 Hydrologic soil-cover complex number procedure

This method uses the available standard CN table (hydrologic soil–cover complex number) of NEH-4 (SCS 1993) to estimate the CN of a watershed based on its land use type and hydrological soil group type. This is used mostly for the ungauged watersheds.

According to SCS, there are four hydrologic soil groups: A, B, C, and D. (1) ‘A’ Soils having high infiltration rates, even when thoroughly wetted and consisting chiefly of deep, well to excessively drained sands or gravels. These soils have a high rate of water transmission; (2) ‘B’ Soils having moderate infiltration rates when thoroughly wetted and consisting chiefly of moderately deep to deep, moderately fine to moderately coarse textures. These soils have a moderate rate of water transmission; (3) ‘C’ Soils having slow infiltration rates when thoroughly wetted and consisting chiefly of soils with a layer that impedes downward movement of water, or soils with moderately fine to fine texture. These soils have a slow rate of water transmission; and (4) ‘D’ Soils having very slow infiltration rates when thoroughly wetted and consisting chiefly of clay soils with a high swelling potential, soils with a permanent high water table, soils with a clay pan or clay layer at or near the surface, and shallow soils over nearly impervious material. These soils have a very slow rate of water transmission. Some wet soils are classified as dual hydrological soil groups (A/D, B/D and C/D) that could be
adequately drained. The first letter applies to the drained and the second to the undrained condition. Especially, the soils are assigned to these dual groups if the shallow depth to a permanent water table is the sole criteria for assigning a soil to hydrologic group D. Of late, Golding (1997) noticed several discrepancies where the SCS has classified the soils as being A/D and B/D, which are supposed to reflect a high ground water table. Further, Golding (1997) added that urbanization of an area could change the height of the ground-water table. In addition, professionals tend to use A or B rather than D classification to economize the project.

The CN values of NEH-4 tables represent the average median site CN (the CN corresponding to the curve that separated half of the plotted P–Q data from the other half for the given site) values with the indicated soil, cover, and surface condition. This is denoted as CN_{II}, corresponding to AMC II (average runoff potential). Further this approach is done in two ways; (1) Weighted CN approach and (2) Weighted Q approach. In the first one, the CN values of the respective hydrological–soil cover complex were multiplied to the respective per cent areal coverage of the complexes, that is,

$$CN_{aw} = \frac{\sum_{i=1}^{n} (CN_i \times A_i)}{\sum_{i=1}^{n} A_i}$$

(2.5)

where $CN_{aw}$ = the area-weighted curve number for a watershed; $CN_i$ = the curve number for each land use–soil group complex; $A_i$ = the area for each land use–soil group complex; and $n$ = the number of land use–soil group complex in a watershed. Then, based on this weighted CNs, the runoff is estimated.
The second one primarily calculates the respective runoff (Q), with the corresponding CNs of the hydrological–soil cover complex, and finally the Q values on each complexes, were weighted similar to the above. It is obvious that the weighted Q method is superior to the weighted CN method, as the former is more rational than the latter for water balance reasons. However, the weighted CN is easier to work with the watershed having many complexes or with a series of storms. Mishra and Singh (2003c) pointed out that the computed runoff by the earlier two approaches would significantly deviate for a wide range of CNs for various complexes in a watershed. In general, the weighted CN method is less time-consuming but tends to be less accurate when compared to the actual measured runoff depth. Therefore, again it is clear that weighted Q method is superior to weighted CN method.

Two problems arise while using this ‘hydrologic soil–cover complex number’ approach:

1. The calculation is much more sensitive to the CN chosen than it is to the rainfall depths (Hawkins 1975; Bondelid et al 1982).

2. It is difficult to accurately select the CNs from the available handbook CN tables (Hawkins 1984).

Recently, this approach has been tried with the aid of remote sensing and GIS techniques in case of distributed modelling. Hawkins (1984) suggested that the determination of CNs from field data is better than hydrologic soil–cover complex number method, as later one leads to variable, inconsistent, or invalid results.
2.3.3 Other methods

Due to the SCS-CN model being sensitive to accurate CN estimation for accurate runoff estimation, some researchers tried entirely different approaches. For example, Bonta (1997) evaluated the derived frequency distribution approach for determining watershed CNs from measured data, treating P and Q data as separate frequency distributions. This method gives fewer variable estimates of CN for a wide range of sample sizes than do the methods of asymptotic and median-CN for CN estimation. It is advantageous in limited P–Q data situation, and does not require watershed response type to estimate CN, as needed in the asymptotic method. Mishra and Dwivedi (1998) presented an approach to determine the upper and lower bounds or enveloping CNs, which are useful in high and low flow studies, respectively. McCuen (2002) found the quantity (100-CN) to fit the gamma distribution, which he used for developing the confidence intervals for CNs ranging from 65 to 95, with parameter estimation by Method of Moments (MOM). Later, Bhunya et al (2002, 2003) provided a more reliable procedure for estimation of confidence interval by employing the Method of Maximum Likelihood (MOML), and Method of L-moment in addition to MOM as parameter estimation. These methods however require testing on a large dataset.

2.4 LOW P–HIGH CN BIAS

For every CN estimation method described earlier, the low P–high CN bias should be carefully considered prior to their applications. Hjelmfelt (1991) pointed out that the CNs presented in NEH-4 (SCS 1985) were developed based on annual flood events and that use of smaller events could bias the results towards larger CNs. Therefore, in case of 'hydrologic soil–cover complex number’ approach this should be taken into account for
runoff estimation. Further, Hawkins (1993) and Hawkins and Cate (1998) found a strong secondary relationship between the found CNs and causative rainfall P (spurious correlation). Paradoxically, the lowest CNs comes with the larger storms. So, this effect should be judiciously considered particularly in case of CN estimation methods from field data.

It is found that this bias of ‘low P–high CN’ is due to the following (Hawkins 2005; Schneider and McCuen 2005):

1. The data is ‘censored’ to the extent that no events of Q=0 are included, so that the only events that survive in the dataset for low rainfalls are those that indicate a high CN.

2. The SCS-CN equations are subject to two constraints, specifically that Q must be less than P and greater than 0.

3. Many watersheds may be composed of various components of different source areas or CNs, a condition that also leads to declining CNs with P.

4. Errors in the CN model itself, in either structure or concept, or in coefficients (such as 0.2).

5. Non-linear models, such as power models, are inherently biased, as are exponential and logistic models. So, the non-linearity of SCS-CN equation contributes to the bias.

6. The fitting of the CN by least squares inherently puts more weight on the larger Q values where the CN tends to be larger.
Hawkins (2005) provided the following guidelines for the removal of small storms to overcome the bias: Rainfalls, which are less than 1 in. can be avoided for further analysis or the storms that satisfy the $P/S \leq 0.456$ in. (Hawkins et al 1985) should be avoided and considered as small storms for the SCS-CN model application. The latter one may be more rational than the former, which is based on a crude assumption of $P < 1$ in. The Hawkins et al (1985) approach of ‘large storms’ suggests the following to obtain $P$-independent CN storm data:

1. Consider natural $P$–$Q$ pair, and use the biggest storm to calculate $S$ from SCS-CN equation (Equation (A.1.17)).

2. Check for $P/S > 0.456$ in.

3. If satisfied, add the next biggest storm in calculation. Use mean (or median) CN for those selected storms.

4. Repeat step (2).

5. Consider all the events down to point where the last $P$ divided by the mean (or median) $S$ is greater than 0.456 in. in analysis.

The above ‘0.456 in.’ was considered due to the following reasons (Hawkins et al 1985):

1. Smith and Montgomery (1980) stated as ‘$P/S < 0.4$… poorly (if at all) define a CN in any case’, though they gave no reasons.

2. Hjelmfelt (1982) stated as ‘…a small storm is one which… $P < 0.2$ S where $S$ is determined from AMC I (dry condition)
curve number’, and therefore, elimination of small events from the dataset is warranted.

3. In Hawkins et al’s (1985) approach, $P < 0.2 \ S_{I}$, where $0.2 \ S_{I} = 0.2 \times 2.281 \ S_{II} = 0.456 \ S_{II}$. Here, $S_{II}$ is associated with AMC II curve number.

4. There exists less than a 10% chance of not including events (i.e., $P/S > 0.456$ in.) because $Q=0$.

5. Inspection of $P:Q$ data plot yields a clear break away from the $P$-axis.

### 2.5 ANTECEDENT MOISTURE CONDITION

Here, it is useful to provide a brief description of the antecedent moisture condition (AMC), an important determinant of CN in runoff estimation. The AMC is defined as the initial moisture condition of the soil prior to the storm event of interest. The SCS-CN model expresses this parameter as an index based on seasonal limits for the total 5-day antecedent rainfall as follows:

1. AMC I conditions represent dry soil with a dormant season rainfall (5-day) of less than 12.7 mm and a growing season rainfall (5-day) of less than 35.56 mm.

2. AMC II conditions represent average soil moisture conditions with dormant season rainfall averaging from 12.7 to 27.94 mm and growing season rainfall from 35.56 to 53.34 mm.
3. AMC III conditions represent saturated soil with dormant season rainfall of over 27.94 mm and growing season rainfall of over 53.34 mm.

Normally, AMC II is taken as the base with reference to which CNs are adjusted to estimate the runoff. Depending on the 5-day antecedent rainfall amount, AMC II (CNII) is convertible to AMC I (CNI) or AMC III (CNIII) using any of the relations given by Sobhani (1975); Chow et al (1988); Hawkins et al (1985); Neitsch et al (2002) (Table 2.1), and also directly from the NEH-4 tables (SCS 1972) for runoff estimation. Due to the availability of more than one formulation, a critical review on the CN conversion formulae discussed earlier is presented here based on the comparative study. The subscripts I–III in Table 2.1, and elsewhere in the text refer to AMC I–AMC III, respectively.

2.5.1 A critical review on CN-conversion formulae

The AMC-dependent CN-values given by NEH-4 (SCS 1972) in tabular form can be fairly represented by mathematical expressions given by Sobhani (1975). Later, Smith and Williams (1980); Hawkins et al (1985); Chow et al (1988) also suggested expressions for the same CN-conversion. Of late, Neitsch et al (2002) also provided CN-conversion formulae entirely different in form and these are being used in the popular SWAT model. Since the accuracy of runoff computation largely depends on the correctness of CN-value, it is in order to compare these conversion formulae and discuss their validity.
Table 2.1 Popular AMC-dependent CN-conversion formulae

<table>
<thead>
<tr>
<th>Method</th>
<th>AMC I</th>
<th>AMC III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sobhani (1975)</td>
<td>( CN_I = \frac{CN_{II}}{2.334 - 0.01334CN_{II}} )</td>
<td>( CN_m = \frac{CN_{II}}{0.4036 + 0.005964CN_m} )</td>
</tr>
<tr>
<td>Hawkins et al (1985)</td>
<td>( CN_I = \frac{CN_{II}}{2.281 - 0.01281CN_{II}} )</td>
<td>( CN_m = \frac{CN_{II}}{0.427 + 0.00573CN_m} )</td>
</tr>
<tr>
<td>Chow et al (1988)</td>
<td>( CN_I = \frac{4.2CN_{II}}{10 - 0.058CN_{II}} )</td>
<td>( CN_{III} = \frac{23CN_{II}}{10 + 0.13CN_{II}} )</td>
</tr>
<tr>
<td>Neitsch et al (2002)</td>
<td>( CN_I = CN_{II} - \frac{20(100-CN_{II})}{(100-CN_{II}+exp[2.533-0.0636(100-CN_{II})])} )</td>
<td>( CN_m = CN_m \exp[0.00673(100-CN_m)] )</td>
</tr>
</tbody>
</table>

2.5.1.1 Sobhani formulae

The Sobhani (1975) formulae for CN conversion from AMC II (\( CN_{II} \)) to AMC I (\( CN_I \)) and AMC III (\( CN_{III} \)) are given in Table 2.1. In an analysis of the SCS (1972) table for CN, Sobhani (1975) found the existence of linear relationships between the potential maximum retention, S, for AMC II and that for AMC I or AMC III. A substitution for S from CN-S relationship (Equation (A.1.15)) into these linear relations yields the CN-relations shown in Table 2.1. These equations are reportedly applicable in the CN-range (55, 95), which encompasses the most estimated or experienced range of CN-variation. To add, CNs of every 5th of the range (55, 95) was used to get the relationship (Hawkins 2005).

2.5.1.2 Smith and Williams formulae

A field scale model for Chemicals, Runoff, and Erosion From Agricultural Management Systems, CREAMS, has adopted a CN-conversion
formula (only for $CN_{II}$ to $CN_I$) in polynomial form (Smith and Williams 1980), as discussed here.

$$CN_I = -16.91 + 1.348 \times CN_{II} - 0.01379 \times CN_{II}^2 + 0.0001177 \times CN_{II}^3$$ \hspace{1cm} (2.6)

As the CREAMS model is concerned about only to determine the maximum available water storage in the soil profile, which is related to $CN_I$, the relationship of $CN_{II}$ vs $CN_{III}$ was not found out and considered as unnecessary (Knisel 2005). Actually the CN is not used in the CREAMS model to calculate runoff directly, but the tabulated CN values for AMC II is only used to estimate $CN_I$, and thus the maximum available storage. Later on, runoff is estimated on a daily basis using the available storage in the soil profile on a specific day as determined from a daily soil water accounting procedure. In 1987, GLEAMS model was developed and published which has a vastly improved soil representation and other improvements over CREAMS.

Later, Schroeder et al (1994), assumed the 4th order polynomial to fit the relationship between $CN_{II}$ and $CN_I$, better than the 3rd order polynomial used in CREAMS model, and expressed as:

$$CN_I = 3.751 \times 10^{-1} \times CN_{II} + 2.575 \times 10^{-3} \times CN_{II}^2 - 1.639 \times 10^{-5} \times CN_{II}^3 + 5.143 \times 10^{-7} \times CN_{II}^4$$ \hspace{1cm} (2.7)

This conversion equation is used in ‘The Hydrologic Evaluation of Landfill Performance (HELP)’ Model. The CREAMS publication was published in 1980, before the development of the Personal Computers and its word processing capabilities. Therefore, the Equation (2.7) might be better than Equation (2.6).
2.5.1.3 Hawkins formulae

Based on the smoothened CN-data obtained by fitting straight lines through the plot on normal probability paper (Ponce and Hawkins 1996), Hawkins et al (1985) found the existence of the following relations:

\[ S_{I} = 2.281 \ S_{II} \quad r^2 = 0.999 \ \text{and} \ \ S_{e} = 5.2324 \ \text{mm} \quad (2.8) \]

\[ S_{III} = 0.427 \ S_{II} \quad r^2 = 0.994 \ \text{and} \ \ S_{e} = 2.2352 \ \text{mm} \quad (2.9) \]

where \( r^2 \) is coefficient of determination and \( S_e \) is the standard error of estimate. These equations are also applicable in the range \( 55 \leq \text{CN} \leq 95 \).

Substitution of Equations (2.8) and (2.9) into CN-S relationship leads to expressions shown in Table 2.1. The CN\(_I\) expression was derived with \( r^2 = 0.996 \) and \( S_e = 1.0 \ \text{CN} \), and CN\(_{III}\) expression was obtained with \( r^2 = 0.994 \) and \( S_e = 0.7 \ \text{CN} \). These expressions, along with their derivation, are similar to those suggested by Sobhani (1975). The only difference with Sobhani (1975) is that CNs of all in the range (55, 95) was used, hopefully to get a better relationship. Due to this, the denominator values (Table 2.1) of Hawkins et al (1985) formulae were slightly changed (not significant) with that of Sobhani (1975). It was found out that the relationship from both formulations deteriorated quickly for CN\(_{II}\) less than 55 (Hawkins 2005).

2.5.1.4 Chow formulae

The formulae of Chow et al (1988) and those of Sobhani (1975) and Hawkins et al (1985) (Table 2.1) resemble with the following general form:
\[ Y = \frac{aX}{10 \pm bX} \]  

(2.10)

where \( Y \) and \( X \) are, respectively, the dependent and independent variables, and \( a \) and \( b \) are empirical parameters. Here, \( Y \) corresponds to \( \text{CN}_{\text{II}} \); \( X \) to \( \text{CN}_{\text{I}} \) or \( \text{CN}_{\text{III}} \); and the \(-\) sign and + sign for AMC I and AMC III, respectively. As an example, the Chow et al equations can be recast by dividing them by 4.2 and 23 to derive the same forms as of the \( \text{CN}_{\text{I}} \) and \( \text{CN}_{\text{III}} \) Sobhani and Hawkins et al equations, respectively. In the derived relations (Table 2.1), \( \text{CN}_{\text{I}} \) represents the lowest runoff potential, and \( \text{CN}_{\text{III}} \) the highest runoff potential. The Chow et al (1988) equations are reportedly applicable in the whole range of \( \text{CN} \)-variation (0,100).

2.5.1.5 Neitsch formulae

The \( \text{CN} \)-conversion formulae (Table 2.1) given by Neitsch et al (2002) are entirely different in form from all others and these are used in the SWAT model developed by the Agricultural Research Service of the United States Department of Agriculture (USDA-ARS). This is a continuous long-term yield model that predicts the impact of land management practices on water, sediment, and agricultural chemical yields in large complex watersheds with varying soils, land use, and management conditions (Neitsch et al 2002). Its documentation, however, does not provide clear guidelines for the applicability of the conversion formulae, except \( \text{CN}_{\text{I}} \) and \( \text{CN}_{\text{III}} \) (Table 2.1) are further adjusted for actual moisture content.

The full development detail of the formulae was unknown, except that the formulae also based on the NEH-4 CN table values. To add on, Mishra et al (under re-review, 2006) found out that the formulae yielded the undesirable negative values of \( \text{CN}_{\text{I}} \) in \( \text{CN}_{\text{II}} \) range (1, 19). Here, it is noted that
the CN-values obtained for most soil-cover-moisture complexes in the field are generally greater than 40 (SCS 1972). However, the occurrence of negative CN-values is conceptually not rational. Based on the work of Mishra et al (under re-review, 2006), it was found out that the Hawkins et al (1985) CN-conversion formulae performs better among others, though there was about 0.1% difference among them all over the range of CN_{II} values from 50 to 100 for either the CN_{I} or CN_{III} conversions. Therefore, the Hawkins et al (1985) formulae were recommended for CN-conversion and, in turn, runoff computation.

2.5.2 Developments in AMC

The AMC procedure prescribed by NEH-4 suffers from three major weaknesses (Hope and Schulze 1981): (1) the relationship between AMC and antecedent rainfall holds for discrete classes, rather than continuous (Hawkins 1978b); (2) the use of 5-day antecedent rainfall is not based on physical reality, but on subjective judgement; (3) evapotranspiration (ET) and drainage are not considered in depletion of catchment storage.

As nothing was known on the actual field data that went into making the NEH-4 AMC table, and also the methodology adopted to make it, the table can be seen as a convention. Its application is administrative hydrology, not scientific hydrology, and ‘true’ only inside the CN world. It is to note that early editions of NEH-4 show some variation in table from what is now offered. This is due to the smoothing of data CN_{II} vs CN_{I}, CN_{III} on normal-normal probability paper and published after 1956 edition of NEH-4 (Rallison and Cronshey 1979). Due to the incertitude of NEH-4 AMC table values, Williams and LaSeur (1976); Hawkins (1978b); Bales and Betson (1981) reviewed critically the issues of CN adjustment with the watershed’s moisture status.
Bales and Betson (1981) noticed that if SCS-CN tables were used for determining a hydrologic soil-cover complex number and if the wettest antecedent moisture condition was assumed, the runoff volumes would be regularly under-predicted in the regions represented by these data. The runoff volumes will apparently be under-predicted even for the higher yield events, for which the SCS-CN methodology best applies. According to Chen (1981), a drastic (discrete) change of AMC over a short period of time may cause a serious error in CN-value and hence the estimated runoff. Further, Hjelmfelt et al (1981) found that the AMC conversion table described the 90% (AMC I), 50% (AMC II), and 10% (AMC III) cumulative probabilities of exceedance of runoff depth for a given rainfall. Again, Hjelmfelt (1982) tested the association of CN variation with antecedent precipitation and with peak discharge. He found good correlation with antecedent precipitation while it is poor with peak discharge. Gray et al (1982) assumed four AMC classes with respect to initial infiltration capacities for each soil type, instead of three AMC classes defined by SCS, and performed a regression analysis using average annual precipitation. According to Ponce and Hawkins (1996), the AMC table (SCS 1972) of NEH-4 does not account for regional differences or scale effects and, therefore, an antecedent period longer than 5 days might be required for large watersheds.

Besides the quality of the measured P–Q data, the accuracy of runoff prediction largely depends on accurate estimation of the lumped parameter CN (Ponce and Hawkins 1996) which varies with (1) spatial and temporal variability of storm and watershed characteristics, and (2) antecedent rainfall and associated soil moisture. According to Ponce and Hawkins (1996) and McCuen (2002), AMCs are assumed to be the primary cause of the storm to storm variation of CN on any one watershed. It is noted that a watershed would have more than one CN, indeed, a set of CNs (SCS 1985; Hjelmfelt 1991). In response to the aforementioned criticisms on the procedure of
AMC, the reference to AMC was removed in CN-portion of NEH-4 (Hawkins 1996), and variability is incorporated by considering CN as a random variable (Hjelmfelt et al 2001), and, in turn, the terminology changed to ‘antecedent runoff condition’ or ARC, that explains only a part of the CN-variation (Van Mullem et al 2002). Heggen (2001) found that the three-parameter Normalized Antecedent Precipitation Index (NAPI) model outperforms the one-parameter (AMC$_n$) CN model. Recently, using the 5-day antecedent rainfall, Mishra and Singh (2002b) proposed a SCS-CN-based model incorporating non-linear continuous variation of antecedent moisture (M).

Therefore, it is evident that the AMC is still one of the major sources of CN-variability, and the accuracy of runoff computation largely depends on the correctness of CN-value. Contradictorily, in many climates, a more important source of variability is rainfall intensity and its pattern within the storm, and this cannot be accounted for by the SCS-CN model. According to Smith (1997), the antecedent moisture for most storms has a far lower variability than does the storm CN. Walker et al (1998) used the baseflow, rather than the antecedent rainfall, for quantifying the watershed wetness prior to the storm event of interest. More recently, McCuen (2002) prescribed AMC limits statistically and showed that confidence intervals can be used to assess the variation in CN. According to Woodward et al (2002), a number of other factors (than the ones listed in NEH-4, namely, soil type, land use, hydrologic condition and antecedent moisture) affecting CN such as stage of crop growth and soil moisture also explain the individual CN-variation with storms.

Therefore, the best approach to define antecedent condition is to use a model to establish antecedent conditions. A more rational approach, however, should be to adjust the soil moisture status in continuous modelling, such as in SWAT. Ironically, such a description of the variation in CN is also
not proper though it is being widely used. In future, more efforts are required for testing the validity of 5-day antecedent rainfall or soil moisture accounting procedure using the field data.

2.6 **I_a–S RELATIONSHIP**

An elementary expression for conservation of rainfall into runoff is \( Q = P - L \), where \( L \) is the hydrologic abstraction, difficult to quantify in nature (Ponce and Hawkins 1996). These abstractions include interception; surface storage; evaporation from water bodies such as ponds, lakes, etc.; infiltration; and evapotranspiration from all types of vegetation. Of these, infiltration is the most important for storm analysis (short-term), where as evaporation and evapotranspiration are the most important for seasonal or annual yield evaluations (long-terms). The remaining two losses (interception and surface storage) are usually of secondary importance. Out of these, initial abstraction (\( I_a \)) accounts for depression (surface) storage, interception, and infiltration, occurring before runoff begins. The interception and depression storage vary widely with types of vegetative cover, wind, depressed area and depth, etc. and are extremely difficult to quantify accurately.

During the initial efforts in SCS-CN model formulation (Plummer and Woodward 2002), the inclusion of initial abstraction was not considered, but as development continued, it was included as a fixed ratio of \( I_a \) to \( S \) (Equation (2.4)). This relationship was justified on the basis of measurements in watersheds less than 10 acres in size despite a considerable scatter in the resulting \( I_a–S \) plot (SCS 1985). NEH-4 (SCS 1985) reported 50% of data points to lie within \( 0.095 \leq \lambda \leq 0.38 \), leading to a standard value of \( \lambda = 0.2 \) (Ponce and Hawkins 1996). Besides the wider variability in the resulting \( I_a–S \) plot (SCS 1985), a simple assumption of \( I_a = 0.2S \) leads to the severe criticism and modification since its inception. For example, Central Unit for Soil
Conservation (1972) recommended a $\lambda$ value of 0.3 for all regions of India, except for black cotton region for which it is 0.1 under AMC II and III conditions. Aron et al (1977) suggested $\lambda \leq 0.1$ and Golding (1979) provided CN-dependent $\lambda$-values for urban watersheds: $\lambda = 0.075$ for $\text{CN} \leq 70$, $\lambda = 0.1$ for $70 < \text{CN} \leq 80$, and $\lambda = 0.15$ for $80 < \text{CN} \leq 90$. Springer et al (1980) found $\lambda = 0.2$ not appropriate for both arid and humid watersheds and cautioned against its use for other watersheds. In his mathematical treatment, Chen (1981) physically signified $\lambda$ as a square root ratio of initial ($f_o$) and final infiltration rates ($f_\infty$) and varied $\lambda$ from 0 to 1. Here, it is worth to emphasize that Chen (1981) analysed $I_a$–$S$ relation using two assumptions of ‘$S$ includes $I_a$’ and ‘$S$ excludes $I_a$’. Since $S$ does not include $I_a$, the NEH-4 was corrected accordingly (Van Mullem et al 2002).

It is interesting to note the conclusion of a publication on the NRCS website, as follows:

Each relationship of $I_a$ to $S$ requires a unique set of runoff curve numbers. Simple revision of the relationship of $I_a$ to $S$ to something other than $I_a = 0.2S$ requires more than a simple change of the runoff equation. There is no linear relationship between the runoff curve numbers for the two $I_a$ conditions. It also requires a new set of runoff curve numbers developed from analysis of small watershed data.

From these findings, it is probably not justifiable to tweak this relationship as part of the development of a design hydrograph for a site with no calibration data available. If played with the existing relationship, the standard CN values are no longer valid (Rallison and Miller 1981). It was for this reason that Rallison (1980) did not recommend its further refinement.
Indeed, a critical examination of $I_a$–$S$ relationship and a logical refinement is needed for pragmatic applications.

Cazier and Hawkins (1984) suggested $\lambda = 0.0$ which best fitted their dataset, and according to Ramasastri and Seth (1985); Jain and Seth (1997); Jena and Tiwari (2002), $\lambda$ can vary in the range $(0, 0.3)$. As an alternative, Bosznay (1989) suggested to treat $I_a$ as a random variable. Since many storm and landscape factors interact to define the initial abstraction (Hjelmfelt 1991), fixing of $\lambda$ at 0.2 is tantamount to regionalization based on geologic and climatic settings (Ponce and Hawkins 1996). Consequently, the number of methods increases when CN is determined from the measured P–Q data and $\lambda$ is allowed to vary (Bonta 1997). Walker et al (1998) pointed out that the sources of error associated with $I_a$-estimates and listed in NEH-4 include the likelihood of some abstracted rainfall to have eventually appeared at the outlet and emphasized further that some of this rainfall might have contributed to quick response in tile-drained watersheds.

Based on their mathematical analysis, Mishra and Singh (1999a,b) found $\lambda$ to vary from 0 to $\infty$. They explained the functional behaviour of the SCS-CN model using $I_a$ as a key descriptor and derived $C-I_a^*-\lambda$ spectrum, where $C$ is the runoff factor ($=Q/P$) and $I_a^*$ is the non-dimensional initial abstraction ($=I_a/P$). Among others (e.g., Bonta 1997; Woodward et al 2002), Hawkins and Khojeini (2000); Hawkins et al (2002) examined the data-supported values of $I_a/S$ ratio and suggested accommodations for updating its role employing two techniques, event analysis and model fitting, to determine $I_a/S$ from field data. Only ‘large’ storms were used to avoid the biasing effects of small storms towards high CNs. Both ‘natural’ and ‘ordered’ datasets were used to establish a relation between $S_{0.05}$ and $S_{0.20}$ and then convert CNs based on $\lambda = 0.2$ to those based on $\lambda = 0.05$. Here, subscript $0.05$ and $0.2$ of $S$ represent $\lambda$-values. Since $\lambda$ varied from storm to storm or
watershed to watershed, $\lambda = 0.05$ fitted better than $\lambda = 0.2$, which was found to be unusually high. However, the values of median $\lambda$ varied from 0.0005 to 0.4910, with a median of 0.0476 for the datasets in event analysis. In model fitting, it varied from 0 to 0.996, with a median of 0.0 for ‘natural’ datasets, and 0 to 0.9793 with a median of 0.0618 for ‘ordered’ datasets. $\lambda = 0.05$ was found to significantly affect the low P/S situations, and subsequently, hydrograph structures defined by time and peak values (especially at lower CNs). Jena and Tiwari (2002), however, found $\lambda = 0.2$ most appropriate for their study area. While describing the origin and derivation of $I_a/S$ in the runoff CN system, Plummer and Woodward (2002) considered $\lambda$ in the range (0, 0.2) and emphasized that the refinement was a cooperative effort of hydrologists from Forest Service (FS), ARS, and NRCS. Interestingly, while explaining the SCS-CN proportionality concept (Equation (2.3)) using the volumetric concept of soil–water–air, Mishra and Singh (2003c) described $\lambda$ as the degree of atmospheric saturation. They also provided a complete SCS-CN-based initial abstraction model incorporating infiltration, interception, evaporation, and surface depression separately. For infiltration only, $\lambda = f_o t_p / S$ or $\alpha t_p$, where $f_o$ is the initial infiltration rate, $t_p$ is the time to ponding, and $\alpha$ is the infiltration decay parameter analogous to Horton (1938) infiltration decay parameter. Of late, Michel et al (2005) linked $S$ and $S_a$ (a summation of $I_a$ and soil moisture store level at the beginning of an event), instead of $S$ and $I_a$, for simplification in case of continuous modelling.

2.7 STORM DURATION

As seen from the SCS-CN formulation (Appendix 1), it does not contain any expression of time. It was not incorporated perhaps largely due to non-availability of reliable data (Cowan 1957 in Woodward et al 2002). While attempting to incorporate rainfall intensity or its duration for runoff
estimation, Mockus (1949) modified the Sherman (1949) concept of plotting direct runoff vs storm rainfall by incorporating storm duration as a factor, in addition to soil type, areal extent and location, land use, antecedent rainfall, storm rainfall depth, average annual temperature, and date of storm. Further attempts (Smith 1978; Hawkins 1978a in Rallison and Miller 1981) proposed CN-based infiltration relationship and found CN to vary with storm intensity and storm duration. The CN decreases as storm duration increases. Thus, the rainfall intensity or indirectly the storm duration is one of the most influencing factor to runoff generation. This is, however, in contrast with the concept that the precipitation rate affects only runoff rates, not runoff volume (Steenhuis et al 1995). Rallison (1980) attributed the runoff variation to varying infiltration rates at the soil surface strongly affected by rainfall impact and, in turn, rainfall intensity. According to Bales and Betson (1981), the peak flow rate is affected by rainfall intensity, storm yield (runoff/rainfall), initial moisture conditions and season, as well as rainfall and runoff volume.

Introducing an additional parameter ‘surface detention’ to produce a dynamic equation, Chen (1981) included the time in SCS-CN procedure. For simplicity, the effect of surface detention on infiltration was assumed to be negligibly small. During rainfall (of uniform intensity and continuing indefinitely), the cumulative surface detention was found to grow rapidly in the early stage and then very slowly converging to a maximum value. It depends mainly on the roughness characteristics and the slope of the soil surface on which rainwater moves. In general, high-intensity precipitation events occur less frequently than do low-intensity events, and the duration of a high-intensity event is likely to be shorter than that of a low-intensity event. Therefore, Smith (1997) proposed to account for not only the rainfall intensity but also its pattern in the SCS-CN model, for a particular storm that can produce different runoff hydrographs depending on rainfall intensity.
These attempts led Yu (1998) to assume a probability distribution of rainfall intensity in time and infiltration rate in space to derive the SCS-CN equation analytically. Of late, Mishra et al (2002) proposed an SCS-CN-based runoff rate equation coupled with routing to generate the time distribution of runoff volume. These attempts, however, need further refinement.

2.8 SOURCE AREA CONCEPT

Variable source areas or partial areas denote the areas of a watershed actually contributing flow to the stream at any time. They expand during rainfall and contract thereafter around the streams (Chow et al 1988). This concept was not considered in the SCS-CN model before 1970s. In 1973, using a large set of data from several small western forested watersheds, Hawkins (1973) showed the existence of a strong relationship between CN and storm rainfall. Based on the observation, he later (Hawkins 1979) allowed CN to vary with rainfall volume on watersheds apparently exhibiting a constant source area. In design of surface drains, Varshney et al (1983) suggested the use of areal correction factor in determination of runoff from the SCS-CN model. Later, Steenhuis et al (1995) found the SCS-CN model to be interpretable using the principles of partial area hydrology and its efficacy to predict the contributing area. Steenhuis et al (1995) and Gburek et al (2002) in their studies assumed the surface runoff to generate from rainfall on the expanding and contracting saturated zones and CN to be considered exclusively for these areas (Garen and Moore 2005). On the other hand, Suwandono et al (1999) used unit hydrograph concept to generate rainfall hyetographs and runoff hydrographs, and to estimate sediment loss from the source area using the SCS-CN model.
2.9 APPLICATIONS

The SCS-CN model was originally formulated and intended for the conservative engineering design of agricultural water management projects. Its application elsewhere should always be accompanied by good discretion and sound engineering judgement. Though the SCS-CN model originated as an empirical, event-based procedure for flood hydrology, it has been adapted and used in various models for simulating the runoff behaviour of ordinary as well as large rainfalls and daily time series as well as events (Garen and Moore 2005). This model was found to be performing best in agricultural sites, fairly in range sites, and poorly in forest sites.

In 1982, McCuen provided guidelines for using SCS-CN model for hydrologic analysis. Heggen (1981) and Srinivas et al (1997) illustrated relative runoff estimation by CN Nomograph for $\lambda=0.2$ and $\lambda=0.3/0.1$ (Indian catchments), respectively. Based on the experience, the joint work group of NRCS recognized three distinctly different modes of application for CNs (Hjelmfelt et al 2001; Van Mullem et al 2002): (1) determination of runoff volume of a given return period, given total event rainfall for that return period; (2) determination of direct runoff for individual events, explaining the variability from event to event, as used in continuous simulation models; and (3) determination of infiltration rates for short time intervals as used with unit hydrograph development of flood hydrographs. By latest, Mishra and Singh (2003c) presented an up-to-date account of the SCS-CN model and discussed its potential for practical applications other than those originally intended.

To state a few different applications of SCS-CN model apart from its original, Svoboda (1991) used the CN concept to calculate the soil-water content and subsequently, the rainfall contribution to direct runoff and ground water. Pandit and Gopalakrishnan (1996) determined annual storm runoff
coefficients (ASRCs) by a continuous simulation technique, based on the SCS-CN model. Hawkins and Ward (1998) found distinct relationship between cover and CN and did comparisons with the NEH-4 table values. Recently, Mishra (2000) and Mishra and Singh (2004b) developed a SCS-CN based long-term hydrologic model for simulating daily runoff from two Indian catchments. Putty and Hareesha (2001) used the CN model for piped catchments of wet mountainous region of the Western Ghats in South India to simulate subsurface quickflow, source area runoff, and delayed flow. Pandit (2002) used the model for a continuous annual load simulation model (CALSIM) to determine annual or average annual pollutant loads from watersheds.

Mishra et al (2003) modified the SCS-CN model (SCS 1956) by accounting for the static portion of infiltration and the antecedent moisture in its basic proportionality concept (Equation (2.3)) and found that the modified model performed well on the same datasets as used in the NEH-4 (SCS 1971). However, there exists a scope for further improvement in the results of the modified version using infiltration data. On a large set of rainfall–runoff data of 234 watersheds in USA, ranging from 0.01 to 310.3 km², Mishra et al (2004a) evaluated the modified version of the Mishra and Singh (2002b) (MS) model which is based on the SCS-CN model and incorporates the antecedent moisture in direct surface runoff computations. This modified MS model was found to be performing far better than the existing SCS-CN model. Later, Mishra et al (2005b) proposed a catchment-area-based evaluation on this modified version of the MS model.

Mishra et al (2005a) investigated the general SCS-CN-based MS (Mishra and Singh 1999b) model and its eight variants for their field applicability using a large set of rainfall–runoff events, derived from a number of US watersheds varying in size from 0.3 to 30351.5 ha, grouped
into five classes based on the rainfall magnitude. The five classes of rainfall adopted for their (Mishra et al 2005a) study were: (1) rainfall \(\leq 12.7\) mm; (2) \(12.7 < \text{rainfall} \leq 25.4\) mm; (3) \(25.4 < \text{rainfall} \leq 38.1\) mm; (4) \(38.1 < \text{rainfall} \leq 50.8\) mm; and (5) rainfall > 50.8 mm. Mishra et al (2005a) concluded that the existing SCS-CN model generally performs significantly poorer than all the general model variants on all datasets with rainfall \(\leq 50.8\) mm, and therefore, it is appropriate for high rainfall (>50.8 mm) data. Of late, Michel et al (2005) adopted a change of parameterization and a more complete assessment of an initial condition to deliver a renewed SCS-CN procedure based on continuous soil moisture accounting procedure.

In case of special application of metal partitioning in an urban pollutant transport, Mishra et al (2004b) examined the partitioning of 12 metal elements, Zn, Cd, Pb, Ni, Mn, Fe, Cr, Mg, Al, Ca, Cu, and Na, between dissolved and particulate-bound forms using the basic proportionality concept (Equation (2.3)) of the SCS-CN model. To apply this metal partitioning analogue, Mishra et al (2004b) postulated two parameters, the potential maximum desorption, \(\Psi\), and the partitioning CN, PCN, as analogous to the SCS-CN model parameters, S and CN, respectively. Further, Mishra et al (2004b) found that the PCN-based ranking of metals is in general agreement with that available in the literature. Later on, Mishra et al (2004c) extended the PCN-based metal partitioning in urban snowmelt, rainfall–runoff, and river flow systems.

2.10 LONG-TERM HYDROLOGIC SIMULATION

Since the SCS-CN model is considered an infiltration loss model, its applicability is restricted to modelling storm losses (Ponce and Hawkins 1996). The model has, however, been used in long-term hydrologic
simulation and several models have been developed in the past two decades. Few notable models among others are due to Williams and LaSuer (1976); Huber et al (1976); USDA (1980); Soni and Mishra (1985); Mishra (2000); Mishra and Singh (2004b).

The Williams and LaSuer (1976) model has only one parameter (CN), uses a 1-day time interval, has simple inputs such as measured monthly runoff, daily rainfall, and average monthly lake evaporation. But the model is in conflict with the SCS-CN concept due to the physically unrealizable decay of soil moisture with lake evaporation. Later on, Hawkins (1978b) developed a continuous soil-moisture accounting model in which the S-value was also varied with evapotranspiration, a significant feature of the model, as it plays a significant role in long-term hydrologic simulation. Hawkins (1978b) considers the SCS-CN model to be based on a (I_a+S) scheme, whereas I_a is separate from S. Evaluating most of the earlier models, Mishra and Singh (2003b,c, 2004b) proposed a more versatile SCS-CN-based continuous simulation model. Later on, using the concept of Soil Moisture Index (SMI), which is generally used in long-term hydrologic simulation for water balance, Mishra and Singh (2004a) proposed an extension of the SCS-CN model for computing infiltration and rainfall-excess rates.

2.11 DISTRIBUTED MODELLING

Distributed models are developed to represent the variability in physical watershed characteristics. On the other hand, lumped models integrate watershed characteristics over a given area, neglecting heterogeneity within the area resulting in simplified runoff conditions. Initially, lumped models were developed and the distributed approaches were tried later to exploit the computing power incessantly increasing over the last two decades.
In general, distributed models involve division of the area of interest into cells (often rectangular grids) at which basic computations are undertaken. These models raise a number of issues including increased data requirements, effects of cell resolution on model outputs, etc. The SCS-CN model was originally developed as spatially and temporally lumped model for conversion of storm rainfall depth to direct runoff volume. Its incorporation in the infiltration-capacity-equivalent form (Aron et al 1977; Hawkins 1978a, 1980; Chen 1981; Mishra and Singh 2002a,b) extends the method to the domain of distributed modelling. Compared to the composite approach, Grove et al (1998) showed a 100% increase of predicted runoff volume in distributed CN approach. In an attempt by Michand and Sorooshian (1994) and Moglen (2000), it was found that it is a simple model to perform as accurate as a complex distributed model, provided calibration was performed. Furthermore, the differences in simulation results due to various models could be explained either by differences in complexity of the modelling approach or resolution of input data (e.g., Hughes 1994). On the other hand, Chandana and Aggarwal (2001); Jena and Tiwari (2002) showed that the distributed approach performs better than the lumped approach. Moglen (2000) also found that the orientation of land use affects the CN-predicted runoff significantly in case of distributed modelling.

In general, the relative advantages of distributed modelling against lumped modelling are not easily determinable, and in practice, the acceptable amount of lumping is a function of problem scale. Semi-distributed models form a compromise between fully distributed models and lumped models. The choice ultimately depends on the desired model output and the nature of possible management interactions (Merritt et al 2003). In the present age of growing computing powers, the distributed procedure may be well coupled with the SCS-CN model on the scale of hydrological response unit (Beven 2002).
Remote Sensing (RS) helps in acquisition of data in different aspects of land use and soil cover, essential for runoff estimation using SCS-CN model. Though the runoff cannot be directly measured by RS techniques, there are two general areas where RS can be used in hydrologic and runoff modelling: (1) determining watershed geometry, drainage network, and other map-type information; and (2) providing input data such as soil moisture or delineated land use classes that are used to define runoff coefficients. Land use is an important characteristic of runoff process that affects infiltration, erosion, and evapotranspiration. Most of the work on adapting RS to hydrologic modelling has involved the SCS-CN model, for which RS data are used as a substitute for land cover maps obtained by conventional measures, such as those described by Nagaraj et al (2002) and others.

Ragan and Jackson (1975, 1980); Jackson et al (1977); Slack and Welch (1980) assert that Landsat-based information provides similar or better results than traditional methods, for land cover analysis. Further, Slack and Welch (1980), and Still and Shils (1985) recommended the use of Landsat digital data to determine land use and land cover. Kumar et al (1991) used IRS-1A LISS II digital database for establishing CN-values. An improved land use/land cover database benefits the runoff estimation or forecasting, if watershed response is calculated separately from each land use/land cover classification. Remote sensing based approach is found to be cost-effective, especially for larger basins or for multiple basins in the same general hydrological area. Ragan and Jackson (1980) have shown that land use or vegetation data for the SCS-CN model can be obtained using remotely sensed data, which can greatly reduce the cost of data collection.
A few investigators utilized the aerial photographs and satellite data along with others to estimate the CNs (e.g., Ragan and Jackson 1980; Slack and Welch 1980; Hill et al 1987; Tiwari et al 1991; Colombo and Sarfatti 1995; Rao et al 1996; Sharma et al 2001; Pandey and Sahu 2002). Owing to its pixel format, RS data can be easily merged with the Geographical Information System (GIS), which enhances the possibility of data integration, synthesis, and analysis. Although accuracy associated with practical use of RS data varies, the applicability of remotely sensed data is not limited by the degree of accuracy (Rango et al 1983).

2.13 COUPLING OF RS AND GIS

Geographical information system is defined by the National Science Foundation as a computerized database management system used for capture, storage, retrieval, analysis, and display of spatial data. The technology can be used to overlay and combine data into a single computerized map that can summarize geographic, cultural, and scientific land attributes. The use of RS technology involves large amount of spatial data management and requires an efficient system to handle such data. GIS provides suitable alternatives for efficient management of large and complex databases. It plays a vital role in water resources planning and management (Leipnik et al 2001; Xu et al 2001). Integration of GIS and RS in hydrological modelling can enhance the quality of the hydrological models (Greene and Cruise 1995; Turcotte et al 2001). It is capable of handling spatial and aspatial data when compared to conventional information system.

In their studies, Mohd and Mansor (1999); Sharma and Dubey (2001); Nagaraj et al (2002); Jena and Tiwari (2002) found the GIS-derived SCS-CN results to be agreeable and preferable to those due to conventional methods. U.S. Army Corps of Engineers has made a first step towards the
integration of spatially distributed data for the runoff computation utilizing the GIS techniques and distributing the basin into number of square cells. In this approach, soil and land use information derived using these techniques for each cell provides a better method for the rainfall-excess computation.


The most difficult phase here is to acquire data, and input that into GIS. GIS is advantageous, if the study area is large, runoff is modeled repetitively, and alternative land use/land cover scenarios are explored. However, in developing countries such as India, these latest techniques need to be explored extensively in hydrological modelling applications.
2.14 ADVANTAGES AND LIMITATIONS

The SCS-CN model is simple enough to be used by people, having little experience with hydrology. The advantages of this model are (Bales and Betson 1981; Ponce and Hawkins 1996; Beven 2002) as follows:

1. It is a simple, predictable, and stable conceptual model.
2. Its calculations are straightforward and intuitively logical.
3. It relies on only one parameter (CN).
4. The required input is generally available.
5. The technique may be applied to ungauged basins.
6. Methodology is well established and accepted.
7. It is the only agency methodology that features readily grasped and reasonably well-documented environmental inputs (soil, land use/treatment, surface condition and AMC).
8. The model is featured in most of the hydrologic computer models in current use.
9. Its responsiveness to major runoff-producing watershed properties (soil, land use/treatment, surface condition and AMC).
10. The model does best in agricultural sites, for which it was originally intended, and extended to urban sites.
11. It provides a relatively easy way to update the model (in view of distributed modelling) with the application of RS and GIS.

12. As the model was formulated on the basis of small catchment measurements, not on the point scale measurement, it is likely to be revisited in the future, due to the booming of point scale process.

Chen (1981); Bales and Betson (1981); Ponce and Hawkins (1996); Willeke (1997); Smith (1997); Mani et al (2002) reviewed the SCS-CN model for its limitations as follows:

1. The success of the SCS-CN model is mainly limited by the watershed size and to a lesser extent by the magnitude of runoff events. Actual distributions of the rainfall and infiltration rates would indicate whether or not the SCS-CN model is appropriate for the watershed in question (Yu 1998).

2. In the absence of clear guidelines, it is assumed to apply to small-size and mid-size catchments. Its application to large catchments (say > 100 sq. miles or 250 sq. km) should be viewed with caution.

3. It was never intended to match individual storms (i.e., it was supposed to predict an average trend, and not the response of individual storms, which could deviate from the average trend).
4. In many climates, a more important source of variability is the rainfall intensity and its pattern within the storm, and this cannot be accounted for by the SCS-CN methodology.

5. The CN derived for a watershed will inherently reflect the particular storms for which it was fitted (e.g., annual series).

6. This model is not intended for continuous simulation; rather, only an event-by-event basis.

7. Its applicability is restricted to modelling storm losses. Barring appropriate modifications, the model should not be used to model the long-term hydrologic response of a catchment.

8. It was not supposed to account for indirect runoff (interflow and groundwater flow); only direct runoff.

9. Because no information has been published on the range of return periods of the annual floods used to develop the tabulated CN values, some question still remains as to the size of the event (either rainfall or runoff) for which methodology is suited.

10. Saturation overland flow was the most likely runoff mechanism to be simulated by the model, and not necessarily Hortonian overland flow or Crusting.

11. Since the model was originally developed using regional data, some caution is recommended for its use in other geographic or climatic regions.
12. A lack of clear guidance on how to vary antecedent condition. The model may be very sensitive to CN and antecedent conditions, for lower CNs and/or rainfall depths. The discrete relation between CN and AMC, which is not realistic.

13. The model does best in agricultural sites, for which it was originally intended, and extended to urban sites. But, it has varying accuracy for different biomes.

14. The fixing of the initial abstraction ratio ($\lambda$) at 0.2, preempting a regionalization based on geologic and climatic setting.

2.15 SPECIFIC ISSUES PREVAIL IN THE SCS-CN MODEL

In spite of its widespread and lasting success, several issues continue to exist in the conventional SCS-CN model. Garen and Moore (2005) pointed out that a number of things about the CN procedure, however, are apparently not well known and have led either to a misinterpretation of its results or its usage well beyond its realm of applicability. Based on the review of literatures on the SCS-CN model, the following issues are identified to exist in the conventional SCS-CN model:

1. Implementation of AMC procedure.

2. Consideration of ‘mean’ or ‘median’ CN as a representative CN of a watershed in the model for which CN is a sensitive parameter.

3. $I_a$–S relationship.
4. Potential maximum retention (S) parameter usage in the model.

5. Effect of storm intensity or duration in the runoff estimation.

Based on these identified issues, the present research work was brought into a shape and methodology was formulated to satisfy the objectives of the research.