INVESTIGATION OF SCS-CN METHODOLOGY ON EXPERIMENTAL PLOT AND CATCHMENT SCALES

Ph.D. THESIS

by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled "**INVESTIGATION OF SCS-CN METHODOLOGY ON EXPERIMENTAL PLOT AND CATCHMENT SCALES**" in partial fulfilment of the requirement for the award of the Degree of Doctor of Philosophy and submitted in the Department of Water Resources Development and Management of the Indian Institute of Technology Roorkee, Roorkee is an authentic record of my own work carried out during a period from January, 2013 to October, 2018 under the supervision of Dr. S. K. Mishra, Professor & Head, Department of Water Resources Development and Management, Indian Institute of Technology Roorkee, Roorkee, and Dr. Yogendra Kumar, Professor & Head, Department of Irrigation and Drainage Engineering, G.B. Pant University of Agriculture and Technology, Pantnagar, Uttarakhand.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institution.

(MOHAN LAL)

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

(Yogendra Kumar) **(S. K. Mishra)**

Co-Supervisor **Supervisor**

The Ph. D Viva-Voce Examination of Mr. Mohan Lal, Research Scholar, has been held on May 16, 2019.

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ABSTRACT

Runoff is one of the most important variables used in planning and design of hydraulic structures and assessing the water yield potential of a watershed. Runoff is a function of many variables such as rainfall duration and intensity, soil moisture, land use/land cover, soil infiltration capacity, watershed slope etc. There are a number of models available in literature considering different variables governing the surface runoff. Among them, the lumped conceptual models are quite useful for simple yet realistic analyses. The Natural Resources Conservation Service curve number (NRCS–CN) formerly known as the Soil Conservation Service curve number (SCS–CN) method is the most popular method to determine the storm event runoff from an ungauged small watershed for a given amount of rainfall. The SCS-CN method was developed in 1954. It is documented in Section 4 of the National Engineering Handbook (NEH-4) published by the Soil Conservation Service (now called the Natural Resources Conservation Service), United States. Department of Agriculture in 1956. The document has since been revised several times. The SCS-CN method is the result of exhaustive field investigations carried out during 1930s and 1940s. The method has since then witnessed myriad applications world over. It is one of the most popular methods for computing the surface runoff for a given rainfall event from small agricultural, forest, and urban watersheds. It is simple, easy to understand and apply, stable, and useful for ungauged watersheds. Due to its low input data requirements and simplicity, many erosion, hydrologic, and water-quality models have employed this method for determination of runoff. The primary reason for its wide applicability and acceptability lies in the fact that it accounts for most runoff producing watershed characteristics: soil type, land use/treatment, surface condition, and antecedent moisture condition. The only parameter of this methodology, i.e. the Curve Number (CN), is crucial for accurate runoff prediction. Based on exhaustive field investigations carried out in the United States, curve numbers were derived for different land uses, soil types, hydrologic condition, and management practices and these are reported in NEH-4. These numbers have seldom been verified for Indian watersheds.

Evidently, most studies have concentrated on the application of the existing SCS-CN method utilizing CN derived from NEH-4 tables. No systematic effort appears to have been made for evaluating the SCS-CN methodology experimentally, particularly for Indian watersheds, which invokes the need of the study. The aim of present research was to enhance the understanding of SCS-CN methodology by investigating its different parameters employing naturally observed P-Q datasets. This study covers relative accuracy of different CNs

determination methods and comparing them with NEH–4 tables CN values; evaluating the effect of initial abstraction coefficient and antecedent moisture on CN and runoff; evaluation of existing AMC–dependent CN formulae, which are otherwise developed using United States datasets. The AMC–dependent CN formulae incorporating initial abstraction coefficient effect is also tested for enhancing runoff estimation.

The present study uses the rainfall (P)–runoff (Q) dataset of various climatic settings. Locally measured and published literature data have been used in the investigation of different parameters of SCS-CN methodology. For locally monitored data, the natural P–Q events were captured on 35 plots of 22m length and 5m width having different slope (5%, 3%, and 1%), land use (agricultural land use: Sugarcane, Maize, Black gram, Fallow land, Lentil, and Chana), and hydrologic soil group (HSG) during August 2012–April 2015 (or three crop growing seasons in study area) for the experimentation work carried out at Roorkee, India. The experimental field (Lat.: 29° 50′ 09″ N and Long.: 77° 55′ 21″ E) is situated at the right bank of Solani River, a tributary of Ganga River, the largest river basin in India. Precipitation was recorded with the help of Tipping Bucket rain gauge and a non-recording rain gauge installed within the experimental site. The surface runoff generated during rain storms was collected in separate chambers equipped with multi-slot divisor (5-slot) (1m × 1m × 1m) constructed at the downstream end of each plot and the variation in depth of water stored with respect to time was monitored regularly, but manually. Infiltration tests were conducted for each plot using the double ring infiltrometer. Soil water measurements were taken by time domain reflectometry (TDR) probe of the 'Fieldscout TDR-300'. Besides, the published literature P-Q data were collected for 36 plots/watersheds having different size, land use, slope and soil consisting heterogeneous climatic conditions.

The rainfall (P)–runoff (Q) behaviour pattern was analysed using naturally observed P–Q data from experimental study plots located at Roorkee site and it was found that non–linear variation of runoff coefficient (Rc) with P is similar to the variation of Q with P, but the correlation between Rc and P is much lower than that between Q and P. As expected, the mean runoff coefficient (Rc_m) was higher for the plots having HSGs C followed by B and A. The concept of runoff initiation threshold (I) also called rainfall threshold for runoff generation confirms the runoff generation phenomenon of generating low runoff from lighter soils as the values of I was highest for HSGs A followed by B and C. These finding indicates that HSG (or indirectly soils infiltration capacity, *f*c) seems to play a major role in controlling runoff in the plots. The Kruskal–Wallis (K–W) test analysis performed to analyse the effect of land use, soil type, and plot slope on Q (or Rc) show that, Q is more significantly influenced by soil type rather than land uses or slopes as *f*c is the main explanatory variable for runoff (or CN) production in the study plots. In present study experimental plots, CN is inversely related to *f*c, which supports the applicability of NEH–4 tables CNs declining with *f*c (or HSG). Further to check the dependency of observed CN on in-situ antecedent moisture content, CN (or, potential maximum retention, S) values showed a higher degree of dependence on the physically observed 1-day antecedent soil moisture (θ_{o1}) than other duration antecedent soil moisture values.

The performance of eight different CN estimation methods, viz. storm event mean and median, rank-order mean and median, log-normal frequency, S-probability (SP), geometric mean and least square fit, was evaluated using P–Q data measured on small agricultural plots located in India. The Kruskal−Wallis test multiple comparison analysis show that there was no single method which has produced significantly higher (or lower) CNs than other. The least square fit method was observed to estimate significantly lower CN than other methods except log-normal frequency method. Based on the overall score and ranking system calculated from different goodness of fit indices, the method performance in runoff estimation was as follows: S-probability > geometric mean > storm event mean > rank-order median > rank-order mean > least square fit > storm event median > log-normal frequency. The comparison of observed P-Q data based CNs with tabulated CNs show that, on the whole, the CN estimates from NEH-4 tables do not match those derived from observed P–Q dataset. As a result, the runoff prediction using former CNs was poor for the data of experimental plots of Roorkee site. However, match was little better for higher CN values, consistent with general notion that the existing SCS-CN method performs better for high P–Q (or CN) events. The reason for tabulated CNs to have performed most poorly is that these are the generalized values derived from the watersheds of United States, consistent with the results of other studies.

The plot-data optimization yielded initial abstraction coefficient (λ) values ranging from 0 to 0.659 for ordered dataset and 0 to 0.208 for natural dataset (with 0 as the most frequent value for both datasets). Mean and median λ values were, respectively, 0.030 & 0 for natural P–Q dataset and 0.108 & 0 for ordered P–Q dataset, quite different from standard λ =0.2, but consistent with the results of other studies carried out elsewhere. Notably, the existence of I_a-S relationship for different plots was also investigated; and in contrast to the existing notion, I_a when plotted against S exhibited no correlation for both natural and ordered datasets, consistent with the findings of Jiang (2001). Runoff estimation was very sensitive to λ and it improved consistently as λ changed from 0.2 to 0.03. Compared to traditionally assumed λ=0.2, a refined

λ=0.03 is recommend for the use in regions of similar to study site. Further, a relationship between $CN_{0.20}$ (λ = 0.20) and $CN_{0.03}$ (λ = 0.03), useful for CN conversion for field application is established.

It is well established phenomenon that accurate estimation of the surface runoff is one of the most important bases for planning and management of water resource systems and environmental quality assessment of water and soil. Therefore, in popular SCS–CN method, correct estimation of AMC–dependent CN values is always necessary. Since CNs varies with climatic condition of watersheds, there is need of using AMC-dependent CN-formulae developed utilizing data of watersheds having heterogeneous climatic conditions. The formulae developed from heterogeneous and large data sets will tend to have wider applicability. The present work evaluated the five existing (Arnold et al. 1990; Chow et al. 1988; Hawkins et al. 1985; Mishra et al. 2008b; Sobhani 1975) and three proposed (MC6, MC7, MC8) CN-AMC formulae. For developing the proposed formulae, CNs were derived for datasets from a large number of naturally observed P–Q events for an agricultural field located at Roorkee, Uttarakhand, India and available published data around the globe using standard initial abstraction ratio (λ) values as 0.20 and 0.030. The analysis shows that the existing Hawkins et al. (1985) formulae performed the best for conversion of CN_2 into CN_1 and CN_3, when tested on NEH–4 AMC defining Tabular CNs considered as targeted values. It might be because the existing formulae were derived from the same datasets used as targeted values (i.e. NEH–4 AMC defining tables). However, all the three proposed MC6, MC7, and MC8 were best of the existing formulae in their application to field data. MC8 incorporating the effect of λ = 0.030 performed the best of all, and MC7 and MC6 better than the other existing formulae. Among the existing formulae, Mishra et al. (2008b) was superior followed by Hawkins et al. (1985). A comparison of the results derived from the eight different methods concluded that the MC8 formula that incorporates the effect of λ into standard SCS–CN method showed a superior performance in runoff simulation than the others. Since the proposed formulae performed the best in field application, these are recommended for field use to improve the accuracy of SCS–CN model.

Keywords: Agricultural field; Curve number; Antecedent moisture condition; Runoff; NEH-4 Table; SCS-CN; NRCS-CN; Initial abstraction coefficient; Infiltration capacity.

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(Mohan Lal)

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviations	description
P	Rainfall depth (mm)
Q	Runoff depth (mm)
NEH	National engineering handbook
NEH-4	National engineering handbook chapter-4
HSG	Hydrologic soil group
CN	Curve number
AMC	Antecedent moisture condition
CN_1	Curve number for dry condition or AMC-1
CN_2	Curve number for average condition or AMC-2
CN_3	Curve number for wet condition or AMC-3
AMC-1	Dry antecedent moisture condition
AMC-2	Average antecedent moisture condition
AMC-3	Wet antecedent moisture condition
CN_{HT}	Curve number derived from NEH-4 table
CN_m	Median curve number derived from P-Q data set
CN_{LSM}	Curve number derived from P-Q data set using least square method for λ = 0.2 (i.e. single way fitting CN)
CN_{LS}	Curve number derived from P-Q data set using least square method for optimized λ (i.e. double way fitting CN)
CN_{LSn}	Curve number derived from P–Q data set using least square method (optimized λ) for natural data series
CN_{LSo}	Curve number derived from P–Q data set using least square method (optimized λ) for ordered data series
CN_{LSMn}	Curve number derived from P–Q data set using least square method (λ = 0.2) for natural data series
CN_{LSMo}	Curve number derived from P–Q data set using least square method (λ = 0.2) for ordered data series
$CN_{HT0.20}$	NEH-4 tables CN associated with λ=0.20

$CN_{HT0.03}$	NEH-4 tables CN associated with λ=0.03
$CN_{0.2}$	Curve number associated with λ = 0.2
$CN_{0.03}$	Curve number associated with λ = 0.03
S	Maximum potential retention (mm)
$S_{0.20}$	Maximum potential retention (mm) associated with λ = 0.2
$S_{0.03}$	Maximum potential retention (mm) associated with λ = 0.03
θ_{o1}	1-day antecedent soil moisture (%)
θ_{o3}	3-day average antecedent soil moisture (%)
θ_{o5}	5-day average antecedent soil moisture (%)
θ	Previous day soil moisture (%)
P_5	5-day antecedent rainfall (mm)
°C	Degree Celsius
n	Number of rainfall events
ln	Natural logarithm operator
POE	Probability of exceedance
GM	Geometric mean
TDR	Time domain reflectometry
AWC	Antecedent wetness condition
LSM	Least square method
PRA	Public road administration
I_a	Initial abstraction (mm)
I	Rainfall threshold for runoff generation
Rc_m	Mean runoff coefficient of plot
Rc	Event runoff coefficient
*f*c	Infiltration capacity (mm/hr)
F	Cumulative infiltration
AFM	Asymptotic fitting method
HEC-HMS	Hydrologic Engineering Center Hydrologic Modeling System
SWAT	Soil and Water Assessment Tool
ANSWERS	Areal Non-point Source Watershed Environment Response Simulation

AGNPS	Agricultural Non-point Source Model
EPIC	Erosion Productivity Impact Calculator
HEC-1	Hydrologic Engineering Center-1
APEX	Agricultural Policy/Environmental eXtender
GLEAMS	Groundwater Loading Effect of Agricultural Management Systems
CREAMS	Chemicals, Runoff, and Erosion from Agricultural Management Systems
USLE	universal soil loss equation
SCS	Soil conservation services
SE	Standard error
E	Nash-Sutcliffe efficiency coefficient
R^2	coefficient of determination
d	index of agreement
RMSE	root mean square error (mm)
PBIAS	Percent bias (%)
Re	Relative error
e	Bias
K-W	Kruskal–Wallis
ANOVA	one-way analysis of variance
LSD	least significant difference
SPSS	Statistical Package for the Social Sciences

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Runoff is one of the most important variables used in planning and design of hydraulic structures and assessing the water yield potential of a watershed. The mechanism of surface runoff generation is a complex process as it relies on a number of variables including rainfall (amount and duration or intensity), soil moisture, land use/land cover, soil type, watershed slope, and so on (Gosain et al. 2005; Muttiah and Wurbs 2002). Consequently, a number of models have been developed and reported in literature for surface runoff analysis (Anderson et al. 2002; Mishra and Singh, 2003). Among them, the lumped conceptual models are quite useful for simple yet realistic analyses (Mishra and Singh 2003).

The National Engineering Handbook (NEH-4) Soil Conservation Service-Curve Number (SCS-CN) method (SCS, 1964, 1972) also known as Natural Resources Conservation Service Curve Number (NRCS-CN) method is one of the most popular methods for computing the depth of direct surface runoff for a given rainfall event. The main reason that this method has been adopted by most hydrologists for predicting surface runoff from small agricultural, forest, and urban watersheds is due to its simplicity and applicability to ungauged watersheds with the use of only single parameter known as curve number (CN) which is derived from catchment features such as land use/cover, soil type, and 5–day antecedent rainfall (P_5) (Mishra et al. 2008a). The SCS-CN method has also been criticized among researcher fraternity due to its inability to consider the important characteristics of rainfall like spatio-temporal distribution and intensity. Besides, slope of the watershed, another significant parameter in runoff generation processes was also not included in original developed method. Despite the shortcomings, as discussed abovementioned, the method has undergone a various amendment including extension from agricultural to forest and urban watersheds. In the course of continuous use of the SCS–CN model world–wide, several modifications have been proposed in literature (Hawkins et al. 1985; Jain et al. 2006a; Mishra and Singh 2003; Mishra et al. 2006a; Sahu et al. 2010a, 2012; Suresh Babu and Mishra 2012; Woodward et al. 2002). Some other notable ones incorporate the effect of slope (Huang et al. 2006; Ajmal et al. 2015b; Sharpley and Williams 1990); the improvement in initial abstraction coefficient (λ) (Hawkins et al. 2002; Jain et al. 2006b; Mishra and Singh 2004a; Mishra et al. 2006b; Woodward et al.

2004; Yuan et al. 2014); the antecedent moisture on continuous basis (Ajmal et al. 2015d; Ajmal et al. 2016; Durbude et al. 2011; Michel et al. 2005; Sahu et al. 2007; Singh et al. 2015); and the antecedent moisture for estimation of initial abstraction, I_a (Mishra and Singh 2002; Mishra et al. 2006b; Sahu et al. 2012). It has also been widely used in a number of standard hydrologic models such as Areal Non-point Source Watershed Environment Response Simulation (ANSWERS) (Beasley et al. 1980), Soil and Water Assessment Tool (SWAT) (Arnold et al. 1990; Arnold et al. 1996; Neitsch et al. 2002), Agricultural Non-point Source Model (AGNPS) (Young et al. 1989), Erosion Productivity Impact Calculator (EPIC) (Sharpley and Williams 1990), Constrained Linear Simulation (CLS) (Natale and Todini 1977), Storm Water Management (Krysanova et al. 1998), Hydrologic Engineering Center-1 (HEC-1) (HEC 1981), Agricultural Policy/Environmental eXtender (APEX) (Williams et al. 2012), Groundwater Loading Effect of Agricultural Management Systems (GLEAMS) (Leonard et al. 1986), and Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) (Knisel 1980; Smith and Williams 1980). In addition, the SCS-CN method has also been coupled with a number of popular models like universal soil loss equation (USLE) (Gao et al. 2012; Karn et al. 2016; Lal et al. 2017a; Mishra et al. 2006c), Modified Linear Spectral Mixture Analysis (Xu et al. 2016), Xinanjiang runoff model (Lin et al. 2014), ModClark (Saghafian et al. 2016), and Muskingum Routing method (Bhadra et al. 2010) for enhancing their ability to improve the runoff, sediment, and environmental river flow estimation. Recently, Ojha (2012) used SCS-CN method in water quality modelling to remove the turbidity at a river bank filtration site in India.

1.2 DEVELOPMENT IN SCS-CN METHODOLOGY

The SCS-CN method combines watershed parameters and climatic factors in one entity called the curve number (CN). It has been established that CN is not constant for a watershed, rather a variable identity which varies with rainfall (Hjelmfelt et al. 1982; McCuen 2002). In practice, for ungauged watersheds, CNs are derived from the well–known National Engineering Handbook chapter–4 (NEH–4) tables using watershed characteristics such as hydrologic soil group (HSG), land use and land condition, and antecedent moisture condition (AMC) (SCS, 1972). The empirical evidences however show that the use of NEH–4 tables CN values normally over-design the hydrological systems (Schneider and McCuen 2005), and therefore, use of CN values based on observed rainfall (P)–runoff (Q) data is recommended (Ajmal et al. 2015a; Hawkins 1993). The selection of correct value of CN is very essential because the direct runoff calculated by the method is highly sensitive to the selected CN

(Hawkins 1975). For a set of observed P–Q data, various approaches for determining watershed's representative CN have been reported in literature (Bonta 1997; Hjelmfelt 1980; Hauser and Jones 1991; Hawkins 1993; Hawkins et al. 2002; Hawkins et al. 2009; Sneller 1985; VanMullem et al. 2002; Woodward et al. 2006; Yuan 1933). The most common and widely used are NEH–4 method also known as storm event method in which mean or median of events wise CNs is considered as watershed representative CN; traditionally recommended by SCS (Hawkins et al. 2009; SCS 1972), geometric mean method (Tedla et al. 2012), least-squares fit method (LSM) (Hawkins et al. 2002), asymptotic fitting method (AFM) (Hawkins 1993), Log-normal frequency method (Schneider and McCuen 2005), Rank-order method (Hawkins et al. 2002) and S-probability method (Hjelmfelt 1991). Of late, several researchers have examined the relative accuracy of various methods of CN determination (Ali and Sharda 2008; D'Asaro and Grillone 2012; D'Asaro et al. 2014; Feyereisen et al. 2008; Schneider and McCuen 2005; Stewart et al. 2012; Tedela et al. 2012), and compared them with those from NEH-4 tables (D'Asaro et al. 2014; Fennessey 2000; Feyereisen et al. 2008; Hawkins 1984; Hawkins and Ward 1998; Sartori et al. 2011; Stewart et al. 2012; Titmarsh et al. 1989, 1995, 1996; Tedela et al. 2012; Taguas et al. 2015). However, in spite of wide-spread use of all approaches, there is no agreed procedure for estimating CN from observed P–Q data (Soulis and Valiantzas 2013) because each one is as good as another (Ali and Sharda 2008; Tedela et al. 2008). Therefore, there is need of regional studies for analyzing the accuracy of each method in runoff prediction using locally measured P–Q data. The accuracy of curve number method for Indian watersheds is rarely been examined due to lack of observed P–Q data from agricultural watershed (Ali and Sharda 2008).

The initial abstraction coefficient ($\lambda=I_a/S$) is another important parameter which plays a significant role in the prediction of surface runoff depth using SCS-CN method. It largely depends on regional (i.e. geologic and climatic factors) conditions of the watershed (Mishra and Singh 2003; Ponce and Hawkins 1996); and consists mainly of interception, infiltration, and surface depression storage during the early parts of a storm (Taguas et al. 2015). Traditionally (SCS, 1964, 1972) λ is often set equal to 0.2 in SCS-CN equation. However, the standard assumption of $\lambda = 0.2$ in original SCS–CN equation has been frequently questioned by various researchers since its inception (Aron et al. 1977; Baltas et al. 2007; Cazier and Hawkins 1984; D'Asaro and Grillone 2012; D'Asaro et al. 2014; Elhakeem and Papanicolaou 2009; Fu et al. 2011; Hawkins and Khojeini 2000; Hawkins et al. 2002; Mishra and Singh 2004a; Menberu et al. 2015; Shi et al. 2009; Woodward et al. 2002; Woodward et al. 2004; Yuan et al. 2014; Zhou and Lei 2011) for its validity and applicability, invoking its critical examination for practical applications. Many studies have indicated λ to be variable from watershed to watershed and event to event. Its value of about 0.05 or less is said to be more practical for various other parts of the world including United States. Of late, nonlinear I_a-S relations have also been suggested (Elhakeem and Papanicolaou 2009; Jiang 2001; Jain et al. 2006a; Mishra et al. 2004, 2006a, 2006b). It is however of common experience that the value of λ losses its significance as rainfall increases by a magnitude significantly higher than I_a, for which the existing SCS-CN method was developed. It is for the reason of generally high CN (and low S) values for high and low rain events, respectively. Alternatively, I_a is insignificant if P is high enough.

The accuracy of runoff prediction, however, largely depends on accurate estimation of the lumped parameter CN (Ponce and Hawkins 1996), which varies with antecedent rainfall and associated soil moisture (Mishra et al. 2014). The watershed moisture condition prior to rainfall is commonly called as antecedent moisture condition (AMC), and P_5 (SCS 1956, 1971) is often utilized as a predictor to categorize AMC into three levels, namely, AMC-1 (dry), AMC-2 (normal), and AMC-3 (wet) (Mishra et al. 2006b). In practice, CNs are first calculated for AMC-2, and then adjusted to AMC-3 or AMC-1 depending on P_5 (Mays 2005). The findings of Hjelmfelt et al. (1981) showed that the AMC tables given by NEH (Table 10.1, SCS 1971) described the AMC into three classes, AMC-3, AMC-2, and AMC-1 (or CN_3, CN_2 and CN_1), which account statistically for 90%, 50%, and 10%, respectively, of the cumulative probability that a given rainfall will exceed the runoff depth. This notion is also well tested and supported by various researchers (Haan and Schulze 1987; Hauser and Jones 1991; Hjelmfelt 1991). Of late, Grabau et al. (2009) and Hawkins et al. (2015) examined the same AMC tables (i.e. Table 10.1, SCS 1971) and found that the concept of AMC-3 and AMC-1 may be better described as 88^{th} and 12^{th} percentiles instead of 90^{th} and 10^{th} percentiles, respectively. The concept of Grabau et al. (2009) and Hawkins et al. (2015) has, however, not yet been tested using P–Q data around the globe. Notably, AMC-2 status is considered as the reference condition, for which CN values are derived from NEH–4 tables (SCS, 1971).

In order to relate the three AMCs, a number of attempts have already been made for converting CNs of AMC-2 to AMC-1 or AMC-3 (Arnold et al. 1990; Chow et al. 1988; Hawkins et al. 1985; Mishra et al. 2008b; Sobhani 1975). Firstly, Sobhani (1975), Hawkins et al. (1985) and Chow et al. (1988) used the tabular NEH–4 (SCS 1956, 1971, 1972) AMC-dependent CN–values for deriving mathematical expressions useful for converting the CN of one AMC to another. Later, Arnold et al. (1990) also developed CN–conversion formulae for using in SWAT model developed by Agricultural Research Service of the United States Department of Agriculture (USDA–ARS). The form of Arnold et al. (1990) formulae is entirely different; the size of data used is however not known, except they are based on NEH–4 table CNs. Of late, Mishra el al. (2008b) also used the same AMC table and provided a new set of mathematical expressions based on Fourier filtration smoothening procedure. Since AMC plays a significant role in runoff generation and the runoff calculated is highly sensitive to CN (Mishra and Singh 2006; Mishra et al. 2008b), a comprehensive comparative evaluation of the existing formulae and discussion on their validity is required.

Antecedent soil moisture can be one of the most important factors controlling hydrologic processes (Ambast et al. 2002; Brocca et al. 2008; Menziani et al. 2001; Roberts and Crane 1997; Stephenson and Freeze 1974; Weiler et al. 2003). The SCS-CN method has been used worldwide for rainfall runoff modeling, but a common problem encountered is the absence of significant relationship between antecedent soil moisture and measured CN values. The existing SCS-CN method uses the P_5 rainfall amount to select three AMC levels. However, the use of three discrete AMC levels implies a sudden jump in CN from one level to another (Hawkins, 1978). The measured values of CN however are not limited to the three AMC levels defined by P_5 rainfall (Rallison and Cronshey 1979). In literature, most of the investigators have used remotely sensed soil moisture (Berg and Mulroy 2006; Houser et al. 1998; Jacobs et al. 2003; Pauwels et al. 2001; Scipal et al. 2005) along with a few in-situ soil moisture measurements (Aubert et al. 2003; Anctil et al. 2004; Brocca et al. 2009; Huang et al. 2007) for rainfall runoff modeling. The findings of Beck et al. (2009); Hawkins and Cate (1998); Kottegoda et al. (2000); Melone et al. (2001); Pfister et al. (2003) show that P_5 rainfall as antecedent wetness condition (AWC) estimated the significantly poor surface runoff volume Therefore, an alternative solution to characterize AWC should be investigated as the use of direct measurements of soil moisture prior to rainfall event, rather than the amount of rainfall only (Brocca et al. 2009; Huang et al. 2007; Young and Carleton 2006).

1.3 MOTIVATION

From the aforementioned discussion it was found that SCS-CN method is the result of exhaustive field investigations carried out during 1930s and 1940s. The method has since then witnessed myriad applications world over. Based on exhaustive field investigations carried out in the United States, curve numbers were derived for different land uses, soil types, hydrologic condition, and management practices and these are reported in NEH-4. These numbers have seldom been verified for Indian watersheds (Bhatt et al. 2011; Gosain and Rao 2004).

Utilizing the originally developed curve numbers, most studies have concentrated on the application of the existing SCS–CN method and no systematic effort appears to have been made for CN verification for Indian watersheds. Further, few efforts have been made for analyzing the relative accuracy of all CN determination methods and compared them with NEH–4 table CN values; evaluating the effect of λ and antecedent moisture on CN and, in turn, the runoff for a given soil and land use/cover, particularly for Indian watersheds and it invokes the need of the study. Secondly, since all the existing AMC-dependent formulae have been derived from the same dataset, their comparison and validity are required to be tested by deriving similar formulae and incorporating the effect of λ into it from new dataset representing different climatic conditions.

1.4 OBJECTIVES OF THE STUDY

In view of the above the present study has been conducted with the following objectives:

1. To assess the rainfall−runoff behaviour in study plots; and to analyze the effect of soil type, land use and slope on runoff and curve number.
2. To analyze the relative accuracy of different CNs determination methods and compare them with NEH-4 CN values for agricultural plots in Indian conditions.
3. To determine the optimal λ and S (or CN) values and assess the performance of the traditional (λ=0.2) SCS–CN method.
4. To explore the existence of a relationship between CN (or S) and AWC to improve the runoff prediction.
5. To investigate the relative accuracy of existing AMC formulae, and proposing a new approach incorporating the effect of λ into AMC formulae.

CHAPTER 2

REVIEW OF LITERATURE

A comprehensive review of literature is an essential aspect of any scientific investigation and to provide an insight into the theoretical framework as well as method and procedure for meaningful interpretation of the study. With this aim, an effort has been made to review some of the relevant studies conducted in the past, related to different curve number determination methods from observed P-Q data and their comparison with NEH-4 Table based CNs, effect of initial abstraction coefficient on curve number and runoff, relationship between initial abstraction and maximum potential retention, relationship between antecedent wetness condition and curve number, and AMC dependent curve number conversion formulae.

2.1 SCS-CN METHOD

The Soil Conservation Service Curve Number (SCS-CN) method was developed in 1954. It is documented in Section 4 of the National Engineering Handbook (NEH-4) published by the Soil Conservation Service (now called the Natural Resources Conservation Service), U.S. Department of Agriculture in 1956. The document has since been revised several times. The SCS-CN method is the result of exhaustive field investigations carried out during 1930s and 1940s. The method has since then witnessed myriad applications world over. It is one of the most popular methods for computing the surface runoff for a given rainfall event from small agricultural, forest, and urban watersheds. It is simple, easy to understand and apply, stable, and useful for ungauged watersheds. The primary reason for its wide applicability and acceptability lies in the fact that it accounts for most runoff producing watershed characteristics: soil type, land use/treatment, surface condition, and antecedent moisture condition. The only parameter of this methodology, i.e. the Curve Number (CN), is crucial for accurate runoff prediction. Based on exhaustive field investigations carried out in the United States, curve numbers were derived for different land uses, soil types, hydrologic condition, and management practices and these are reported in NEH-4. The SCS-CN method in conjunction with different hydrological models is being used worldwide including India to estimate surface runoff satisfactorily (Pandey et al. 2005; Pandey et al. 2006)

The SCS-CN method is based on the water balance equation and two fundamental hypotheses expressed, respectively, as:

Water balance equation

$$P = I_a + F + Q \tag{2.1}$$

Proportional equality (First hypothesis)

$$\frac{Q}{(P - I_a)} = \frac{F}{S} \tag{2.2}$$

I_a – S relationship (Second hypothesis)

$$I_a = \lambda S \tag{2.3}$$

where P = rainfall; I_a = initial abstraction; F = cumulative infiltration excluding I_a; Q = direct runoff; and S = potential maximum retention or infiltration. The current version of the SCS-CN method assumes λ equal to 0.2 for routine practical applications. As the initial abstraction component accounts for surface storage, interception, and infiltration before runoff begins, λ can take any value ranging from 0 to ∞. Combining Equations 2.1 and 2.2, Q can be expressed as follows:

$$Q = \frac{(P - \lambda S)^2}{(P + S - \lambda S)} \quad \text{for } P > \lambda S;\ Q = 0 \text{ otherwise} \tag{2.4}$$

Equation 2.4 is the general form of the popular SCS-CN method and is valid for $P \geq \lambda S$; Q = 0 otherwise. For λ = 0.2, Equation 2.4 leads to

$$Q = \frac{(P - 0.2S)^2}{(P + 0.8S)} \tag{2.5}$$

Equation 2.5 is the popular form of the existing SCS-CN method. Thus, the existing SCS-CN method with λ = 0.2 is a one parameter model for computing surface runoff from daily storm rainfall. Since parameter S can vary in the range of $0 \leq S \leq \infty$, it is mapped onto a dimensionless curve number CN, varying in a more appealing range $0 \leq CN \leq 100$, as:

$$CN = \frac{25400}{S + 254} \tag{2.6}$$

where S is in mm. CN = 100 represents S = 0, an impermeable watershed. Conversely, CN = 0 represents a theoretical upper bound of S = ∞, an infinitely abstracting watershed. However, the practical design values validated by experience lie in the range (40, 98). For a given set of rainfall and runoff data, S can be determined from Equation 2.6 as:

$$S = 5[(P + 2Q) - (4Q^2 + 5PQ)^{1/2}] \tag{2.7}$$

Notably, the SCS-CN method does not consider the effect of slope on runoff yield and, in turn, on the resulting CN.

2.1.1 Factors affecting curve number

The curve number is basically affected by the watersheds characteristics that influences the runoff generation. These important characteristics are Hydrologic Soil Group (HSG), Land Use/ treatment, Land Cover, Hydrologic condition, Antecedent Moisture Condition (AMC), climate and initial abstraction, slope of watershed, season.

2.1.1.1 Hydrologic soil group

SCS described the hydrologic soil groups viz., A, B, C and D based on the infiltration rate of soil. Group A exhibit the low runoff producing soil having high infiltration rate. On the Contrary, group D exhibit the high runoff producing soil having low infiltration rate. Table 2.1 show the different Hydrologic soil groups based on minimum infiltration rate (mm/hr) (Hawkins et al. 2009)

Table 2.1 Hydrologic soil group (HSG) based on soil texture and minimum infiltration rate

HSG	Texture	minimum infiltration rate (mm/hr)
A	Sand, Loamy Sand, Sandy Loam	>7.62
B	Silt Loam or loam	3.81-7.62
C	Sandy clay loam	0.127-3.81
D	Clay loam, Silty clay loam, sandy clay, silty clay or clay	0-0.127

Of late, SCS adopted soil texture as other criteria for defining the HSGs following recommendation from Brakensiek and Rawls (1983) work (Table 2.1). In a study conducted by Romero et al. (2007) concluded that HSG must be defined based on infiltration rate rather than texture of soil as the determination of the hydrologic soil group on the basis of textural characteristics resulted in significantly worse predictions for both tabulated and P-Q data CN values.

2.1.1.2 Land use/land cover

The land use describes the surface condition of the watershed and is related with the degree of cover which ultimately connects with the rate of infiltration. The three major land use/land cover as classified by SCS are wood and forest, cultivated, and urban. These classes were further divided into Bare soil, Crop residue cover, Straight row and Contoured etc. treatments.

2.1.1.3 Hydrologic condition

The hydrologic condition of an agricultural land is defined in terms of the percent of grass cover area. The SCS defined the hydrologic condition based on the combined factors that affect both infiltration and runoff generation. Based on the percentage area of vegetation cover a watershed can be categories as good, fair and poor hydrologic condition watershed. A watershed is in good hydrological condition if it is lightly grazed and more than 75% of the area is covered with vegetation. If a watershed is not heavily grazed and 50–75% of the area is covered with vegetation, it is referred to as being in "fair" hydrological condition, whereas "poor" hydrological condition of a watershed is considered if it is heavily grazed and there is vegetation cover on less than 50% of the area.

2.1.1.4 Antecedent soil moisture conditions

Antecedent moisture condition refers to the wetness of the soil surface or amount of moisture available in the soil profile, or alternatively the degree of saturation before the start of the storm. If the soil is fully saturated, then the whole amount of rainfall will directly convert into runoff without infiltration loss. On the contrary, the situation of entirely different, when the soil is fully dry. The watershed moisture condition prior to rainfall is commonly called as antecedent moisture condition (AMC), and P_5 (SCS 1956, 1971) is often utilized as a predictor to categorize AMC into three levels, namely, AMC-1 (dry), AMC-2 (normal), and AMC-3 (wet) (Mishra et al. 2006b). Based on the P_5 (mm), AMC can be calculated as follows (Ajmal et al. 2015a,b,c; Mays 2005):

Table 2.2 AMC criteria based on the P_5 (mm) amount

AMC	Growing season	Dormant season
1	$P_5 < 35.56$	$P_5 < 12.7$
2	$35.56 \leq P_5 \leq 53.34$	$12.70 \leq P_5 \leq 27.94$
3	$P_5 > 53.34$	$P_5 > 27.94$

The CNs from one AMC into another can be converted using either formulae given in Table 2.3 or AMC tables given by NEH (Table 10.1, SCS 1971).

2.1.1.5 Effect of slope on runoff curve number

For ungauged watersheds, CN-values are usually derived from NEH-4 tables using two static inputs, soil type and land use/land cover (LULC). However, the runoff-generation is also affected by, besides others, the watershed slope (Dodds 1997). The SCS-CN method however does not account for its effect on runoff yield (Ebrahimian et al. 2012a; Ebrahimian et al. 2012b; Garg et al. 2013; Huang et al. 2006, Shi et al. 2009). In an study conducted by El-Hassanin et al. (1993) found that the increasing slope from 8 to 30% increased surface runoff by 160% for Burundi watersheds located in Iran.

The main factors affecting increase in surface runoff due to steeper slope can also be the reduction of initial abstraction (Chaplot and Bissonnais 2003; Fox et al. 1997), decrease in infiltration, and reduction of the recession time of overland flow (Evett and Dutt 1985). Only a few attempts have been made for incorporation of slope factor in the existing SCS-CN method. The Sharpley and Williams (1990) method is often cited for adjusting the CN-values using the following equation:

$$CN_{2\alpha} = a(CN_3 - CN_2)(1 - be^{-c\alpha}) + CN_2 \quad (2.8)$$

where a, b, and c are the empirical parameters, which have the values of 1/3, 2, and 13.86, respectively. Here CN_2 and CN_3 represent CN values for antecedent moisture condition AMC-II (average) and AMC-III (wet), respectively; and α (m m^{-1}) is the land slope; and $CN_{2\alpha}$ is the adjusted CN_2 used in runoff calculations. In Equation 2.8, CN_2 is assumed to correspond to a slope of 5%. The work of Van Mullem (1991) for rangeland and cropland in Montana and Wyoming, King et al. (1999) in Mississippi, Huang et al. (2006) in the Loess Plateau of China, Shi et al. (2009) in China, and Garg et al. (2013) in India concluded that the standard SCS-CN method underestimates large runoff events and over-estimates few small rainfall events; and therefore, the use of slope correction equation was recommended.

2.1.1.6 Other parameters affecting curve number

The other important parameters affecting CN are climate and initial abstraction, Rainfall duration and intensity, and turbidity. Ponce and Hawkins (1996) found that the CN is a variable identity which varies with rainfall and changes from watershed to watershed i.e. climatic condition. The NRCS-CN accounts for the climatic effect in terms of I_a.

It is well established hydrologic phenomenon that a storm of shorter duration allows less time for rainwater to stay on the land surface, which leads to smaller infiltration and consequently greater surface runoff. Larger runoff means larger CN and vice versa.

Turbidity refers to impurities of water that affect infiltration by the process of clogging of soil pores and consequently affecting the soil conductivity. Contaminated water with dissolved minerals, such as salts, affects the soil structures and infiltration rate is affected.

2.2 CURVE NUMBER DETERMINATION METHODS FROM OBSERVED P-Q DATA

A number of approaches are available in the literature which can be employed to estimate the watershed's representative curve number (CN) based on observed rainfall (P)–runoff (Q) data sets. The most common and widely used are NEH-4 storm event method in which median of the event-wise CN series considered as watershed representative CN (SCS 1972; Hawkins et al. 2009). The other methods include the S-probability method (Hjelmfelt 1991), storm event mean method (Bonta 1997), least-squares method (LSM) (Hawkins et al. 2002), Rank-order method (Hawkins et al. 2002), Log-normal frequency method (Schneider and McCuen 2005), asymptotic fitting method (AFM) (Hawkins et al. 2009, Hawkins 1993), and geometric mean method (Hawkins et al. 2009; Tedla et al. 2012). The NRCS (2001) has given that the geometric mean method can be used to determine a watershed curve number if the derived CNs values are lognormally distributed (Yuan 1933). But the log-normality of curve number distributions has not been carried out yet (Tedla et al. 2012). Bonta (1997) used the arithmetic mean curve number but did not justify this choice with evidence that watershed curve numbers are normally distributed. The asymptotic determination method developed by Hawkins (1993) tries to correct the problem arose to derive original equation of SCS-CN on the fundamental concept of hypotheses. Hawkins (1993) applied the frequency matching concept to treating the recorded rainfall and runoff data. The rainfall and runoff depths are sorted separately, and then realigned on a rank-ordered basis to form P-Q pairs of equal return periods. The individual runoffs are not necessarily associated with the original causative rainfalls. The maximum potential retention (S) followed by CN was calculated for each paired event employing standard SCS equation. The calculated CN for each paired event was the displayed on a scatter plot as a function of precipitation to find out the specific watershed response. Three categories were identified as standard, violent, and complacent. The standard is the most common behavior usually seen. The standard response illustrates a decreasing curve number as precipitation increases. The curve number decreases until an asymptotic behavior is observed for larger, more extreme precipitation events. The violent response was observed in a watershed with an increasing curve number as precipitation increases. In complacent behavior, the observed curve number declines steadily with increasing rainfall depth, and no asymptotic behavior was noted and it is said to be the most ambiguous among the three responses.

Similar to Asymptotic Determination, Rank-Order Method is also a popular technique to find out the watersheds representative CN in which naturally occurred P and Q pair is sorted from largest to smallest. The smallest Q now is corresponding to the smallest P, and the new series called as ordered data. This is done in an attempt to decrease the difference in rainfall frequency and runoff frequency. Hawkins et al. (2002) recommend this method because in design work the frequency of the rainfall is generally assumed to match the frequency of the runoff. The estimate of CN for the watershed is the mean or median of all the CNs computed with the ranked pairs of P and Q. In ordered data series, the observed P and Q values were first sorted separately and then realigned by common rank-order basis to form a new set of P–Q pairs of equal return period, in which runoff Q is not necessarily matched with that due to original rainfall P (Hawkins 1993; Hawkins et al. 2009; D'Asaro and Grillone 2012; Soulis and Valiantzas 2013; Ajmal et al. 2015a; Lal et al. 2015).

As an alternative to traditional methods, Schneider and McCuen (2005) have developed a method known as Log-normal frequency method by utilizing the concept of log-normal frequency analysis. In this method, the logarithms of each set of naturally observed P and Q pair were computed. The value of S was then calculated by employing standard SCS-CN equations using mean log P and log Q values (Schneider and McCuen 2005). The main advantage of this method is that it reduces the imbalance of the weights given to the larger P values since taking the logarithms of the rainfall depths reduces all of the values proportionally.

2.3 COMPARISON OF DIFFERENT CN DETERMINATION METHODS

A comprehensive review was conducted for finding the studies related to inter comparison of different CN determination methods. In this regard, the works of Lewis et al. (2000), McCuen (2002), Schneider and McCuen (2005), Ali and Sharda (2008), D'Asaro and Grillone (2012), Stewart et al. (2012), Telda et al. (2012) and D'Asaro et al. (2014) are worth to include.

Lewis et al. (2000) had used 17 annual maximum P-Q events from California Oak woodland watershed in western regions of the United States for comparing the three CN determination methods viz. National Engineering Handbook (NEH-4) median, S-probability and asymptotic fit. They have found that estimated Curve numbers were highest using S probability, intermediate for the asymptotic method and lowest for the NEH-4 method. Based on the Kruskal-Wallis test, the means CNs estimated by the NEH-4 and S probability methods were significantly different ($p=0.009$). The runoff predicted by all the three methods were statistically insignificant with observed runoff. Further, the S-probability and NEH-4 methods respectively predicted the highest and lowest mean peak annual runoff. Lastly, authors concluded that The S probability method most frequently overestimated runoff and is, therefore, a more conservative predictor than the NEH-4 method.

Schneider and McCuen (2005) compared storm-event (mean and median) and rank-order (mean and median) methods with Log-normal frequency and found that Log-normal frequency performed best of all, and storm event method superior to rank order method. Further they have suggested the use of mean CNs values rather than median for both natural and ordered datasets.

Ali and Sharda (2008) used the P-Q data from semi-arid region of Kota and Bundi districts of south-eastern Rajasthan in India for comparison of different CN determination methods. They have collected data observed from three watersheds namely Badakhera, agricultural and Ravinous with P-Q events vary from 31 to 75. In this study, the performance of five different curve number determination methods, viz. rank order, s-probability, National Engineering Handbook (NEH-4), lognormal frequency and storm event were evaluated. These analyses show that S-probability and lognormal frequency methods estimated the larger and smaller, respectively, CN values for all the three watersheds. The lognormal frequency method found to perform superior followed by storm event, rank order, NEH-4, and s-probability in runoff estimation. In addition, the performance of the storm event, rank order, National Engineering Handbook (NEH-4), methods were found to be almost identical except for the S-probability method.

D'Asaro and Grillone (2012) compared the asymptotic fitting method, NEH4 method, and a least-squares methods utilizing the multiday P-Q events for observation period of 1940-1947 in 61 Sicilian basins. The results indicate the CNs estimated by NEH4 method (both mean and median CN) are higher as compared to other methods. The high CN leads to convert most of the rainfall into runoff; and therefore, this method is unable to predicted realistic runoff for Sicilian watersheds. On the other hand, least square fit method found to estimate lowers CN as compared to other methods; and CNs estimated by asymptotic fitting method were in between other two methods. The study further showed that the CNs estimated by least-squares using ordered data set were higher compared to natural datasets.

Stewart et al. (2012) evaluated the four CN determination approaches using the 1284 P-Q events from 16 watersheds in the southwestern U.S. They have used the partial duration series with ordered P-Q pairs (method 1), annual series (based on flood peak) with ordered P-Q pairs (method 2), annual series (based on flood peak) with natural P-Q pairs (method 3), and annual series (based on flood peak) with natural P-Q pairs (Method 4: median CN). The study revealed that method 4 estimated the highest CNs for 14 out of the 16 tested watersheds. On the other hand, CNs estimated by method 3 were smaller, and CNs estimated by Method 1 and

Method 2 were almost similar. Overall, methods 3 and 4 CNs were significantly (at 5%) different to Method 1 and Method 2, latter one did not differ significantly.

Telda et al. (2012) used the P-Q data from 10 small forested watersheds in the mountains of the eastern United States for evaluating the five different viz., storm event-, median and arithmetic mean, geometric mean, least squares fit and standard asymptotic fit CN estimation methods. They have found that CNs estimated by Geometric-mean method are generally larger (seven of 10 watersheds) than CNs estimated by the other methods. In the runoff estimation accuracy, the geometric mean was ranked either first or second for all the tested watersheds. The multiple comparison tests also reveal no significant difference (5% level of significance) in using the median, geometric mean, and arithmetic mean curve numbers to estimate runoff for all 10 watersheds. They have concluded that for some watersheds, the geometric mean CN derived from an annual maximum series of observed P-Q from gaged watersheds provides locally consistent estimates with a probabilistic basis. For some watersheds, each appropriate design storm required a different curve number.

D'Asaro et al. (2014) used the Sicilian basins observed data to compare the NEH-4 median, asymptotic, and least-squares methods being employed for estimating the data-based CN worldwide. For annual maximum multiday events, the NEH4 method estimate the highest CN than other methods. Notably, CN estimated by least square fit were lowest. The ordered data least fir CN were on average 10 units greater than the natural data CNs.

2.4 P-Q DATA-BASED CN COMPARISON WITH TABULATED CN

Hawkins (1984) used observed P-Q data from 110 watersheds located in USA for estimating mean and median CN and comparing them with tabulated CN. He found that comparison between these observed and tabulated CN is less than satisfactory as the there is no relationship exists overall. Further, he compared the tabulated CN landuse wise and found that rainfed agriculture and forested watersheds CNs were respectively fair and poorly matched with tabulated ones. Of late, study conducted by Titmarsh et al. (1989, 1995, 1996) utilizing the observed P-Q data from 105 small agricultural watersheds located in southeast Queensland, Australia found that the design runoff estimated by tabulated CN is highly unreliable as these are smaller than the observed CNs. The tabulated CNs matched poorly when plotted against observed ones. The similar results were also provided from the studies conducted by Hawkins and Ward (1998) and Fennessey (2000) at 21 plots (2m × 2m) at 5 different locations in southern New Mexico and sixty-five watersheds located in USA, respectively.

In a study conducted at Andalusia, southernmost region of Spain on Olive Orchards by Romero et al. (2007) found that tabulated CNs were the worst performer in runoff estimation. The runoff estimated by observed P-Q based CN values was significantly better than the CN values derived from the handbook tables. The RMSE of runoff estimation by observed and tabulated CN were varied respectively between 0.50 to 7.3 mm and 1.4 and 10.4 mm.

Feyereisen et al. (2008) used P-Q data pairs measured on six plots in South Georgia for two tillage treatments under a cotton-peanut crop rotation on a Tifton series loamy sand. This study was conducted to estimate CNs for a cotton-peanut rotation under conventional and strip tillage (ST) methods for growing and dormant seasons. Data based CNs were estimated using three methods viz., averaging, lognormal, and data-censoring methods. The results showed that CNs estimated by averaging and log normal methods were comparatively higher than tabulated ones. For conventional and STs, CNs by the averaging method using year-round data were 89 and 84, respectively, and by the lognormal method were 89 and 83, respectively. Results from the data-censoring method were 81 and 75, respectively, which matched standard table values developed from a long-term series of annual maximum runoff.

Sartori et al. (2011) used the natural P-Q events monitored at three research plots at Instituto Agronômico de Campinas (IAC) at Experimental Center of Campinas located in Campinas City, São Paulo, Brazil for CN analysis. They have used three different land uses viz. bare, minimum tillage with sugarcane crop and Traditional Tillage with sugarcane crop (without burning). The tabulated CNs were compared with data based CNs estimated by both asymptotic and least square fir methods. This study found that runoff estimated by handbook table CNs are not reliable for study region. Instead they have suggested the locally measured CNs for further use. The CN values as 87 for bare, 82 for fallow, 75 for partial cover, 52 heavy cover, 45 full cover were suggested for use in areas with similar soils given in study area.

Stewart et al. (2012) compared the tabulated CNs with data based CNs employing P-Q events from 16 watersheds in the southwestern U.S. using 1,284 events that satisfy rainfall and runoff criteria. The results showed that the tabulated CN values were lower than the CNs (NRCS median method) from the data for 21 of the 30 semiarid desert shrub and herbaceous watersheds and plots.

Telda et al. (2012) used the P-Q data from 10 small forested watersheds in the Appalachian Mountains of the eastern United States for comparing the observed P-Q data and Handbook table based CNs. The observed CNs estimated by five different methods viz. storm event-, median and arithmetic mean, geometric mean, least squares fit and standard asymptotic fit were compared with tabulated CNs. The tabulated curve numbers were ranged from 41 to 70. The runoff estimated by tabulated CNs was modestly correlated with observed runoff for only one watershed. Further, the smaller Nash-Sutcliffe efficiencies showed that runoff estimation using tabulated CNs was biased for 6 out 10 watersheds. The investigation concluded that for 9 out of 10 watersheds, tabulated curve numbers do not accurately estimate runoff, and therefore, use of locally measured geometric mean CNs are suggested.

D'Asaro et al. (2014) used the observed P-Q data from 61 Sicilian basins to compare the tabulated CNs with observed ones. The CN estimated by NEH-4 median, asymptotic, and least-squares methods were compared with tabulated CNs individually. Overall, the general agreement between tabulated and data based CNs was poor. Compared to tabulated CN, NEH-4 median methods estimated the larger CN for 32 out of 36 watersheds. Besides, the relationship between the CNs estimated by these two approaches was also not significant. However, the agreement between these two were good for higher CN values i.e. greater than 80. Further, CNs estimated by asymptotic and least-squares methods also show poor agreement using both natural data and ordered data, and no significant relationships between tabulated and observed data-based CN (for both asymptotic and least-squares) were found. The tabulated CN is almost always greater than asymptotic and least-squares fit CN, and the differences are greater with the smaller CNs.

Recently, Taguas et al. (2015) had conducted a study to check the suitability of reference CN values to simulated runoff effectively in three olive orchard catchments located in Andalusia, Spain. The area of catchments namely La Conchuela, Setenil and Puente Genil lies between 6 to 8 hectares having mean slope in the range of 9 to 15%, and fall in three different climatic conditions. This study shows that reference CNs were lower than the observed P-Q based CNs for all the three watersheds. The reference and estimated CNs were respectively 57 and 83 for Setenil; 73 and 84 for Puente Genil; 82 and 87 for La Conchuela. It will result underestimation of runoff if estimated using the reference CNs, and therefore, use of observed CNs were recommended.

2.5 EFFECT OF INITIAL ABSTRACTION COEFFICIENT (λ)

An accurate assessment of initial abstraction coefficient (λ) is essential as it is one of the crucial parameters used in watershed rainfall–runoff estimation. It largely depends on climatic conditions of the watershed (Ponce and Hawkins, 1996). Traditionally (SCS, 1964, 1972), λ is often set equal to 0.2 in standard SCS-CN equation. However, numerous researchers as given in Table 2.3 (Hawkins and Khojeini 2000; Hawkins et al. 2002; Baltas et al. 2007; Elhakeem et al. 2009; Shi et al. 2009; Zhou and Lei 2011; D'Asaro and Grillone 2012; D'Asaro et al. 2014; Yuan et al. 2014) frequently questioned the validity and applicability of λ=0.2, invoking its critical examination for practical applications. Table 2.3 show the λ values estimated by different researchers in different parts of globe. There are only two methods viz., event analysis and model fitting, which can be used to estimate the λ value. In event analysis method, each naturally occurred P-Q event has been analyzed individually to calculate the λ value.

In model fitting method, entire P-Q events have to be fitted by means of least square fit. Notably, both natural and ordered data series can be fitted; and it gives only one value of λ for all P-Q data set of watersheds. The details of these two methods can be found elsewhere (Jiang 2001; Hawkins et al. 2002).

As far as Indian condition concern, Central Unit of Soil Conservation Ministry of Agriculture, Government of India (1972), suggested relations between initial abstraction (I_a) and maximum possible abstraction (S): I_a = 0.1S for black soil region with AMC-2 and AMC-3, I_a = 0.2S for black soil region with AMC-1 (watershed soils are dry), and I_a = 0.3S for all other soils. These λ values were used by Tripathi et al. (2003) and Tiwari et al. (2006) in Hazaribagh district of Bihar, India and forest micro-watersheds of Shiwaik region, India, respectively.

Jiang (2001) used 307 watersheds or plots across 24 states in the United States to estimate λ values employing both event analysis and least square fit method. Both natural and ordered datasets were fitted in model fitting method. The results analysis shows that λ to vary from 0 to 0.996 for natural and 0 to 0.9793 for ordered datasets. Notably, 0 was the most frequent value in model fit analysis. On the other hand, event analysis method was applied to only 134 watersheds data and λ was found to vary from 0.0005 to 0.4910 with mean and median values as 0.0701 and 0.0476, respectively. The estimated λ values for ordered data were relatively higher than for natural datasets. The work of Hawkins et al. (2002), Shi et al. (2009) and Jiang (2001) suggested the use λ=0.05 for runoff modelling using SCS method. In order to use I_a = 0.05S, the standard SCS equation becomes as:

$$Q = \frac{(P-0.05S)^2}{(P+0.95S)} \text{ for P>0.05S} \tag{2.9}$$

In Equation 2.9, S must be associated to λ=0.05. To this end, Jiang (2001) fitted the data of 307 USA watersheds to give an empirical relationship between the CNs associated to 0.02 and 0.05 as:

Table 2.3 Summary of recent studies on initial abstraction coefficient (λ) Value

Authors	Statistic	λ	Data type and method	Location	Remark
Hawkins et al. (2002)	0.1472 (range 0-0.9793)	Mean	Ordered data, Least square fitting	United States	A total of 28,301 events from 307 watersheds and plots were used
	0.0618	Median			
	0.0734 (range 0-0.996)	Mean	Natural data, Least square fitting		
	0	Median			
Baltas et al. (2007)	0.014 (range 0.004-0.37)	Mean	Natural data, Event analysis	Attica, Greece.	18 events from watershed of area 15.18 km^2
	0.037 (range 0.014-0.054)	Mean	Natural data, Event analysis		5 events from northern sub-watershed
D'Asaro and Grillone (2010)	0.011 (range 0-0.11)	Mean	Natural data, Least square fitting	Sicily (Italy)	Daily runoff of 61 Sicilian watershed (area 10.26–1782.15 km^2) were used
	0	Median			
	0.07 (range 0-0.33)	Mean	Ordered data, Least square fitting		
	0.035	Median			
Shi et al. (2009)	0.053 (range 0.01-0.154)	Mean	Natural data, Event analysis	Three Gorges Area, China	29 events from a basin of area of 1670 ha
	0.048	Median			
Elhakeem et al. (2009)	0.142	Median	Summer storm Simulated data	Iowa (United States)	Experimental plots of size 2.5 m × 1.5 m were used
	0.069	Median	Winter storm Simulated data		
Fu et al. (2011)	0.08 (range 0.01-0.46)	Mean	Natural data, Event analysis	Loess Plateau of China	. 205 rainfall runoff events from 9 plots of size 10 m × 5 m were used
	0.05	Median			
Zhou and Lei (2011)	0.22 (range 0.01-0.59)	Mean	Event analysis	China	14 rainfall runoff events from Qiaozi-West watershed of area 1.14 Km^2 were used
	0.17	Median			
	0.01 (range 0.05-0.16)	Mean	Back calculation		
	0.09	Median			
Hawkins and Khojeini (2000)	0.0499	Mean	Natural data, Least square fitting	United States	Four different data set were used
	0.1432	Mean	Ordered data, Least square fitting		

Table 2.3 (Continued)

Authors	Statistic	λ	Data type and method	Location	Remark
D'Asaro and Grillone (2012)	0.09 (range 0-0.48)	Mean	Ordered data, Least square fitting	Sicily (Italy)	Both ordered and natural dataset from 46 basins of area 10–1782 km^2 were used
	0.05	Median			
	0.02 (range 0-0.47)	Mean	Natural data, Least square fitting		
	0	Median			
Yuan et al. (2014)	0.12 (range 0.01-0.53)	Mean	Natural data, Least square fitting	Southeastern Arizona, United States	11 gauging station data from watershed of area 148 km^2 used
D'Asaro et al. (2014)	0.02 (range 0-0.47)	Mean	Natural data, Least square fitting	Sicily (Italy)	Both ordered and natural dataset from 46 basins of area 10–1782 km^2 were used
	0.0	Median			
	0.09 (range 0-0.48)	Mean	Ordered data, Least square fitting		
	0.05	Median			
Jiang (2001)	0-0.996	Range	Natural data	United States	307 watersheds or plots across 24 states in the United States
	0-0.9793	Range	Ordered data		
Menberu et al. (2015)	0.036 (range 0.030-0.042)	Mean	HEC-HMS model calibration	Finland and Norway	59 events from three watersheds of Finland and Norway
	0.030	Median			
Ajmal et al. (2015c)	0.01	Median	Ordered data	South Korea	15 watersheds data were used for least square fitting

$$S_{0.05} = 1.33 \left(S_{0.02}\right)^{1.15} \tag{2.10}$$

$$CN_{0.05} = \frac{100}{1.879\left(\frac{100}{CN_{0.02}} - 1\right)^{1.15} + 1} \tag{2.11}$$

where $S_{0.05}$ and $S_{0.2}$ are in inches. $S_{0.05}$ and $CN_{0.05}$ are the storage and CN values corresponding to λ=0.05, and $S_{0.20}$ and $CN_{0.20}$ are the values corresponding to λ= 0.2, respectively. The conversion of $CN_{0.20}$ into $CN_{0.05}$ (or other λ based CN) is known as "conjugate" CNs.

Hawkins et al. (2002) used event analysis and model fitting methods to determine the initial abstraction coefficient (λ) from 28301 rainfall-runoff events data from 307 USDA-ARS watersheds and experimental plots located in USA, and found that the coefficient is not a constant from storm to storm, or watershed to watershed, and that the assumption of 0.2 is unusually high, therefore, suggest changing the initial abstraction coefficient (I_a/S) from 0.2 to 0.05 for use in runoff calculations. As per event analysis method, the values of λ varied from 0.0005 to 0.4910, with a median of 0.0476 and more than 90% of λ values were less than 0.2. However, results from model fitting were more varied than those from event analysis. The λ values for natural data ranged from 0 to 0.996, with a median of 0, and with a mean of 0.0734. On the other hand, λ values were varied from 0 to 0.9793 for ordered data set with a mean and median of 0.1472 and 0.0618, respectively. Here, it is to note that 0 was the most frequent values for both natural and ordered datasets fitted from 307 watersheds and experimental plots.

Mishra and Singh (2004a) evaluated the impact of the initial abstraction ratio on the efficiency of a versatile SCS-CN model, and found that as the λ increases the efficiency of model decreases, and maximum efficiency was achieved when the λ was in the order of 0.01.

Lim et al. (2006) explored the effects of initial abstraction and urbanization on estimated direct runoff, and found that that the use of a λ = 0.05 value with modified CN values for a λ = 0.05 value and hydrologic soil group D for urbanized areas can improve long term direct runoff estimation.

Baltas et al. (2007) examined the eighteen naturally observed P-Q events from the experimental watershed is located on the eastern side of Penteli Mountain, in the prefecture of Attica, Greece. The analysis showed that average coefficient (I_a/S) was equal to 0.014 with maximum and minimum values were 0.037 and 0.004, respectively. They have also analyzed the five events from northern sub watershed and λ were found to varied from 0.014 to 0.054

with average value as 0.037. In the concluding remark they have recommended the use 0.05 for present study region in future use.

Based on some recent studies, Shi el al. (2009) determined initial abstraction coefficient (λ) using event analysis method and found that λ values varied from 0.010 to 0.154, with a mean of 0.053 in an experimental watershed in Three Gorges Area, China. The median of λ was 0.048 from the analysis of 6 years P-Q data. They have also suggested the use of 0.05 in the Three Gorges Area of China area as compared to traditionally recommended 0.2.

Fu et al. (2011) used the P-Q data from farmland plots in Shaanxi (205 rainfall events) and Gansu (552 rainfall events) provinces in the Loess Plateau of China, and found the initial λ to vary from 0.01 to 0.46, with an average value of 0.08 and a median of 0.05. Results showed about 95% of the values were less than 0.2. The difference in the event runoff predicted using λ = 0.05 versus λ = 0.2 was significant at a significance level of 0.01.

D'Asaro and Grillone (2012) evaluated the CN methodology at the basin scale from rainfall-runoff multiday events, in the observation period 1940–1997 (recorded length mean equal to 20 years) for 61 Sicilian basins. They have λ to vary from 0 to 0.68 with mean and median as 0.04 and 0, respectively for natural annual maximum multiday event data set. In contrast, λ was varied from 0 to 0.46 with mean and median as 0.06 and 0, respectively for ordered annual maximum multiday event data set. The study concluded that for Sicilian watersheds, the median λ value is 0 for natural data and 0.05 for ordered data, pointing out the need to assume these λ values for application.

Yuan et al. (2014) used 11 gauging station data from Walnut Gulch Experimental Watershed (WGEW) (South eastern Arizona) and its ten nested catchments of area 148 km^2 located in Southeastern Arizona, United States. They have fitted Natural data P-Q data by means of Least square fitting and found that λ to varies from 0.01 to 0.53 with 0.12 as mean value. The effect of initial abstraction ratio on runoff estimation increases with decreasing CNs. Further they have examined the sensitivity of runoff to the initial abstraction ratio and it was seen that for a given rainfall and CN values the estimated runoff was increased by 214% when the initial abstraction ratio was decreased 90% from 0.2 to 0.02. Similar to Jiang (2001), Yuan et al. (2014) also fitted Arizona's watersheds data to present conjugate CNs of λ=0.02 with 0.01, 0.05 and 0.10. Empirical relationships between different CNs was as follows:

$$CN_{0.2}=55.026 \exp(0.0058CN_{0.01}) \quad R^2 = 0.998 \qquad (2.12)$$

$$CN_{0.2}=46.139 \exp(0.0078CN_{0.05}) \quad R^2 = 0.996 \qquad (2.13)$$

$CN_{0.2}$=36.303 exp (0.0105$CN_{0.10}$) R^2 = 0.991 (2.14)

Ajmal et al. (2015c) fitted the ordered P-Q data from 15 watersheds located in South Korea. The results showed λ to ranging from 0 to 0.2 with mean and median as 0.05 and 0.01, respectively. Results confirms that λ value from 0.2 to 0 exhibits better runoff estimation for South Korean watersheds.

Menberu et al. (2015) analysed 59 rainfall-runoff events from two peat-dominated watersheds in Finland (Marjasuo, Röyvänsuo) and one in Norway (Grualia). In their study they have used the HEC-HMS to calibrate CN and λ. The results showed λ to vary from 0.01 to 0.10 for Röyvänsuo, 0.01 to 0.05 for Grualia and 0.01 to 0.09 for Marjasuo. The mean and median values were respectively 0.041 and 0.039 for Marjasuo, 0.027 and 0.026 for Grualia, and 0.027 and 0.026 for Grualia. Overall, combined results from all three watersheds showed λ ranging 0.030 to 0.042 with mean and median as 0.036 and 0.030, respectively.

2.6 I_a–S RELATIONSHIP

Originally, based on the P-Q data from various parts of USA (Rallison, 1980), SCS curve number method (SCS 1985) assumed a linear positive relationship between initial abstraction, I_a and maximum potential retention, S as I_a=0.2S. This relationship was justified on the basis of measurements in watersheds (of less than 10 acres) 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 0.2 (Ponce and Hawkins 1996). Since its inception, I_a and S relationship has been a topic of discussion and modification among research community for its practical utility (Springer et al. 1980; Jiang 2001). For example, Springer et al. (1980) found the λ varied from watershed to watershed and a standard relationship I_a=0.2S must be used carefully in arid or humid watersheds.

Ponce and Hawkins (1996) suggest that the fixing of the initial abstraction ratio at 0.2 may not be the most appropriate number, and that it should be interpreted as a regional parameter. Contrary to traditional assumed linear relationship between Initial abstraction I_a and potential maximum retention S.

Jiang (2001) studied the relationship between I_a and S across different watersheds using the entire data of 307 watersheds of United States. They found no correlation to exist between Initial abstraction I_a and potential maximum retention S for data analysed in United States. Jain et al. (2006a) reviewed the I_a – S relationship, and proposed a new non-linear relation incorporating storm rainfall (P) and S.

Mishra et al. (2006a), employed a large dataset of 84 small watersheds (area=0.17 to 71.99 ha) of USA, and investigated a number of initial abstraction (I_a) – potential maximum retention (S) relations incorporating antecedent moisture as a function of antecedent precipitation.

Elhakeem and Papanicolaou (2009) conducted an experiment using rainfall simulator on Four soybean fields and fourteen corn fields of sizes 1.5 m × 2.5 m located at different location in Lowa state USA to assess the SCS-CN method. They have found that Initial abstraction I_a was not linearly proportional to potential maximum retention S as reported by USDA and was also affected with residue cover.

2.7 CN–AMC CONVERSION FORMULAE

In SCS-CN method, AMC play a significant role in accurate estimation of runoff. CNs from average condition to dry or wet condition have to corrected depending upon the P_5 value. Initially, NEH-4 had given a table for converting CNs from one AMC into another. Of late several researchers have used these AMC based CN tables and represented them into mathematical formulae. In literature, five existing formulae are available to convert one AMC into another.

2.7.1 Sobhani (1975) formulae

The Sobhani (1975) formulae for converting the CNs from AMC-2 (CN_2) to AMC-1 (CN_1) or AMC-3 (CN_3) are presented in Table 2.4. These were developed by analyzing the AMC–dependent CN values as shown in Table 10.1 of NEH–4 (SCS 1971, 1972), in which linear relations were found to exist between the maximum potential retention (S) for AMC-2 and that for AMC-1 or AMC-3. Sobhani (1975) equations are applicable in CN–range (55, 95) as these were developed by considering every 5th CNs (or 9 data-points) in the range (55, 95).

2.7.2 Hawkins et al. (1985) formulae

Hawkins et al. (1985) also used the same above AMC based NEH-4 CN table and derived the following expressions using smoothened CN–data derived from straight line plot on normal probability paper (Mishra et al. 2008b; Ponce and Hawkins 1996):

$S_3 = 0.427\ S_2$ R^2=0.994; Standard Error (SE) =2.2352 mm (2.15)

S_1= 2.281S_2 R^2=0.999; Standard Error (SE) =5.2324 mm (2.16)

Similar to the Sobhani (1975) expressions, Equations 2.15 and 2.16 are also valid in the CN range (55, 95). Here, the number of data point used is 41. The substitution of equations 2.15 and 2.16 into the definition of CN leads to simplified forms as shown in Table 2.4.

2.7.3 Chow et al. (1988) formulae

As shown in Table 2.4, Chow et al. (1988) formulae are based on the same data but the number of data points is 100. These are applicable in CN range (1, 100).

2.7.4 Arnold et al. (1990) formulae

Arnold et al. (1990) proposed entirely different forms of CN–conversion expressions, as shown in Table 2.4. This form was initially developed for use in SWAT model. Its documentation, however, does not provide clear guidelines for the applicability of the conversion formulae (Table 2.4), except CN_1 and CN_3 (Table 1) are further adjusted for actual moisture content. The full development details of the formulae and the size of the dataset used (N) are not available, except that the formulae are based on the NEH-4 CN table values.

2.7.5 Mishra et al. (2008b) formulae

Similar to Hawkins et al. (1985), Mishra et al. (2008b) derived a new set of expressions using AMC–dependent 41 number of CN data points (55, 95) based on Fourier filtration smoothening procedure as below:

$$S_3 = 0.430\, S_2 \qquad R^2=0.9967; \quad SE=1.8616 \text{ mm} \tag{2.17}$$

$$S_1 = 2.2754\, S_2 \qquad R^2=0.9992; \quad SE=4.4373 \text{ mm} \tag{2.18}$$

The CN forms of above equations are given in Table 2.4.

Mishra et al. (2008b) also compared the Hawkins et al. (1985), Chow et al. (1988), Sobhani (1975) and Arnold et al. (1990) formulae, and found that Sobhani formula performed best in CN_1-conversion, and the Hawkins formula in CN_3-conversion, when tested using NEH-4 CN as target values. Thus, the Sobhani and Hawkins formulae can be asserted to be closer to NEH-4 values than any other formulae. Further all these five formulae were also compared using field data derived from the USDA-ARS Water Database, United State and it was found that Mishra et al. (2008b) formulae perform the best, and those due to Arnold the poorest in field application. Overall, all the five methods based on average RMSE (range of variation: 0.02–0.38 mm) values derived from their application to P–Q data sets of 82 watersheds can be ranked as follows:

Mishra > Hawkins > Sobhani > Chow > Arnold

Table 2.4 AMC dependent curve number conversion formulae

Method	AMC-3	AMC-1
Sobhani (1975)	$CN_3 = \frac{CN_2}{0.4036 + 0.005964\ CN_2}$	$CN_1 = \frac{CN_2}{2.334 - 0.01334\ CN_2}$
Hawkins et al. (1985)	$CN_3 = \frac{CN_2}{0.427 + 0.00573\ CN_2}$	$CN_1 = \frac{CN_2}{2.281 - 0.01281\ CN_2}$
Chow et al. (1988)	$CN_3 = \frac{23CN_2}{10 + 0.13\ CN_2}$	$CN_1 = \frac{4.2CN_2}{10 - 0.058\ CN_2}$
Arnold et al. (1990)	$CN_3 = CN_2 \exp[0.00673(100 - CN_2)]$	$CN_1 = CN_2 - \frac{20(100 - CN_2)}{[100 - CN_2 + \exp\{2.533 - 0.0636(100 - CN_2)\}]}$
Mishra et al. (2008b)	$CN_3 = \frac{CN_2}{0.430 + 0.0057\ CN_2}$	$CN_1 = \frac{CN_2}{2.2754 - 0.012754\ CN_2}$

2.8 EFFECT OF ANTECEDENT WETNESS CONDITION (AWC) ON CURVE NUMBER

Soil moisture is the key state variable in hydrology, because it controls the proportion of rainfall that infiltrates, runoff, or evaporates from the land. In particular, the runoff depth was found to be influenced by total rainfall, rainfall intensity and the antecedent wetness condition (AWC); and of these three factors AWC is the most significant one (Brocca et al. 2008; Brocca et al. 2009). Determination of the antecedent moisture condition (AMC) plays an important role in selecting the appropriate CN value. Soil moisture appears to be a better criterion than the 5-day antecedent rainfall depth to select an appropriate AMC value (Huang et al. 2007). Montgomery and Clopper (1983) used a 15-day antecedent precipitation index (API) in place of NEH-4 recommended P_5 rainfall and showed subsequent effect on runoff prediction in six agricultural watersheds. Melone et al. (2001) obtained poor results with errors in surface runoff volume up to 100% when used 5-day antecedent rainfall as antecedent wetness condition (AWC), and similar type of results were obtained by other investigators (Hawkins and Cate 1998; Kottegoda et al. 2000; Pfister et al. 2003; Beck et al. 2009). Aubert et al. (2003) argued that assimilating locally measured soil moisture data in a continuous conceptual rainfall runoff modeling greatly improves the flood forecasting in an agricultural catchment of France. Jacobs et al. (2003) used remotely sensed soil moisture data of depth 5cm to adjust CN and a reduction of nearly 50% in RMSE was observed in runoff estimation for five watersheds located in southwestern Oklahoma, USA.

Huang et al. (2007) conducted a study in a 4.7 km^2 experimental watershed located in the Loess Plateau of China to measure the in-situ soil moisture by 10 cm increments from depths of 10 to 100 cm. The experiment was conducted for 10 years on four plots of different sizes, land uses and slopes. Results showed a non-linear relationship between the measured CN values and soil moisture in the 0–15 cm and the 0–30 cm soil depths. Brocca et al. (2009) tested the four indices viz., Two antecedent precipitation indices (API), Degree of saturation and one base flow index (BFI) in estimation of wetness conditions. They found that observed degree of saturation was reliable AWC of the five nested catchments in central Italy.

On the contrary, several researchers have found AWC as insensitive to runoff generation, particularly in the case of large rainfall events (Kostka and Holko 2003; Scherrer et al. 2007; Nadal-Romero et al. 2008; Zhang et al. 2011; Rodríguez-Blanco et al. 2012). All these researchers found that the surface generated runoff is largely controlled by rainfall amount rather than AWC.

Romero et al. (2007) concluded that Soil moisture differs significantly among management systems and the standard 5-d antecedent rainfall (P_5) procedure might not been able to fully consider those differences. Further studies should provide more detailed information to properly model those two issues.

Fu et al (2011) argued that studies are needed to focus on the effect of variation of λ values with antecedent soil moisture on model performance of the SCS-CN method.

Tagaus et al. (2015) study demonstrated that CNs do not correlate well with cumulated precipitation of previous days. Future studies should investigate if an evaluation of antecedent hydrological conditions based on measured, or predicted, soil water content can link CN to a physically measurable parameter suitable to be incorporated into a mechanistic model.

2.9 RESEARCH GAP

1. As seen from the literature review that most studies have concentrated on the application of the existing SCS-CN method utilizing the originally developed curve numbers. Most approaches of CN estimation relied on standard tables of NEH-4 which might not be applicable to the climatic conditions in India. No systematic effort appears to have been made for their verification for Indian watersheds, and it forms the primary objectives of this study.
2. As mention by Hawkins (1993) and Ajmal (2015b) that in hydrologic design work the λ and CN as the regional and climatic parameters should be calibrated from available rainfall and runoff data, first and then employed in the runoff estimation. As seen from the literature review no single study related to this using Indian watershed data was available where λ and CN were calibrated using measured data.
3. All the existing AMC-dependent formulae have been derived from the same dataset (i.e. NEH-4 tables), their comparison and validity are required to be tested by deriving similar formulae and incorporating the effect of λ into it from new dataset representing different climatic conditions, particularly Indian.
4. As pointed out by Fu et al (2011) and Tagaus et al. (2015), there is need of a relationship between CN (or S) and physically measured soil moisture be incorporated into a mechanistic model to improve runoff estimation. There is hardly any study related to this linkage using physically observed data, particularly for Indian climatic conditions.

CHAPTER 3

MATERIALS AND METHODS

This chapter deals with the methods and experimental techniques followed to investigate the different parameters of SCS-CN methodology to fulfill the objectives of the study.

3.1 STUDY AREA

The present study uses the rainfall (P)–runoff (Q) data from various climatic settings. Locally monitored (i.e. Roorkee experimental site) and published literature P–Q data have been used in calibration and validation. The characteristics of experimental runoff plots (i.e. observation carries out locally at Roorkee) and watersheds/plots (i.e. published data) used in the study are given in Table 3.1.

The detailed description about Roorkee experimental site is given below:

The locally monitored P–Q observations were carried out at an experimental agricultural field located at 29° 50’ 09” N and 77° 55’ 21” E, in Roorkee, district Haridwar, Uttarakhand (India) (Figure 3.1). This field falls in River Solani watershed, which is a sub–watershed of River Ganga–the largest river basin in India. River Solani emerges from Shivalik range of great Himalayas having three main topographic zones, hills, piedmont, and flat terrain. The study site is located in flat terrain of Solani watershed at about 30–60 km south of the foothills of Himalayas and about 180 kilometres north of Indian capital New Delhi. The average elevation of site is about 266 m above mean sea level (amsl).

3.1.1 Climate

The climate at the experimental site is sub-tropical type characterized by hot summers and cold winters, along with three pronounced seasons; summer, monsoon and winter. Extreme variation in summer and winter temperatures can be seen in the study area. The period of summer season is late March to mid–June where the variation in maximum and minimum monthly temperatures is 45 °C and 20 °C, respectively. Similarly, the winter season starts from late November to February end where maximum and minimum monthly temperatures are 18 °C and 10 °C, respectively. The monsoon season starts from mid–June and last to first week of September, during which about 75% of average annual rainfall is received (Yousuf et al. 2015). The annual rainfall varies from 1120 to 1500 mm. The average humidity varies from 30-100 % and potential evapotranspiration is of the order of 1300 mm.

Table 3.1 Characteristics of seventy-one watersheds/plots used in the Study

Watershed/ Plot No.	n	Land use	Slope (%)	*fc* (mm/hr)	HSG/soil type	Area (km^2)	Rainfall (mm)	Altitude (m)	Climate type	Study location	Reference
1	15	Sugarcane	5	7.36	B	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
2	15	Sugarcane	3	8.77	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
3	15	Sugarcane	1	6.51	B	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
4	10	Fallow	5	12.1	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
5	10	Fallow	3	6.15	B	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
6	10	Fallow	1	10.28	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
7	10	Maize	5	4.24	B	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
8	10	Maize	3	5.52	B	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
9	10	Maize	1	2.82	C	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site

Table 3.1 (continued)

Watershed/ Plot No.	n	Land use	Slope (%)	*fc* (mm/hr)	HSG	Area (km^2)	Rainfall (mm)	Altitude (m)	Climate type	Study location	Reference
10	10	Blackgram	5	15.22	A	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
11	10	Blackgram	3	13.82	A	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
12	10	Blackgram	1	5.66	B	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
13	13	Sugarcane	5	25.5	A	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
14	13	Sugarcane	3	10.18	A	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
15	13	Sugarcane	1	14.9	A	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
16	11	Maize	5	10.25	A	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
17	11	Maize	3	26.9	A	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
18	11	Maize	1	22.05	A	110× 10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site

Table 3.1 (continued)

Watershed/ Plot No.	n	Land use	Slope (%)	*fc* (mm/hr)	HSG	Area (km^2)	Rainfall (mm)	Altitude (m)	Climate type	Study location	Reference
19	11	Blackgram	5	21.5	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
20	11	Blackgram	3	19.4	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
21	11	Blackgram	1	18.5	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
22	13	Fallow	5	22.92	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
23	11	Fallow	3	7.9	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
24	13	Fallow	1	19.8	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
25	10	Sugarcane	5	2.68	C	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
26	10	Sugarcane	3	3.5	C	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
27	10	Sugarcane	1	3.1	C	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site

Table 3.1 (continued)

Watershed/ Plot No.	n	Land use	Slope (%)	*fc* (mm/hr)	HSG	Area (km^2)	Rainfall (mm)	Altitude (m)	Climate type	Study location	Reference
28	4	Maize	5	2.67	C	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
29	4	Maize	3	3.96	C	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
30	4	Maize	1	3.45	C	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
31	5	Lentil	5	4.24	B	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
32	5	Lentil	3	5.52	B	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
33	5	Chana	5	15.22	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
34	5	Chana	3	13.82	A	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
35	5	Chana	1	5.66	B	110×10^{-6}	1120-1500	266	humid sub–tropical	Solani river catchment (India)	Data monitored at present site
36	40	Sorgham	-	-	Light textured red soil	765 × 10-6	746	515	Semi-arid tropical	Experimental Plot in CRIDA, Hyderabad	Mandal et al. (2012)

Table 3.1 (continued)

Watershed/ Plot No.	n	Land use	Slope (%)	*fc* (mm/hr)	HSG	Area (km^2)	Rainfall (mm)	Altitude (m)	Climate type	Study location	Reference
37	10	Natural grassland	-	-	D	18.7	1100	41.3	Humid subtropical	Canada de Los Chanchos basin (Uruguay)	Silveira et al. (2000)
38	21	Rangeland, dry farm land, forest	-	-	Loamy, sandy clay loam	448.2	296.4	1320-2960	Semi-arid	Kardeh Watershed (Northeast Iran)	Ebrahimian et al. (2012b)
39	24	Forests, field crop	-	-	Clay, sandy loam, loamy sand, clay loam	153	960	255-1330	Monsoon tropical climate with dry and wet seasons	Upper Lam Ta Kong watershed (Thailand)	Phetprayoon (2015)
40	25		-	-		713					
41	18	Corn, soybeans crop	-	-	B and C	69.10	990	175-235	Temperate climate	Upper Little Vermilion River watershed (USA)	Walker et al. (2005)
42	18	Wood, pasture and agriculture	-	-	Sandy loam, silty loam	12.90	940	312-798	Mediterranean semi-humid	Colorso stream catchment (Central Italy)	Brocca et al. (2008)
43	12	Agriculture, forest land, non cropped	-	-	Clay, sandy loam, loamy sand, clay loam	26.10	1087	-	Temperate	St. Esprit watershed located in Quebec (Canada)	Perrone and Madramooto (1997)
44	16	Forest, wetlands, agriculture	-	-	D	114	1420	3.6 - 72	Mediterranean climate	Simms Creek watershed (Florida, USA)	Melesse and Graham (2004)
45	40	Alpine grassland, small shrubs	-	-	Clay loam, silty clay loam	1.90	1220	1835-3152	Alpine climate	Rio Vauz Basin catchment (Italian Dolomites)	Penna et al. (2011)

Table 3.1 (continued)

Watershed/ Plot No.	n	Land use	Slope (%)	*fc* (mm/hr)	HSG	Area (km^2)	Rainfall (mm)	Altitude (m)	Climate type	Study location	Reference
46	27	Forest, arable lands, grasslands	-	-	alluvial soils, river sands and gravels	237.80	850	859.50	Temperate	Catchment area of the Kamienica river (Southern Poland)	Walega et al. (2015)
47	10	Orchard, Forest , farm land	-	-	Sandy soil, Sandy loam soil	7.03	409	1080-1270	Semiarid continental monsoon climate	Liudaogou watershed (Northern China)	Xiao et al. (2011)
48	20	Open grazing	-	-	Deep loamy sand soil	05	1286	1800	Humid and cold	Matash spring-fall mountainous rangeland (Iran)	Sadeghi et al. (2007)
49	20	Alfalfa cultivation	-	-							
50	16	Cork oak forests and agriculture	-	-	Marl and sandstone	655	1100	1600	Mediterranean	Mdouar catchment in northern Morocco (Africa)	Tramblay et al. (2012)
51	15	Wood land, Crop land, Range land, Pasture and Urban	-	-	Layered sandstones, alluvial deposits constituted by gravel and sand	137	930	249-887	Mediterranean	Niccone at Migianella (Italy)	Brocca et al. (2009)
52	15		-	-		104				Niccone at Reschio	
53	15		-	-		57				Vallaccia at Molino	
54	15		-	-		35				Vallaccia at P. Marte	
55	15		-	-		13				Colorso at P. Marte	
56	29	Agriculture	-	-	Purple soil and paddy soil	16.70	1016	184-1180	Subtropical	Wangjiaqiao watershed (China)	Shi et al. (2009)

Table 3.1 (continued)

Watershed/ Plot No.	n	Land use	Slope (%)	*fc* (mm/hr)	HSG	Area (km^2)	Rainfall (mm)	Altitude (m)	Climate type	Study location	Reference
57	14	Farm land, grass land	-	-	Loamy black cinnamonic soil	1.14	542	1330–1707	Dry and continental climates	Qiaozi-West watershed (China)	Zhou and Lei (2011)
58	16	Forests, arable soils and grasslands	-	-	Alluvial deposits, conglomerates, sand, clayey	109	400	0-909	Subtropical Mediterranean	Rafina catchment in eastern Attica (Greece)	Massari et al. (2014)
59	10	Corn and soybean	-	-	Silt loams, with some sandy loams	0.055	059	275-393	humid-temperate continenta	North Appalachian watershed (Ohio, USA)	Wu et al. (1993)
60	31	Natural savannah	-	-	Clayey soil	9.624	1371	1057-1200	Tropical savanna	Capetinga catchment (Brazil)	Silva et al. (1999)
61	24	Pasture, road, buildings, rock	-	-	Sandy Loam, Sandy Clay Loam	7.84	595	280-950	Mediterranean semi-arid	Upper Lykorrema, Penteli Mountain (Greece)	Soulis et al. (2009)
62	23	Pasture, road, buildings, rock	-	-	Sandy Loam, Sandy Clay Loam	7.36	595	146-643	Mediterranean semi-arid	Entire Penteli Mountain (Attica, Greece)	Soulis et al. (2009)
63	13	-	-	-	-	254	1500	575	Moist and temperate climate	Amicalola Creek watershed (USA)	Mishra and Singh (2004b)
64	30	Forest, arable lands, grasslands	-	-	Alluvial soils, river sands and gravels	237.8	850	859.5	Temperate	Catchment area of the Kamienica river (Southern Poland)	Wałęga and Rutkowska (2015)

Table 3.1 (continued)

Watershed/ Plot No.	n	Land use	Slope (%)	fc (mm/hr)	HSG	Area (km^2)	Rainfall (mm)	Altitude (m)	Climate type	Study location	Reference
65	8	Forest, residential area, rice field	-	-	Loam and sandy loam	609.15	1200	26-911	Continental monsoon climate	Hoideok watershed (South Korea)	Moon et al. (2014)
66	12		-	-		208.4				Jungrangkyo watershed (South Korea)	
67	48	Forest, Agriculture	-	-	Silty loam (B)	4661	1547	509-900	Sub-tropical and sub-humid	Mohegaon catchment (India)	Mishra et al. (2008a)
68	17	Wetlands	-	-	Sandy loams with clayey sub soils	1.6	1370	3.7 - 10	Humid subtropical	Tributary of Huger Creek (South Carolina)	Epps et al. (2013)
69	15	Agriculture, Pasture, shrub land	-	-	Loam, Clay loam, clay	21	1000	2600-3000	semiarid	Godigne catchment, Tekeze river basin (Ethiopia)	Zelelew (2017)
70	42	Natural vegetation groundcover= 70%	-	-	Silt and clay (D)	0.02	867	217	Subtropical steppe as classified by Köppen classification; Semiarid as classified by Thornthwaite's	South central region of the state of Ceará (Brazil)	Andrade et al. (2017)
71	40	Thining vegetation groundcover = 100%	-	-		0.015					

(n, number of rainfall events; fc, infiltration rate mm/hr; HSG, hydrologic soil group defined as per Table 2.1)

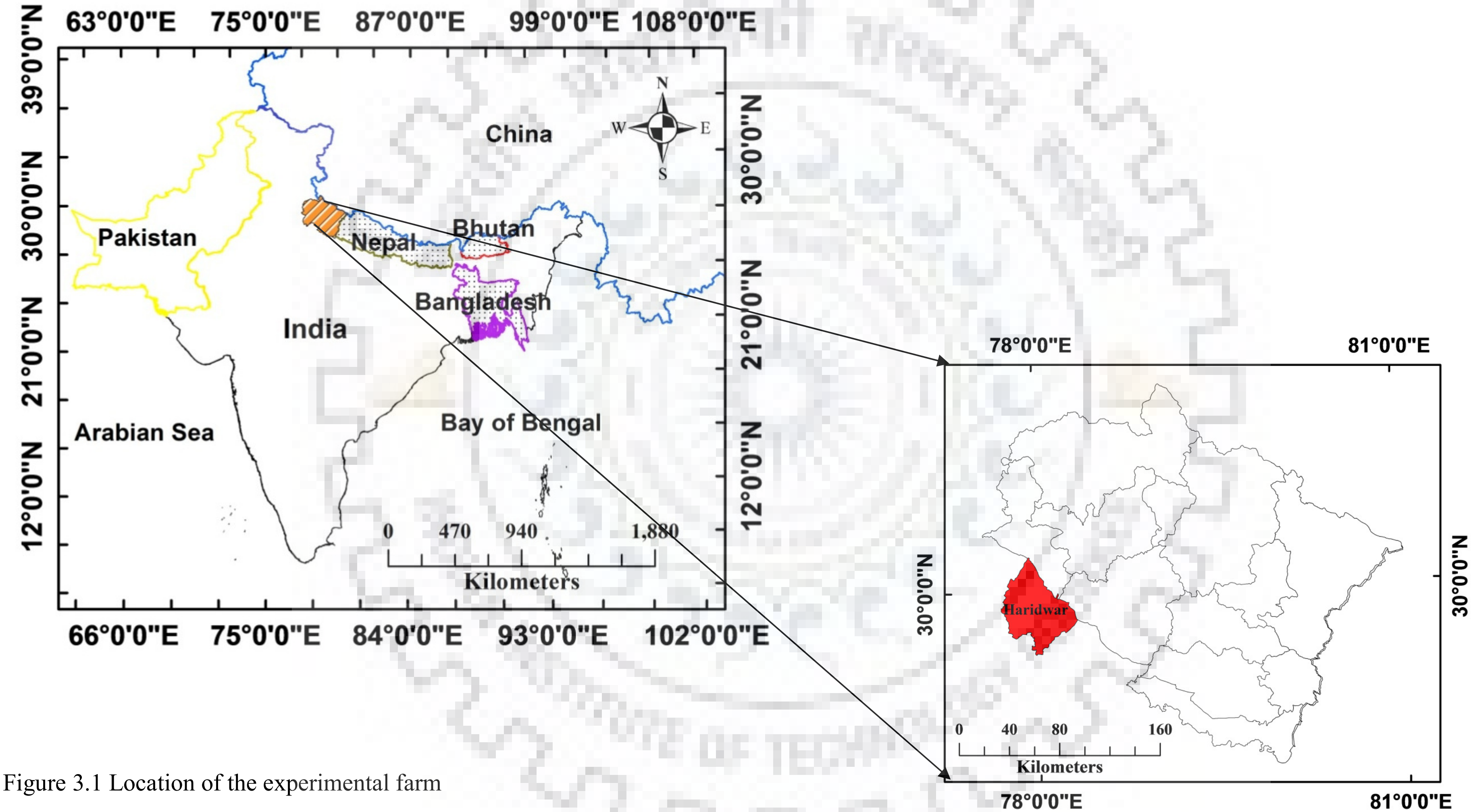

Figure 3.1 Location of the experimental farm

3.1.2 Soil type and Land use

The type of soil in Solani watershed is mainly comprised of loam, loamy sand, sandy loams, and sandy clay (US Bureau of Soil and PRA Classification) with an average proportion of 50–55 % of sand, 35–42 % silt and 8-15 % clay (Kumar et al. 2012). The upper hilly area mainly consists of sandy loam whereas lower flat terrain (where study site is located) is dominated by loam and loamy sand (Garg et al. 2013; Kumar et al. 2012). Forest land, bare soil, and vegetated land are the main classes of land cover in study area. Forest cover is around 30% of the total area especially in hilly part of the watershed, and more than 50% is agricultural land in lower flat terrain. A significant portion of the land lies in agricultural area with more than 35% of vegetal cover. Forests cover around 30% of the total area especially in hilly part of the watershed and more than 17% of the total land belongs to fallow land. Sugarcane is cultivated as the perennial crop and wheat, maize, potato and pulses grow as seasonal crops (Garg et al. 2013).

3.2 EXPERIMENTAL SETUP AT ROORKEE SITE

The experimental farm having total plot size of 70 m × 50 m with plain agricultural topography, was taken on lease in the year 2012. The design and layout plan of the experimental farm is shown in Figure 3.2. The selected agricultural field for experimental work was divided into plots of 22 m length and 5 m width with three independent variables: soils, land use, and slope/gradient. Four different land uses such as Sugarcane, Maize, Black gram and Fallow land were selected for monitoring rainfall and runoff. It is well known that Maize and Black Gram are seasonal (kharif season in India) crop. Therefore, the plots having Maize and Black Gram were replaced by Chana and Lentil in another season. The plots were constructed in such a way that each land use covered three different slopes (5%, 3% and 1%). The layout of the experimental plots is shown in Figure 3.3. The experimental work was conducted during August 2012 – April 2015 (or three crop growing year in study area) in which rainfall (P) and runoff (Q) was monitored for a total 35 experimental plots of various slopes, land use, and hydrologic soil group (HSG) (i.e. Infiltration capacity). During the first year of study (i.e. August 2012 – May 2013), P–Q data were measured for six plots with land use of sugarcane and Maize having slopes of 1%, 3%, and 5%. However, to change the soil property during the second year (i.e. June 2013 – May 2014) of experimental work, a sandy soil was added to the existing soil, and rainfall and runoff were monitored in twelve plots having four different land use covers: sugarcane, maize, blackgram, and fallow land with slopes of 1%, 3% and 5%. Similarly, for the third year (i.e. June 2014 – April 2015), sand was again added to the previous year soil, and rainfall-runoff monitored on the twelve plots having three different land use covers: sugarcane, maize, and fallow land with slopes of 1%, 3% and 5%. Here it is worth to note that during second year (i.e. June 2013 – May 2014), after kharif season completion, the plots having maize and blackgram were sown by Lentil and Chana, respectively. Along with sugarcane and fallow plots (note: these plots were kept for P-Q observation throughout the year), few winter rain P-Q events were also captured plots having Lentil and Chana land use. Here, it is worth to mention that the Lentil crop in one plot was damaged, so P-Q observation were not possible in that plots; therefore, the P-Q were monitored in only 5 (3 Chana + 2 lentil) out of 6 plots. The Figure 3.4 shows the glimpses of mixing of sandy soil for preparation of field for crop sowing. It is worth emphasizing that the normal agricultural practices of mixing of soil, seed selection etc. were followed for cultivation of crops throughout the study period.

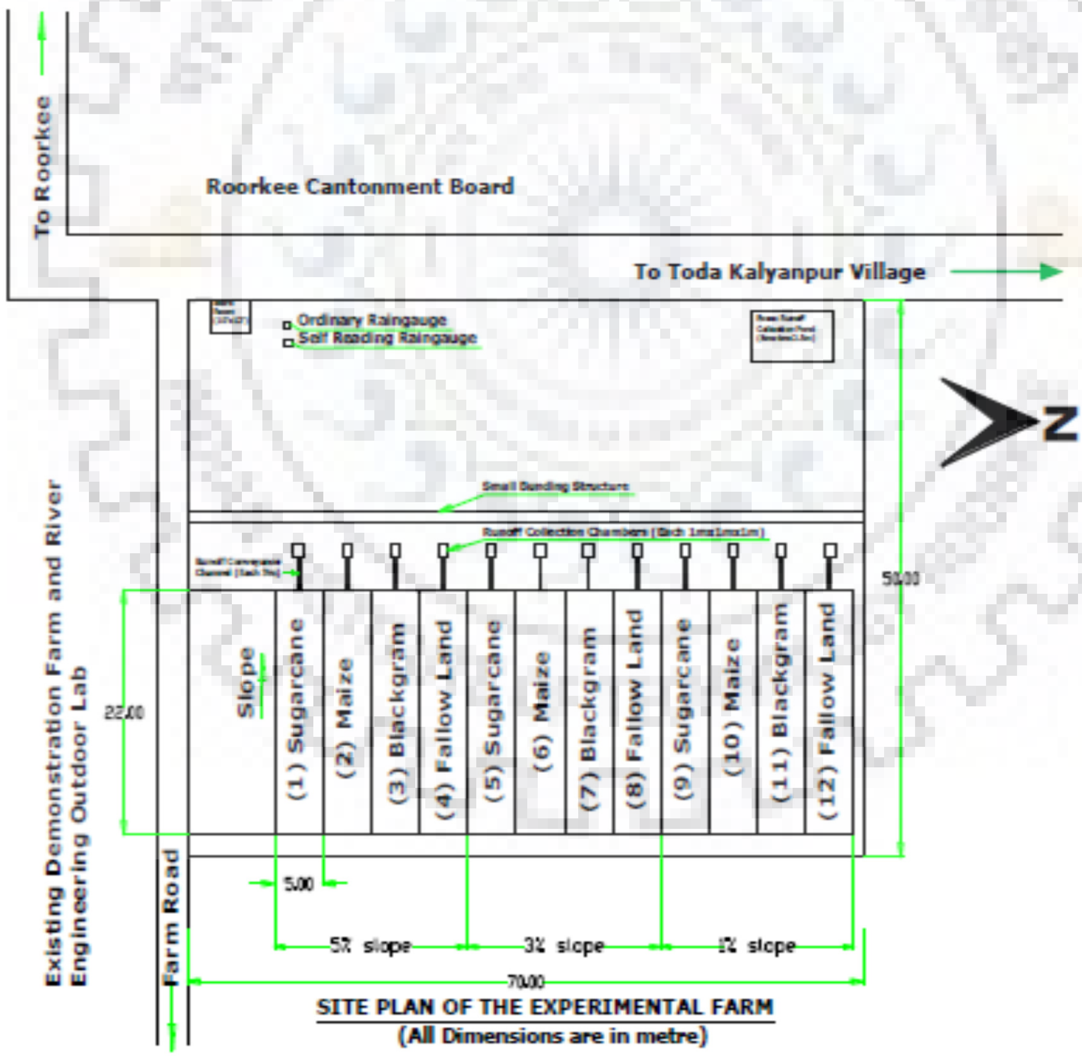

Figure 3.2 Design and layout plan of the experimental farm

Figure 3.3 Layout of the experimental plots near Roorkee, district Haridwar, Uttarakhand, India

Figure 3.4 Addition of sandy soil to change the properties of parent soil

3.3 DATA COLLECTION AT EXPERIMENTAL SITE

3.3.1 Rainfall measurement

Rainfall was recorded with the help of both tipping bucket rain gauge and a non-recording raingauge installed at the study site (Figure 3.5a & b). The figure 3.5b shows the measuring of rainfall using measuring cylinder of non-recording type raingauge. The distribution of rainfall measured during study period is shown in Table 3.2. As seen from this table, a total number of 101 rainfall events were captured with rainfall amount varying from 0.5 mm to 93.8 mm and only 42 events produced significant amount of runoff for measurement. A total of 11, 18, and 13 runoff producing events were captured during the first, second, and third years, respectively. In this study, the lowest rainfall value was 5.6 mm which generated runoff in a year whereas the highest rainfall of 17.6 mm did not generate runoff in another year, during which the highest storm rainfall was 75.8 mm.

Table 3.2 Rainfall characteristics during the study period (August 2012–April 2015)

Rainfall depth (mm)	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	>80
No. of events	59	8	13	5	6	4	2	3	0
No. of events generating runoff	5	4	13	5	6	4	2	3	0

Figure 3.5a Non Recording and Recording rain gauge installed at experimental site

Figure 3.5b Rainfall measurement using non recording rain gauge

3.3.2 Runoff measurement

Each experimental plot was border dyked and surface runoff generated during rain storms was collected in separate chambers of size 1 m × 1 m × 1 m constructed at the downstream end of each plot followed by a 3 m long conveyance channel intercepted by a multi–slot divisor having 5 slots; and the variation in depth of water stored with respect to time was monitored regularly, but manually. The multi-slot devisors were used to reduce the volume of runoff to be measured in the collection chamber. In other words, it reduces the frequency of chamber filling. The volume of flow collected in these tanks when multiplied by 5 yielded the plot runoff for a storm–event (during past 24 hours) (Figure 3.6a & b). Figure 3.6a shows the runoff generation from a fallow plot of 1% slope during an rainfall event. Similarly, figure 3.6b shows the measuring of runoff depth in the runoff collection chamber with the help of metallic scale after 24 hr of rainfall event. The rainfall runoff data observed at experimental plots are given in appendix A.

Figure 3.6a Photograph showing the runoff collection from fallow land plot

Figure 3.6b Runoff depth measurement in the collection tank using metallic scale

3.3.3 Infiltration test

Double ring infiltrometer is the most commonly used method for the measurement of the infiltration. Infiltration tests were conducted for each plot using the double ring infiltrometer (45/30) for identification of the hydrologic soil group (HSG) (SCS, 1972) (Figure 3.7 a & b). Two sets of concentrating rings having internal and external diameter as 30 cm and 45 cm respectively with height of 30 cm as shown in Figure 3.7a, were used to determine the minimum infiltration capacity of the soil. The figure 3.7a shows the penetrating of both the rings into soil with the help of hammer. The figure 3.7b, shows the rings filled with water along the plastic scale for marking and marking the water level. The infiltration experiment was continued for at least 6-7 hours until the rate of infiltration reached a constant reading. The resulting minimum infiltration capacity and corresponding HSGs for different plots are shown in Table 3.1. As seen from this table, the hydrologic soil group (HSG) of experimental plots fall in groups A, B and C with infiltration capacity varying from 2.68 to 25.50 mm/hr, following Hawkins et al. (2009) and SCS (1985) criterion. The data of infiltration test for few selected plots are given in appendix B.

Figure 3.7a Installation of double ring infiltrometer in the fallow plot

Figure 3.7b Measurement of water level in the double ring infiltrometer

3.3.4 Soil water measurement

Soil water measurements were monitored by a portable unit using a 2-wire connector type time domain reflectometry (TDR) probe of the 'Fieldscout TDR-300'. This instrument measures the percentage soil moisture directly in volumetric water content (VWC). The soil water was sampled every day (at around 9.00 am Indian Standard Time) throughout the study period from the soil surface down to a depth of 20 cm, and these were replicated at three (upstream, middle, and downstream) locations in each of the plots. Statistical comparisons of soil water contents from these three locations did not show significant difference at $p > 0.05$. For each measurement date, a single soil water content value was computed by averaging the three values. The antecedent one-day (θ_{o1}), three-day average (θ_{o3}), and five-day average moisture (θ_{o5}) contents for each plot prior to each rainfall event were used in examination of dependency of CN on antecedent soil moisture. Figure 3.8 shows the measurement of soil moisture with the help of TDR having probe length 20 cm in sugarcane plot at middle side. The observed previous day soil moisture for different plots are given in appendix A.

Figure 3.8 Measurement of soil moisture in sugarcane plot at middle side

3.4 BASICS OF SCS-CN METHODOLOGY

The SCS–CN method was developed based on the water balance equation (Equation 3.1) incorporating two fundamental hypotheses (Equations 3.2 and 3.3) (Mishra and Singh 2003).

$$P = Q + F + I_a \tag{3.1}$$

In Equation 3.1, P (mm) is the rainfall, Q (mm) is the direct surface runoff, I_a is the initial abstraction (mm), and F is the cumulative infiltration (mm).

The first hypothesis equates the ratio of actual amount of direct surface runoff (Q) to the total rainfall (P) (or maximum potential surface runoff) to the ratio of actual infiltration (F) to the amount of the potential maximum retention (S) (Figure 3.9) (Mishra and Singh 2003).

$$\frac{Q}{(P - I_a)} = \frac{F}{S} \tag{3.2}$$

The second hypothesis relates the initial abstraction (I_a) to the potential maximum retention (S) (Mishra and Singh 2003).

$$I_a = \lambda S \tag{3.3}$$

In above Equation, S is the potential maximum retention (mm), and λ is known as the initial abstraction coefficient.

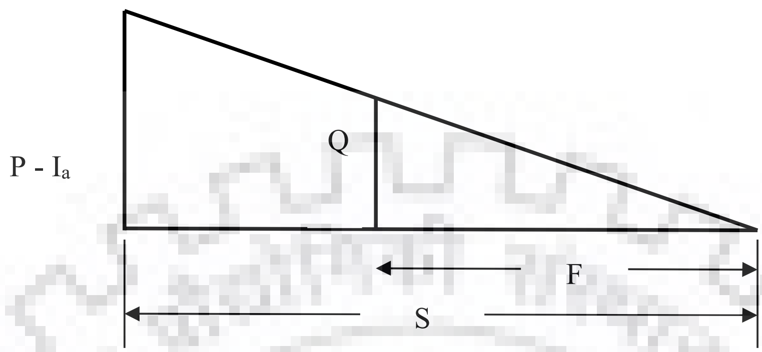

Figure 3.9 Proportionality concept of the existing SCS-CN method

The combination of Equations 3.1 and 3.2 leads to the general form of the SCS–CN method as given below (SCS, 1972):

$$Q = \begin{cases} \dfrac{(P - I_a)^2}{(P + S - I_a)}, & P > I_a \\ 0 & P \leq I_a \end{cases} \tag{3.4}$$

The existing version of the SCS–CN method recommended a standard value of λ=0.20 in field applications (SCS 1972, 1985). The research community however pointed out that the standard value of λ = 0.20 is vague and a value of about 0.05 or less is more practical for various parts of world (Baltas et al. 2007; Shi et al. 2009; D'Asaro et al. 2014; Fu et al. 2011; Zhou and Lei 2011; Yuan et al. 2014; Lal et al. 2015; Menberu et al. 2015).

The use of $I_a = \lambda S$ in Equation 3.4 amplifies it as:

$$Q = \frac{(P - \lambda S)^2}{(P + S - \lambda S)} \quad \text{for } P > \lambda S\text{; otherwise } Q = 0 \tag{3.5}$$

For λ=0.2 (SCS 1972, 1985), Equation 3.5 reduces to

$$Q = \frac{(P - 0.2S)^2}{(P + 0.8S)} \quad \text{for } P > 0.2S\text{; otherwise } Q = 0 \tag{3.6}$$

For a given observed rainfall (P)–runoff (Q) data, S can be calculated by solving Equation 3.5, as follows (Hawkins 1973; Hawkins 1993):

$$S = \frac{\left(\{2\lambda P + (1-\lambda)Q\} - \sqrt{\{2\lambda P + (1-\lambda)Q\}^2 - 4(\lambda P)^2 + 4\lambda^2 QP}\right)}{2\lambda^2} \text{ for } 0 < Q < P \tag{3.7}$$

Further, for λ=0.2 (SCS 1985), Equation 3.6 reduces to

$$S = 5[(P + 2Q)-(4Q^2+5PQ)^{1/2}] \tag{3.8}$$

Here, S can vary in the range of $0 \leq S \leq \infty$. Therefore, it can be transformed into CN varying in a more appealing range, $0 \leq CN \leq 100$, and vice versa:

$$CN = \frac{25400}{S + 254} \tag{3.9}$$

In Equation 3.9, S is in mm and CN is the dimensionless entity.

3.5 MEAN RUNOFF COEFFICIENT DETERMINATION

The mean runoff coefficient of plot was determined as given in Equation 3.10 (Lal et al. 2015):

$$\text{Mean runoff coefficient } (Rc_m) = \frac{\sum_i^n \frac{Q_i}{P_i}}{n} \tag{3.10}$$

where Q_i is the direct surface runoff for event i, P_i is the rainfall amount for event i, and n is the total number of events.

3.6 ESTIMATION OF CN FROM OBSERVED P–Q DATA

In the present study, eight different CN estimation methods for available P–Q data have been used for comparison. The details of each one is as follows:

3.6.1 Storm event method

In this method, natural P-Q data set is used to derive event wise CN using standard Equations 3.8 and 3.9. The mean of all event wise CNs was considered as representative CN correspond to the average antecedent moisture condition (AMC-2) of the plot (Bonta 1997). In present paper, representative mean CN method is designated as M1.

3.6.2 Least square fit method

Based on the observed P–Q data, the only parameter S (or CN) was estimated using least square fit minimizing the sum of squares of residuals (Equation 3.11) (Hawkins et al. 2002) employing Microsoft Excel (solver):

$$\sum_{i}^{n}(Q_i - Q_{ci})^2 = \sum\left\{Q_i - \left[\frac{(P-0.2S)^2}{(P+0.8S)}\right]\right\}^2 \Rightarrow \text{Minimum} \tag{3.11}$$

where Q_{ci} (mm) and Q_i (mm) are the respectively predicted and observed runoff for rainfall event i, n is the total number of rainfall events. Here, the least square fit CN method is designated as M2.

3.6.3 Geometric mean method

The step wise procedure for deriving the CN (AMC-2) using Geometric mean method is given below (Hawkins et al. 2009; Tedla et al. 2012).

i. Derive the event wise S using standard Equation 3.8.

ii. Calculate the Logarithm of the events S (i.e. log S).

iii. Calculate the arithmetic mean of the log S series.

iv. Estimate the geometric mean (GM) of the S (S_{GM}) by taking the antilogarithm of the mean of log S (i.e. $S_{GM} = 10^{\log S}$).

v. Calculate the geometric mean CN as given below:

   $CN_{GM} = 25400/(254 + 10^{\log S})$.

The Geometric mean CN method is designated as M3.

3.6.4 Log-normal frequency method

In this method, the logarithms of each set of natural P and Q pair were computed individually. The value of S was then calculated by employing Equation 3.8 using mean log P and log Q values (Schneider and McCuen, 2005). Finally, the representative CN (AMC-2) value for plot was computed using Equation 3.9. Here, this method is designated as M4.

3.6.5 NEH-4 median method

This method is traditionally recommended by SCS (SCS 1972; NRCS 2001; Hawkins et al. 2009), in which the median of event wise CN derived using standard Equations 3.8 and 3.9 was considered as representative CN of plot. Here, the median CN method is designated as M5.

3.6.6 Rank-Order method

This method requires ordered series of P–Q pairs (Hawkins et al. 2009). The naturally measured P and Q values were sorted separately and then realigned by common rank order basis to form a new set of P–Q pairs of the equal return period, in which runoff Q is not necessarily matched with the original rainfall P (Hawkins et al. 2009; D'Asaro and Grillone 2012; Soulis and Valiantzas 2013). For each ordered P–Q pair, S and CN were determined employing Equations 3.8 and 3.9, respectively. The representative CN (AMC-2) of the plot is mean or median of the event wise CNs series computed with the ranked P–Q pairs. Here, mean and median are designated as method M6 and M7, respectively.

In method M1 to M7, the AMC was decided based on the 5-day antecedent rainfall (P5). In order to determine AMC of a rainfall event used in runoff prediction, P_5 was used as follows: AMC-1 if $P_5 < 35.56$ mm in growing season or $P_5 < 12.7$ mm in dormant season, AMC-2 if $35.56 \leq P_5 \leq 53.34$ mm in growing season or $12.70 \leq P_5 \leq 27.94$ mm in dormant season, and AMC-3 if $P_5 > 53.34$ mm in growing season or $P_5 > 27.94$ mm in dormant season (Ajmal et al. 2015a,b,c; Mays 2005).

For wet (CN_3) and dry (CN_1) conditions curve number, the CN_2 (AMC-2) values were adjusted using Equations 3.12 and 3.13, respectively, as given by Hawkins et al. (1985).

$$CN_3 = \frac{CN_2}{0.427 + 0.00573\ CN_2} \quad (3.12)$$

$$CN_1 = \frac{CN_2}{2.281 - 0.01281\ CN_2} \quad (3.13)$$

3.6.7 S-probability method

For each set of natural P–Q pair, the value of S (or CN) is determined using Equations 3.8 and 3.9. The Weibull's plotting position was then used to derive the lognormal probability distribution for the calculated values of S. The S values corresponding to 90, 50 and 10% probability levels were used to estimate the representative CN values for AMC-3, 2 and 1, respectively (Hjelmfelt 1980; Hjelmfelt 1991; Ali and Sharda 2008). Here, this method is designated as M8.

3.7 COMPARISON BETWEEN NEH-4 TABLES AND OBSERVED P–Q DATA-BASED CURVE NUMBERS

In order to check the suitability of NEH–4 tables CN (CN_{HT}) for agricultural plots of study region, the P–Q data based CNs determined by NEH–4 median and least square fit methods were compared with CN_{HT}. The NEH–4 median CNs (CN_m) were estimated using the procedures given in section 3.6.5 for method M5. Further, the least square fit CNs were also estimated by two different approaches. In the first approach (i.e. single way fitting), the only parameter S (or CN) was estimated using least square fit minimizing the sum of squares of residuals as given in Equation 3.11. Notably, each P-Q dataset yields only one value of S, i.e. only one representative value of S (or CN) for a plot. This CN value of a plot is designated as CN_{LSM}. In the second approach (i.e. double way fitting), the parameter S is determined by iterative least squares fitting (or best fit) procedure for both λ and S of the SCS-CN equation (Equation 3.14), consistent with the work of Hawkins et al. (2002). The objective of the fitting is to find the values of λ and S such that the following is a minimum:

$$\sum_{i=1}^{n}(X_i - Y_i)^2 = \sum\left\{X_i - \left[\frac{(P-\lambda S)^2}{(P+(1-\lambda)S)}\right]\right\}^2 \Rightarrow \text{Minimum} \tag{3.14}$$

where Y_i (mm) and X_i (mm) are respectively the predicted and observed runoff for storm event i, and n is the total number of storm events. Here also, each P-Q dataset yields only one value of S, i.e. only one representative value of S (or CN) for a plot. This CN value of a plot is designated as CN_{LS}.

In two of the above least square fit approaches, both natural and ordered data series were used to fit the CNs. For approach first (i.e. single way fitting), these CN values of a plot are designated as CN_{LSMn} and CN_{LSMo} for natural and ordered datasets, respectively. On the other hand, CN values of a plot are designated as CN_{LSn} and CN_{LSo} for natural and ordered datasets, respectively, for approach two (i.e. double way fitting). The natural P–Q data consists of the actually observed dataset. In ordered data series, the observed P and Q values were first sorted separately and then realigned by common rank-order basis to form a new set of P–Q pairs of equal return period, in which runoff Q is not necessarily matched with that due to original rainfall P (Hawkins 1993; Hawkins et al. 2009; D'Asaro and Grillone 2012; Soulis and Valiantzas 2013; Ajmal et al. 2015a; Lal et al. 2015). Here, it is noted that only large storm events with P >10 mm were used to avoid the biasing effects of small storms towards high CNs. For statistical analysis, only plots having more than 10 rainfall–runoff events were considered for λ and CN calculation.

The CN values (CN_{HT}, CN_m, CN_{LSMn}, CN_{LSMo}, CN_{LSn}, and CN_{LSo}) thus estimated are taken to correspond to the average antecedent moisture condition (AMC-2) of the plot. For wet (CN_3) and dry (CN_1) conditions curve number, the CN_2 (AMC-2) values were adjusted using Equations 3.12 and 3.13, respectively.

3.8 DERIVATION OF λ VALUES FROM OBSERVED P-Q DATA

To derive λ values, both S and λ were optimized by iterative least squares fitting (or best fit) procedure of the general SCS-CN Equation 3.14, consistent with the work of Hawkins et al. (2002). Similar to the CNs, model fitting yields only one value of λ from all P–Q events of plot, i.e. only one representative value of λ for a plot. Also, the both natural as well as ordered dataset consisting of only large storm events with (arbitrary) P >15 mm criterion to avoid biasing effect, but to retain sufficient number of P–Q data for analysis were used. Only plots having at least 10 observed rainfall–runoff events were considered for optimization study.

3.9 PROPOSED MODEL BASED ON OPTIMIZED λ VALUES

Performance of the existing SCS-CN model (Equation 3.5) with traditional λ = 0.2 was compared with that employing an average λ= 0.03 value derived from 27 natural P–Q plot-dataset. The average is considered instead of median as the former yielded the smallest standard error (Fu et al. 2011). Here, it is notable that all runoff producing rainfall events only were used in this analysis.

3.10 SENSITIVITY OF λ TO CN AND RUNOFF

The effect of variation in λ on CNs (or runoff) has been evaluated using the randomly selected 5 plot-data. In addition, the relative change in estimated runoff with progressive changes in λ-value was also analysed as follows (Yuan et al. 2014):

$$\Delta Q_i = \frac{(Q_i - Q_a)}{Q_a} \times 100 \tag{3.15}$$

Where ΔQ_i is the relative change of runoff at step i, and Q_{ci} and Q_{ca} are respectively the estimated runoff at step i and step a. Initially, λ = 0.2 was fixed for step a and then reduced by 10 % at each step down to 0.02, and runoff was estimated at each step using Equation 3.5 consistent with the work of Yuan et al. (2014). The average CN_{LSo} (=78.92) was estimated from event-based CNs of the 27-plotdata and was used for the S computation in Equation 3.9. P = 30 mm was used in Equation 3.5 due to its having the highest frequency of occurrence.

3.11 EMPIRICAL CONVERSION EQUATION FOR CONVERSION OF $CN_{0.2}$ INTO $CN_{0.03}$

Similar to Hawkins et al. (2002), Jiang (2001) and Yuan et al. (2014), an conjugate CN empirical conversion equation for converting CNs associated with λ = 0.2 ($CN_{0.2}$) to λ = 0.03

($CN_{0.03}$) is proposed based on direct least squares fitting of Equation 3.14 using 27 plots natural P-Q data sets.

3.12 RELATIONSHIP BETWEEN CN AND ANTECEDENT WETNESS CONDITION (AWC)

It is of common experience that CN is a function of AWC of the watershed, which may refer to the soil moisture prior to rainfall event. Expressed mathematically,

$$CN = f\,(AWC) \tag{3.16}$$

where AWC is a soil moisture index which can be described as 1–day antecedent soil moisture (θ_{o1}), 3–day average antecedent soil moisture (θ_{o3}), 5–day average antecedent soil moisture (θ_{o5}), 5–day antecedent rainfall (P_5), and so on. To evaluate the effect of AWC on CN (or S), regressions between CN derived from P–Q dataset and corresponding observed antecedent soil moisture indices such as θ_{o1}, θ_{o3}, θ_{o5}, and P_5 were developed, and their dependency on predicted runoff analyzed. The regression analysis used three forms, viz. linear, exponential, and logarithmic to fit the experimental data as follows:

$$CN = x + y\theta \tag{3.17}$$

$$CN = x\,\exp^{y\theta} \tag{3.18}$$

$$CN = x + y\ln(\theta) \tag{3.19}$$

where θ is the antecedent soil moisture index, CN is the curve number, ln is the natural logarithm operator, x and y are two regression coefficients to be estimated. The Equations 3.8 and 3.9 were employed for estimating the even wise CNs. The above relations lead to infer that as antecedent soil moisture increases, CN increases or S decreases, and vice versa. To validate the existence of such a relation, the randomized series of the total collected events were generated to represent fair coverage of all wetness situations. Thus, the 60% percent of events were used for calibration, and the remaining 40% percent for validation.

3.13 PERFORMANCE EVALUATION OF CN–AMC CONVERSION FORMULAE

3.13.1 Comparison of existing AMC based formulae

The five existing formulae developed by Sobhani (1975), Hawkins et al. (1985), Chow et al. (1988), Arnold et al. (1990) and Mishra et al. (2008b) for converting the CNs from AMC-2 (CN_2) to AMC-1 (CN_1) or AMC-3 (CN_3) are presented in Table 3.3.

Here, Hawkins et al. (1985), Mishra et al. (2008b), Chow et al. (1988), Sobhani (1975), and Arnold et al. (1990) formulae were designated with their respective IDs as given in Table 3.3. The performance of these existing formulae is analyzed numerically as well using field data observed naturally at experimental plots and collected from published literature.

3.13.2 Proposed AMC based formulae

As seen from Table 3.3, the existing formulae can generally (except for Arnold et al. 1990) be recast in a general form given below:

$$CN_x = \frac{CN_2}{a + b\,CN_2} \tag{3.20}$$

where $b = \frac{(1-a)}{100}$, and CN_x will be as CN_3 or CN_1 depending on the values of a and b.

In the present study, Equation 3.20 was optimized using least square fit minimizing the sum of squares of residuals for CN_2 and CN_1 or CN_3 utilizing the large P–Q dataset from 62 plots/watersheds monitored at the study site as well as data collected from published literature (excluding plot nos. 28-35 due to $n < 10$). The respectively 39 and 24 plots/watershed P-Q data were used in derivation and validation of formulae.

The derived three models, viz., MC6, MC7, and MC8, are also presented in Table 3.3. In model MC6, natural P–Q data series were used for calculating the event–wise values of S using Equation 3.8, and event–wise CN values derived using Equation 3.9. The Equation 3.20 was then fitted for CN_3 and CN_1 (Table 3.3) by utilizing CN-values for various AMC conditions established using 10% (CN_1) and 90% (CN_3) probability of exceedance (POE) (Hjelmfelt et al. 1981). These derivations used 39 study plot/watershed datasets, and derived CN values of the different AMC condition (i.e. CN_1, CN_2 and CN_3) are given in Table 3.4. Figure 3.10 shows probability distributions for CN_1 and CN_3.

Similarly, MC7 was developed using same criteria as MC6, except CN-values for various AMC conditions were derived following Grabau et al. (2009) and Hawkins et al. (2015) (i.e. CN_1 and CN_3 with 12% and 88% POE, respectively). For MC7, the derived values of CN_1, CN_2, and CN_3 are given in Table 3.3, and their distributions in Figure 3.11.

Table 3.3 List of existing and proposed AMC dependent curve number conversion formulae

Model ID	Method	AMC-3	AMC-1
MC1	Hawkins et al. (1985)	$CN_3 = \frac{CN_2}{0.427 + 0.00573\ CN_2}$	$CN_1 = \frac{CN_2}{2.281 - 0.01281\ CN_2}$
MC2	Mishra et al. (2008b)	$CN_3 = \frac{CN_2}{0.430 + 0.0057\ CN_2}$	$CN_1 = \frac{CN_2}{2.2754 - 0.012754\ CN_2}$
MC3	Chow et al. (1988)	$CN_3 = \frac{23CN_2}{10 + 0.13\ CN_2}$	$CN_1 = \frac{4.2CN_2}{10 - 0.058\ CN_2}$
MC4	Sobhani (1975)	$CN_3 = \frac{CN_2}{0.4036 + 0.005964\ CN_2}$	$CN_1 = \frac{CN_2}{2.334 - 0.01334\ CN_2}$
MC5	Arnold et al. (1990)	$CN_3 = CN_2 \exp[0.00673\ (100 - CN_2)]$	$CN_1 = CN_2 - \frac{20(100 - CN_2)}{[100 - CN_2 + \exp\{2.533 - 0.0636(100 - CN_2)\}]}$
MC6	Equation 3.20 fitted for CN_1 and CN_3 (λ=0.2) with 10% and 90% POE, respectively	$CN_3 = \frac{CN_2}{0.50503 + 0.00495\ CN_2}$ $R^2 = 0.640$	$CN_1 = \frac{CN_2}{1.92192 - 0.00922\ CN_2}$ $R^2 = 0.472$
MC7	Equation 3.20 fitted for CN_1 and CN_3 (λ=0.2) with 12% and 88% POE, respectively	$CN_3 = \frac{CN_2}{0.53072 + 0.00469\ CN_2}$ $R^2 = 0.641$	$CN_1 = \frac{CN_2}{1.84153 - 0.00842\ CN_2}$ $R^2 = 0.512$
MC8	Equation 3.20 fitted for CN_1 and CN_3 (λ=0.03) with 12% and 88% POE, respectively	$CN_3 = \frac{CN_2}{0.42405 + 0.00576\ CN_2}$ $R^2 = 0.715$	$CN_1 = \frac{CN_2}{2.42081 - 0.01421\ CN_2}$ $R^2 = 0.760$

Table 3.4 Curve Number values for different AMC's for the 39 plots datasets used in development of proposed formulae

Plot/Watershed No.	MC6			MC7			MC8		
	CN_2	CN_3	CN_1	CN_2	CN_3	CN_1	CN_2	CN_3	CN_1
1	81.24	88.83	70.01	81.24	88.73	71.29	63.06	83.80	43.26
2	79.88	91.35	65.29	79.88	91.14	66.23	61.73	86.31	37.19
3	81.09	92.12	67.41	81.09	91.95	68.22	63.93	88.74	37.32
4	78.08	88.28	66.03	78.08	87.73	67.61	51.52	79.86	44.86
5	79.21	90.08	63.15	79.21	89.78	66.18	66.36	84.34	39.02
6	77.75	81.78	63.67	77.75	81.59	63.72	46.85	70.18	32.95
7	80.88	90.36	74.68	80.88	90.01	75.35	66.12	85.03	39.13
8	79.78	85.58	73.36	79.78	85.54	74.22	66.17	76.56	39.36
9	81.49	92.08	77.67	81.49	91.43	77.80	70.42	88.44	41.58
10	79.79	90.76	72.98	79.79	90.74	73.59	63.36	87.78	42.87
11	79.17	89.92	67.13	79.17	88.81	68.89	54.84	84.25	38.85
12	80.30	91.60	62.30	80.30	90.58	64.99	56.74	86.82	30.91
13	92.35	97.73	81.47	92.35	97.58	82.55	89.74	97.00	74.83
14	88.10	95.35	80.89	88.10	94.70	80.93	82.66	93.02	71.47
15	86.29	94.35	76.82	86.29	93.71	76.98	80.11	91.53	63.57
16	73.90	78.60	70.30	73.90	76.89	71.86	53.41	63.12	44.32
17	81.94	94.13	70.61	81.94	93.52	72.91	77.26	91.79	62.30
18	90.00	96.08	83.86	90.00	95.84	84.20	84.18	94.14	70.66
19	87.71	94.04	67.39	87.71	93.53	68.51	77.02	90.19	47.07
20	78.71	88.21	60.11	78.71	88.01	60.71	54.08	76.05	28.79
21	82.65	89.31	63.28	82.65	88.81	66.35	69.59	78.97	42.78
22	83.65	88.40	71.88	83.65	87.72	73.41	63.30	76.71	45.40
23	69.66	87.10	58.86	69.66	86.86	59.38	49.85	74.62	30.41
24	73.71	86.52	52.91	73.71	86.21	53.20	46.58	70.92	24.32
25	86.52	92.08	78.63	86.52	91.43	79.81	70.37	84.78	56.02
26	87.92	92.08	86.11	87.92	91.98	86.40	83.89	88.76	82.40
27	86.63	91.50	59.25	86.63	91.20	65.03	58.55	68.23	28.17
28	82.60	89.02	78.41	82.60	89.00	78.91	55.68	66.70	48.61
29	80.17	88.06	73.83	80.17	87.56	74.70	47.68	59.43	34.00
30	87.52	97.60	68.52	87.52	97.45	67.22	81.52	96.95	55.94

Table 3.4 (continued)

Plot/Watershed	MC6			MC7			MC8		
No.	CN_2	CN_3	CN_1	CN_2	CN_3	CN_1	CN_2	CN_3	CN_1
31	89.52	93.42	77.69	89.52	93.16	78.85	81.46	89.80	59.40
32	90.19	93.14	77.17	90.19	92.49	78.42	81.13	88.32	58.25
33	87.29	91.04	76.36	87.29	90.52	76.95	75.50	82.45	54.25
34	87.97	91.59	73.89	87.97	91.29	74.98	75.39	87.91	48.80
35	83.92	91.86	75.50	83.92	91.15	75.88	69.52	84.99	52.07
36	73.09	82.75	61.84	73.09	81.14	62.52	42.84	58.37	31.08
37	74.77	79.89	68.96	74.77	79.47	69.26	53.22	60.82	36.88
38	76.91	86.08	56.60	76.91	85.55	58.31	49.89	63.01	36.75
39	81.81	90.42	67.48	81.81	90.40	67.63	71.70	86.25	37.76

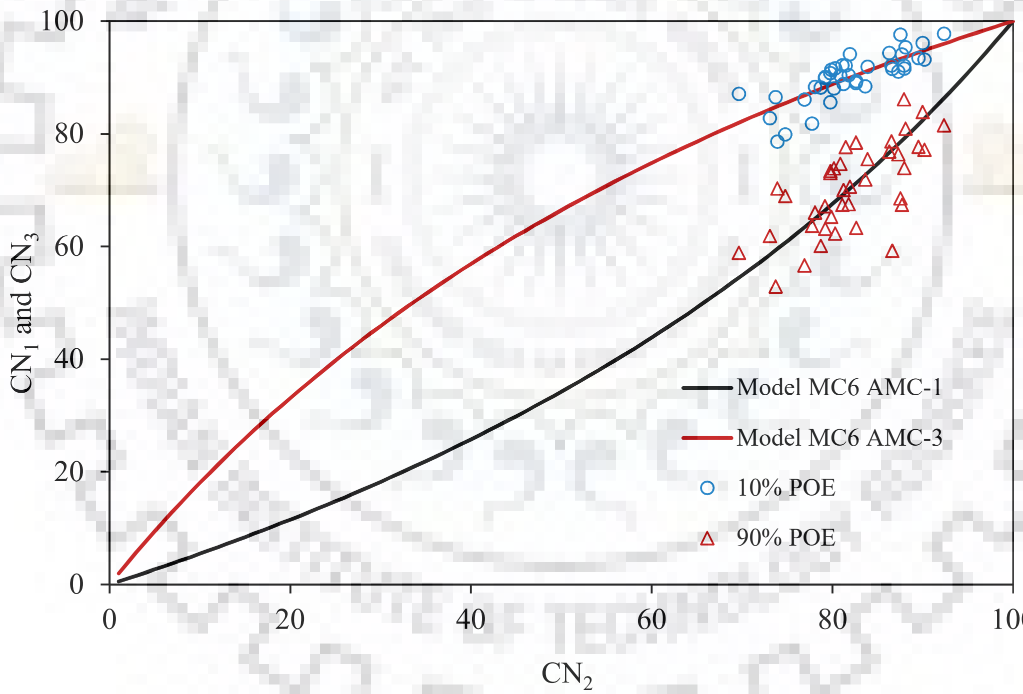

Figure 3.10 Distribution of CN_1 and CN_3 with different POE for model MC6

Further, MC8 was developed incorporating the effect of λ into standard SCS-CN Equation 3.4. Here, natural P–Q data series was used for calculating the event-specific S-values for λ=0.03 employing Equation 3.7, and corresponding CNs from Equation 3.9. The CN values for various AMC's were again derived following Grabau et al. (2009) and Hawkins et al. (2015) (i.e. CN_1 and CN_3 (λ=0.03) with 12% and 88% POE, respectively). The distributions of CN_1 and CN_3 with different POEs are shown in Figure 3.12, similar to Figures 3.10 and 3.11. Notably, the choice of using λ=0.03, which is the mean value, resulting from the optimized λ yielded from the entire 63 plots/watersheds P–Q data sets used in the present study.

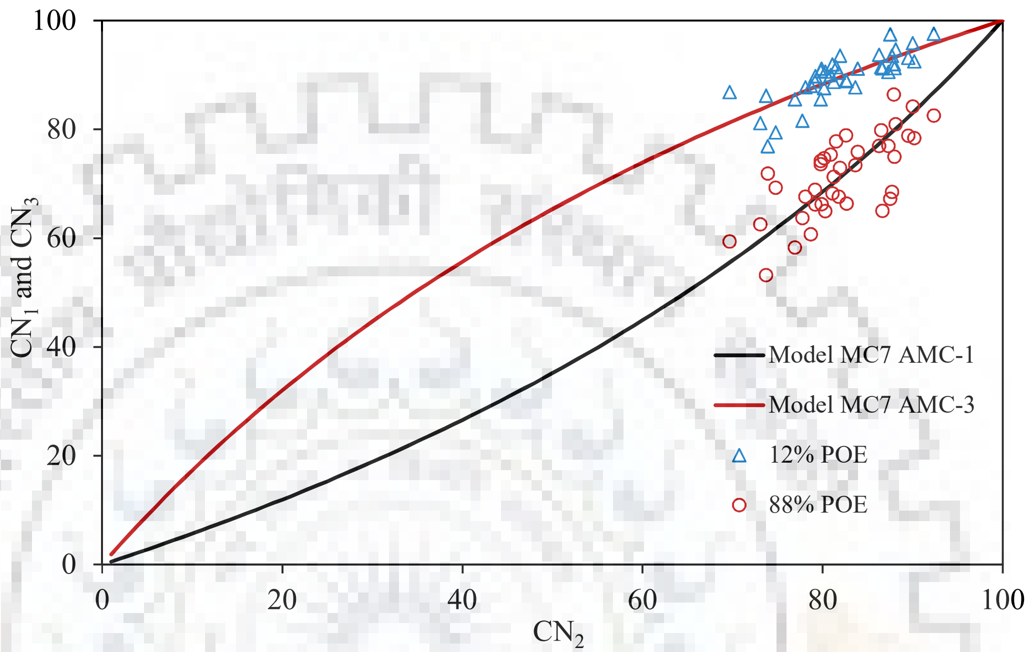

Figure 3.11 Distribution of CN_1 and CN_3 with different POE for model MC7

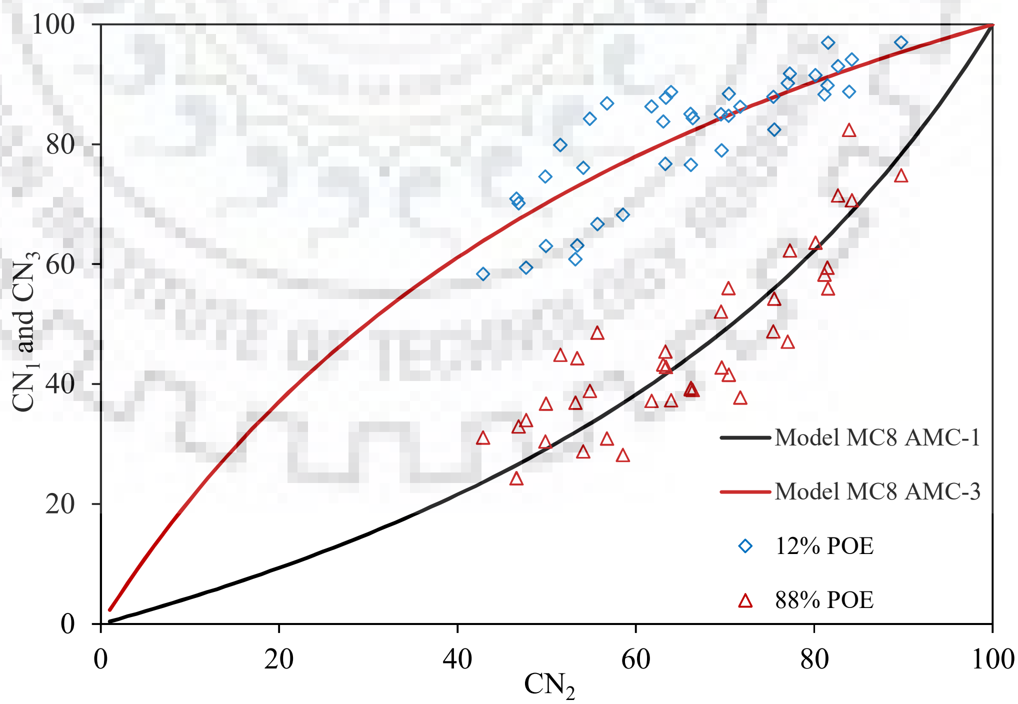

Figure 3.12 Distribution of CN_1 and CN_3 with different POE for model MC8

3.14 STATISTICAL ANALYSIS FOR GOODNESS OF FIT

The goodness of fit between observed and predicted variables was evaluated using coefficient of determination (R^2), Nash-Sutcliffe efficiency coefficient (E) (Nash and Sutcliffe 1970), index of agreement (d) (Legates and McCabe 1999) and root mean square error (RMSE), number of times n_t that the observed variability is greater than the mean error (Ritter and Mu˜noz-Carpena 2013), Percent bias (PBIAS), Relative error (Re), and the Bias (e).

The R^2 expressed as:

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\left[\sum_{i=1}^{n} \left(X_i - \overline{X}\right)^2 \sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2\right]^{0.5}} \right)^2 \tag{3.21}$$

where $\overline{X}$ (mm) is the average of observed runoff for all storm events Xi, $\overline{Y}$ (mm) is the average of predicted runoff for all storm events Yi, and n is the total number of storm events. The R^2 ranges from 0 to 1 and a value close to 1 signify the better degree of association between the observed and estimated runoff. $R^2 > 0.6$ is considered as acceptable for satisfactory agreement between observed and predicted variables (Moriasi et al. 2007; Santhi et al. 2001; Van Liew et al. 2003).

The Nash-Sutcliffe efficiency (E) has been widely used to evaluation of hydrological model (Delleur et al. 1976; EI-Sadek et al. 2001; Fentie et al. 2002; Sahu 2007; Sahu et al. 2007, 2010b; Yuan et al. 2014; Ajmal et al. 2015a,b,c). It is expressed as follows:

$$E = \left(1 - \frac{\sum_{i=1}^{n} \left(X_i - Y_i\right)^2}{\sum_{i=1}^{n} \left(X_i - \overline{X}\right)^2} \right) \tag{3.22}$$

The E ranges from -∞ to 1 and a value close to 1 indicate the perfect agreement between the observed and estimated runoff. Its decreasing values indicate poor agreement. The negative value of E can also occur for biased estimate indicating that the mean observed runoff is a better estimate than predicted. According to Motovilov et al. (1999), Moriasi et al. (2007), Lim et al. (2006), Parajuli et al. (2007, 2009), Santhi et al. (2001), $0.75 < E \leq 1.0$, Very good; $0.65 < E \leq 0.75$, Good; $0.50 < E \leq 0.65$, Satisfactory; $E \leq 0.50$ indicates an unsatisfactory fit.

The root mean square error (RMSE) (Jain et al. 2006b; Mishra et al. 2004, 2006a; Sahu et al. 2007, 2010b; Deshmukh et al. 2013; Ajmal et al. 2015c) is defined as:

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^{n} (X_i - Y_i)^2 \right)^{0.5} \tag{3.23}$$

The RMSE ranges from 0 to ∞ and a value close to zero indicate perfect fit.

The index of agreement (d) is expressed as:

$$d = \left(1 - \frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{\sum_{i=1}^{n}\left(\left|Y_i - \overline{X}\right| + \left|X_i - \overline{X}\right|\right)^2}\right) \tag{3.24}$$

Similar to the interpretation of R^2, the d also varies from 0 to 1, with higher values indicating better agreement.

n_t is expressed as (Ritter and Mu˜noz-Carpena 2013):

$$n_t = \frac{SD}{RMSE} - 1 \tag{3.25}$$

where SD is the standard deviation. $n_t \geq 2.2$ indicates Very Good agreement; $1.2 \leq n_t < 2.2$ implies Good; $0.7 \leq n_t < 1.2$ shows Satisfactory; and $n_t < 0.7$ indicates an unsatisfactory fit.

PBIAS measures average tendency of the estimated data to be larger or smaller than their observed data (Ajmal et al. 2015c; Gupta et al. 1999; Moriasi et al. 2007). It is expressed as:

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(X_i - Y_i) \times 100}{\sum_{i=1}^{n} X_i}\right] \tag{3.26}$$

PBIAS indicates the method to be consistently over-predicting or under-predicting. Its positive values indicate model underestimation, and negative values overestimation (Gupta et al. 1999; Moriasi et al. 2007; Yuan et al. 2014). For perfect agreement, PBIAS = 0. According to Archibald et al. 2014; Donigian et al. 1983; Moriasi et al. 2007; Singh et al. 2004; Van Liew et al. 2003, PBIAS < ±10% indicates Very Good fit; ±10% ≤ PBIAS < ±15%, Good; ±15% ≤ PBIAS < ±25%, Satisfactory; and PBIAS ≥ ±25%, unsatisfactory.

Re, is used to measure the average difference between observations and model simulations of variable Q.

$$R = \left|\frac{\sum_{i=1}^{n}(X_i - Y_i)}{\sum_{i=1}^{n} X_i}\right| \tag{3.27}$$

e is a measure of the systematic error and is calculated as the average difference between the predicted and measured values of a random variable as follows:

$$e = \frac{\sum_{i=1}^{n}\left(Y_i - X_i\right)}{n} \tag{3.28}$$

The bias indicates the amount that a method consistently over predicts or under predicts the Q-value. In Equation 3.28, positive values indicate model overestimation, and negative values underestimation.

This study compares various versions of the same kind of formulae, and therefore, to evaluate the improvement in performance efficiency of the modified model (or best model) over the other one, the r^2–statistic as given in Equation 3.29 is used. It was recommended by Nash and Sutcliffe (1970) and used by Senbeta et al. (1999), Ajmal et al. (2015d), Ajmal et al. (2016) and Lal et al. (2017) and in their researches.

$$r^2 = \frac{E_2 - E_1}{1 - E_1} \times 100 \tag{3.29}$$

where E_1 and E_2 are respectively the efficiencies due to the existing and the proposed formulae. $r^2 > 10\%$ indicates the significant improvement of the proposed relations over the existing one (Senbeta et al. 1999).

In this study, performance evaluation is primarily based on R^2, E, n_t, RMSE, PBIAS, Re, and e for individual plot–data and then their arithmetic mean values are taken as yardstick for overall performance evaluation. Kolmogorov–Smirnov test was used to assess the normality of data, and the non-parametric Kruskal–Wallis (K-W) test to test significance level. Further, the MC1-MC8 models' performance in runoff estimation was compared using K-W test for checking whether the results are significantly different from each other. The K-W test, also known as the one-way analysis of variance (ANOVA) on ranks is a popular technique used to compare the two or more groups of an independent variable for statistically significant difference in results. It is a nonparametric test based on ranks, is very less sensitive to outliers, and does not requires a dataset to be normally distributed (Kruskal and Wallis, 1952). A significant K-W test result indicates that among methods MC1-MC8, the runoff estimated by at least one method differs from another. If the significant difference at $P < 0.05$ level of K-W test is identified, the pairwise differences between all methods (i.e. which method differ from others) can be performed by post-hoc analysis. In the present study, post hoc least significant difference (LSD) multiple comparison analysis is used to determine which methods were different at a significance level of 0.05. To this end, **S**tatistical **P**ackage for the **S**ocial **S**ciences (SPSS) version 20.0 (IBM Corp. 2011) software was used to perform K-W analysis.

CHAPTER 4

RESULTS AND DISCUSSION

The present chapter describe the results of data collected experimentally at Roorkee site and published around the globe. The results were analyzed and presented in five different sections. The first section deals with study of interaction among different hydrological parameters like rainfall, runoff, runoff coefficient and soil moisture; and effect of experimental plots characteristics such as soil type, land use and slope on runoff and curve number monitored during August, 2012 to April, 2015. In the second section, different curve number methods were employed to estimate and compare the observed P-Q based CNs with NEH-4 CN values for agricultural plots in Indian conditions. The initial abstraction coefficient (λ) calculation along with the performance evaluation of the λ based proposed model, sensitivity of λ on CN and runoff, conversion of CNs associated with one λ into another λ were carried out in third section. The existence of a relationship between CN (or S) and antecedent wetness condition were explored in the fourth section using in-situ observed soil moisture. The last section deals with reverification of antecedent moisture condition dependent runoff curve number formulae using both experimental data of Indian watersheds and published data around the globe.

4.1 HYDROLOGICAL ASSESSMENT OF EXPERIMENTAL PLOTS

4.1.1 Relationship among observed runoff (Q), runoff coefficient (Rc), Rainfall (P) and previous day soil moisture (θ)

Regression analysis were performed to investigate relationships of Q-depth and Rc with P-depth and previous day soil moisture (θ) (%) for each plot separately and the results are shown in Table 4.1. In these analyses, all the runoff producing rainfall events, at least 10 in number, monitored at 27 runoff plots (plots 1-27 of Table 3.1) have been used. As seen, non–linear variation of Rc with P is similar to the variation of Q with P, but the correlation between Rc and P is much lower than that between Q and P. An example of non–linear relation between Q and P for plot nos. 1, 8, and 11 are shown in Figures 4.1–4.3 respectively. Similarly, examples of non–linear relation between Rc and P for plot nos. 1, 8, and 11 are shown in Figures 4.4–4.6 respectively. As can be seen from Table 4.1, P–Q relationship was statistically significant ($p<0.05$) for all the tested runoff plots. The highest correlation was observed in plot 8 (maize land use), with a coefficient of determination (R^2) of 0.980; the poorest (R^2 = 0.411) was in plot 23 (fallow land use). In contrast, θ did not correlate well with Q as well as Rc in study plots. The graphical representation of correlation of Q and Rc with θ is shown in Figures 4.7 and 4.8 & 4.9 respectively. Table 4.1 shows that the R^2 ranged from 0.028 to 0.391 for the relationship of θ with Q and Rc. Theoretically, higher θ means higher Q (or Rc), but this was not seen in the dataset. However, in the present study, Q is largely controlled by P, consistent with the findings of Nadal-Romero et al. (2008), Rodríguez-Blanco et al. (2012), Scherrer et al. (2007), Kostka and Holko (2003), and Zhang et al. (2011), rather than θ.

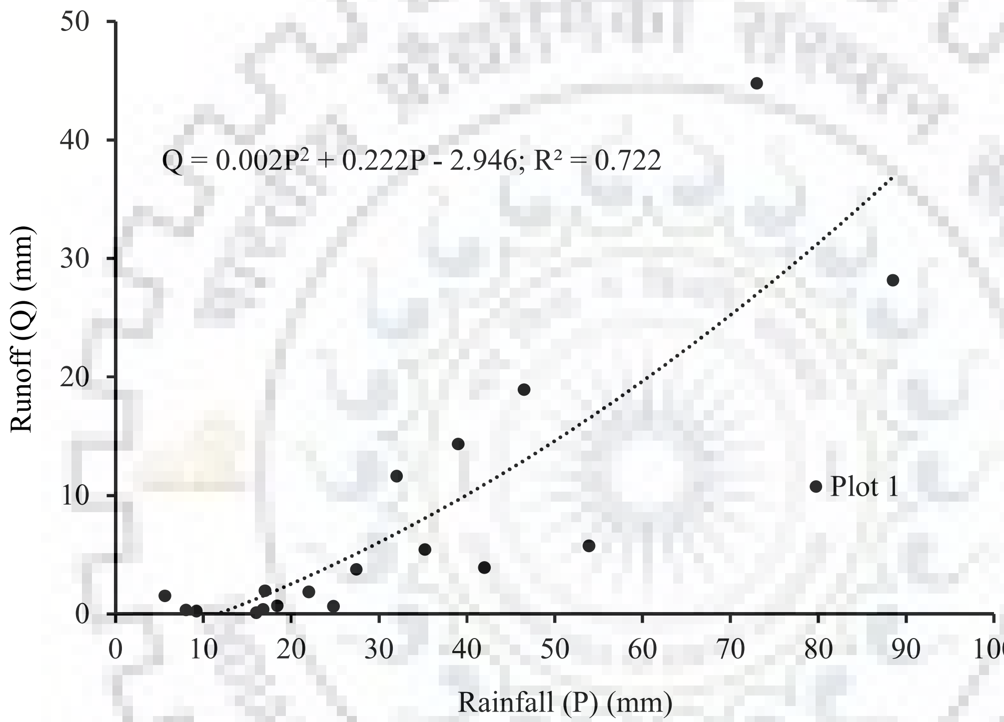

Figure 4.1 Relationship of runoff depth (Q) with rainfall (P) for plot no. 1

4.1.2 Variation of rainfall threshold (I) among experimental study plots

The runoff initiation threshold (I) also known as rainfall threshold for runoff generation was determined for each plot from daily observed P–Q data. Here notable point is that all observed rainfall events have been included in the analysis of I. Table 4.2 gives an overview of rainfall threshold (I) values, and slope (m/m) and intercept of P–Q curves for all plots. The graphical representation for calculation of I for the randomly chosen plot nos. 1, 8, 11 and 15 are shown in Figures 4.10–4.13 respectively. As seen, both vary considerably among plots. The highest I was observed for the plots having HSGs A. In contrast, the lowest I was observed for the plots having HSGs C whereas I for HSG B was in between HSGs A and C. Thus, HSG (or indirectly soils infiltration capacity) seems to play a major role in controlling I in the plots.

Table 4.1 Coefficients of determination (R^2) of daily runoff (Q) (mm) and runoff coefficients (Rc) with daily rainfall (P) (mm) and previous day soil moisture (θ) (%), along with mean runoff coefficient (Rc_m) for each plot

Plot No.	n	Runoff (Q) depth		Runoff coefficient (Rc)		Rc_m
		P	θ	P	θ	
1	18	0.722*	0.075	0.415*	0.066	0.177
2	18	0.680*	0.056	0.431*	0.057	0.161
3	18	0.727*	0.048	0.438*	0.056	0.197
4	12	0.729*	0.028	0.552*	0.097	0.120
5	12	0.692*	0.187	0.409**	0.120	0.159
6	12	0.719*	0.188	0.483**	0.031	0.093
7	13	0.940*	0.152	0.519*	0.029	0.202
8	13	0.980*	0.115	0.742*	0.035	0.157
9	13	0.922*	0.208	0.606*	0.218	0.220
10	13	0.805*	0.035	0.646*	0.064	0.166
11	13	0.843*	0.070	0.593*	0.055	0.135
12	13	0.786*	0.153	0.375**	0.078	0.169
13	13	0.814*	0.034	0.140	0.346	0.191
14	13	0.558*	0.219	0.185	0.167	0.282
15	13	0.600*	0.080	0.148	0.228	0.232
16	11	0.737*	0.090	0.460**	0.344	0.203
17	11	0.820*	0.055	0.342	0.295	0.170
18	11	0.769*	0.093	0.451**	0.322	0.252
19	11	0.621*	0.079	0.313	0.284	0.132
20	11	0.639*	0.113	0.261	0.458	0.194
21	11	0.641*	0.037	0.359	0.231	0.229
22	13	0.435**	0.061	0.079	0.136	0.173
23	11	0.411**	0.124	0.364**	0.365	0.176
24	13	0.516*	0.391	0.381**	0.395	0.184
25	11	0.828*	0.071	0.605*	0.318	0.473
26	11	0.812*	0.053	0.688*	0.219	0.335
27	11	0.722*	0.387	0.616*	0.518	0.284

(* significant at 0.01 level; ** significant at 0.05 level)

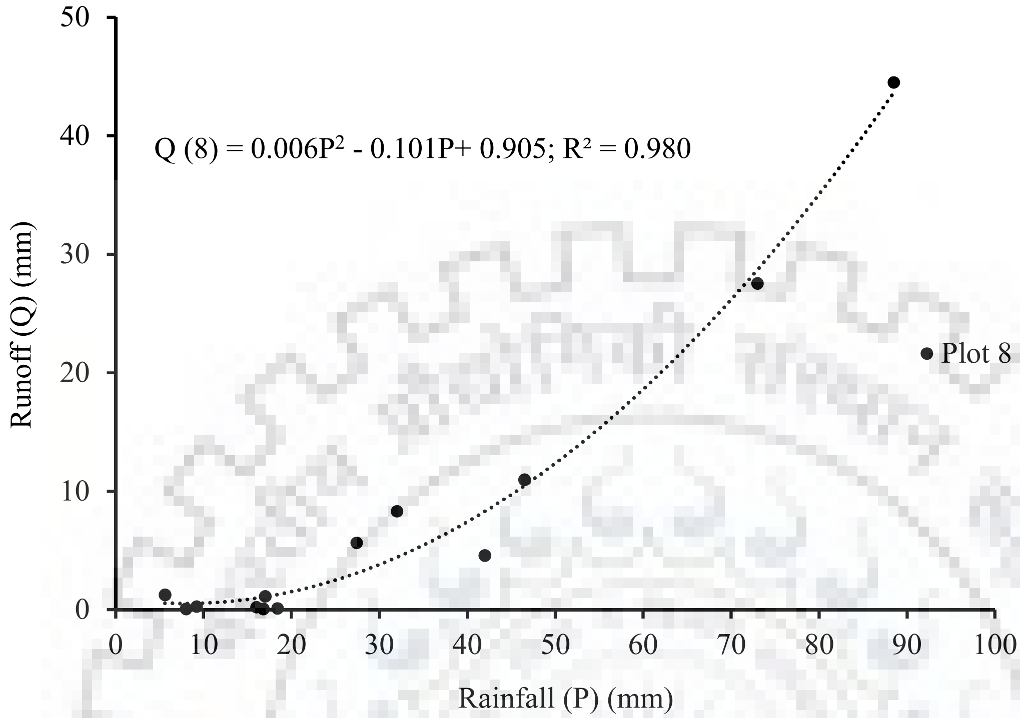

Figure 4.2 Relationship of runoff depth (Q) with rainfall (P) for plot no. 8

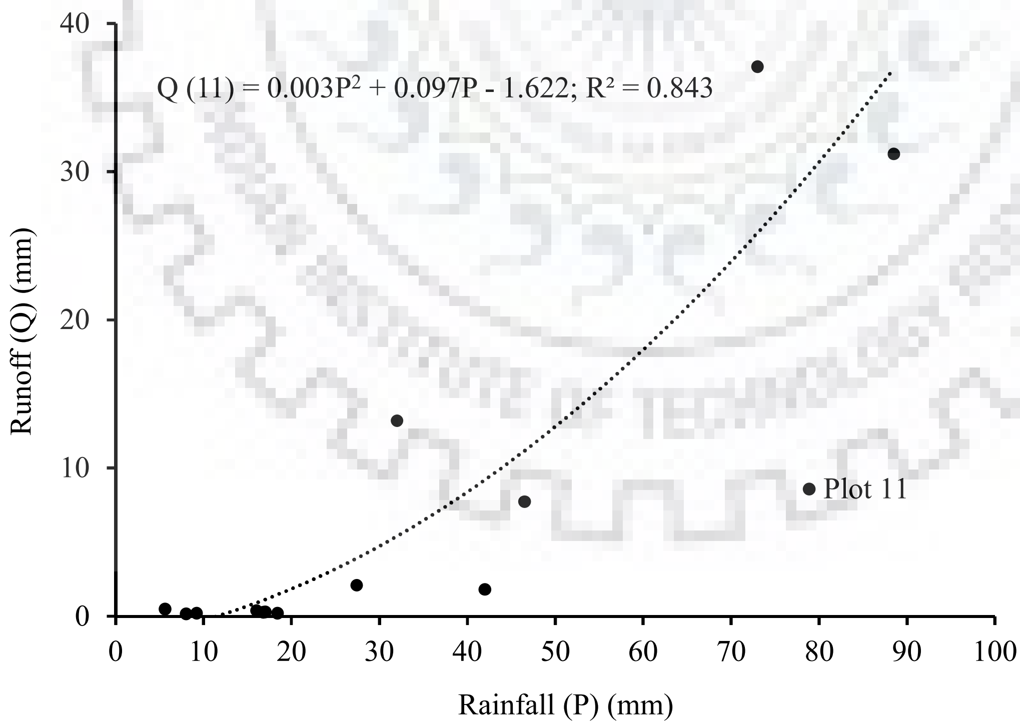

Figure 4.3 Relationship of runoff depth (Q) with rainfall (P) for plot no. 11

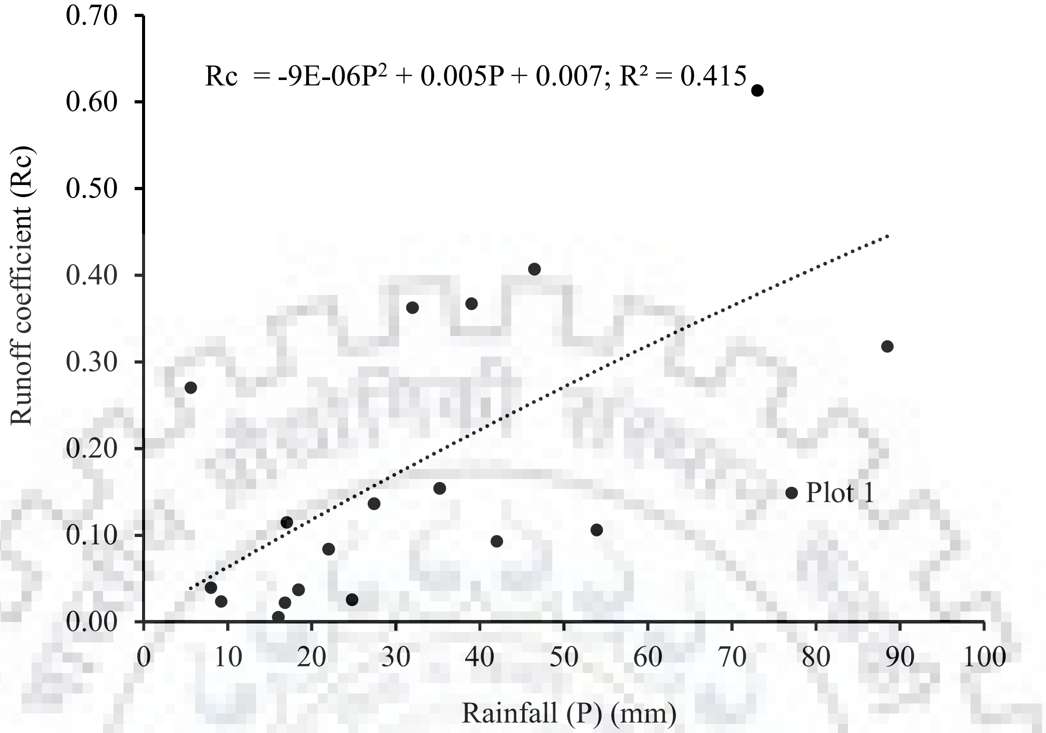

Figure 4.4 Relationship of runoff coefficient (Rc) with rainfall (P) for plot nos. 1

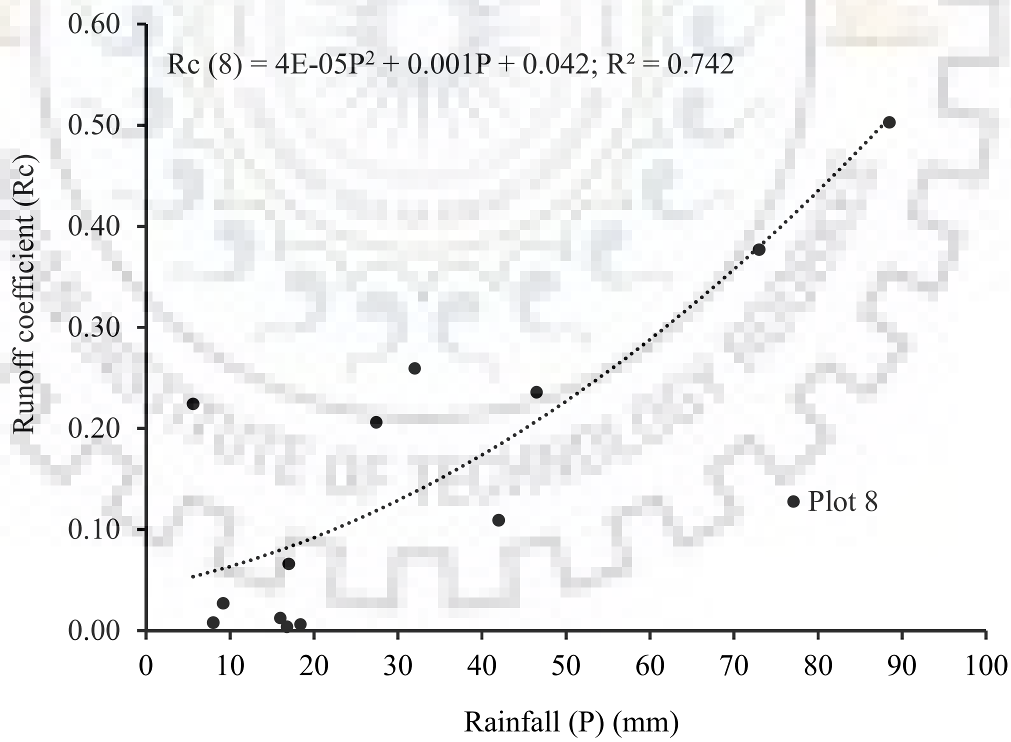

Figure 4.5 Relationship of runoff coefficient (Rc) with rainfall (P) for plot no. 8

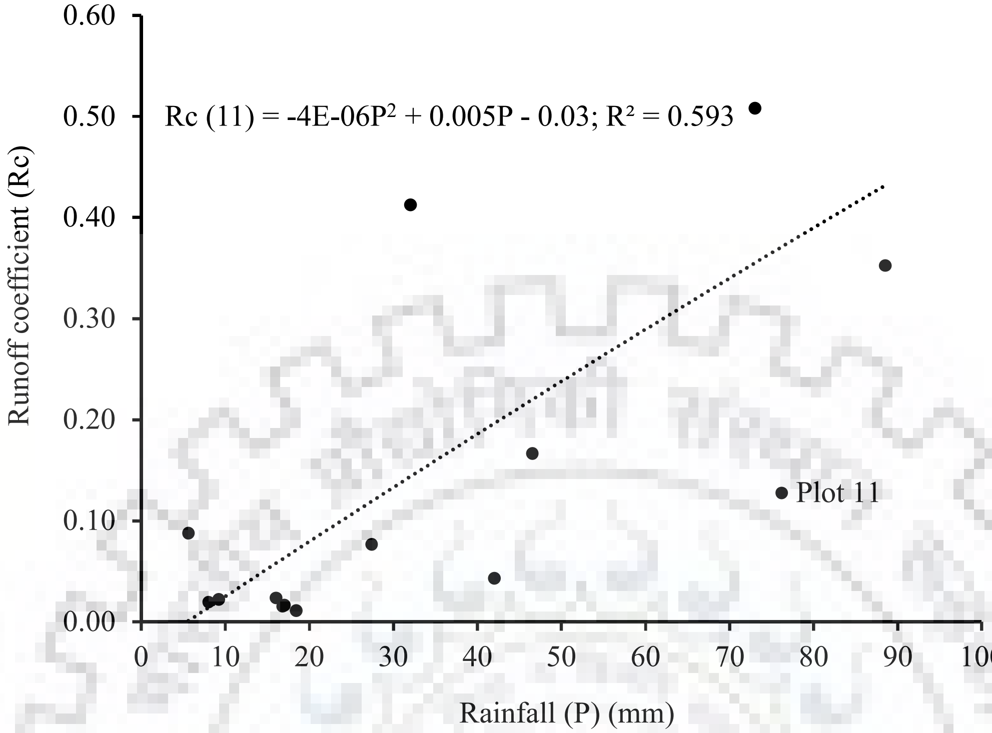

Figure 4.6 Relationship of runoff coefficient (Rc) with rainfall (P) for plot no. 11

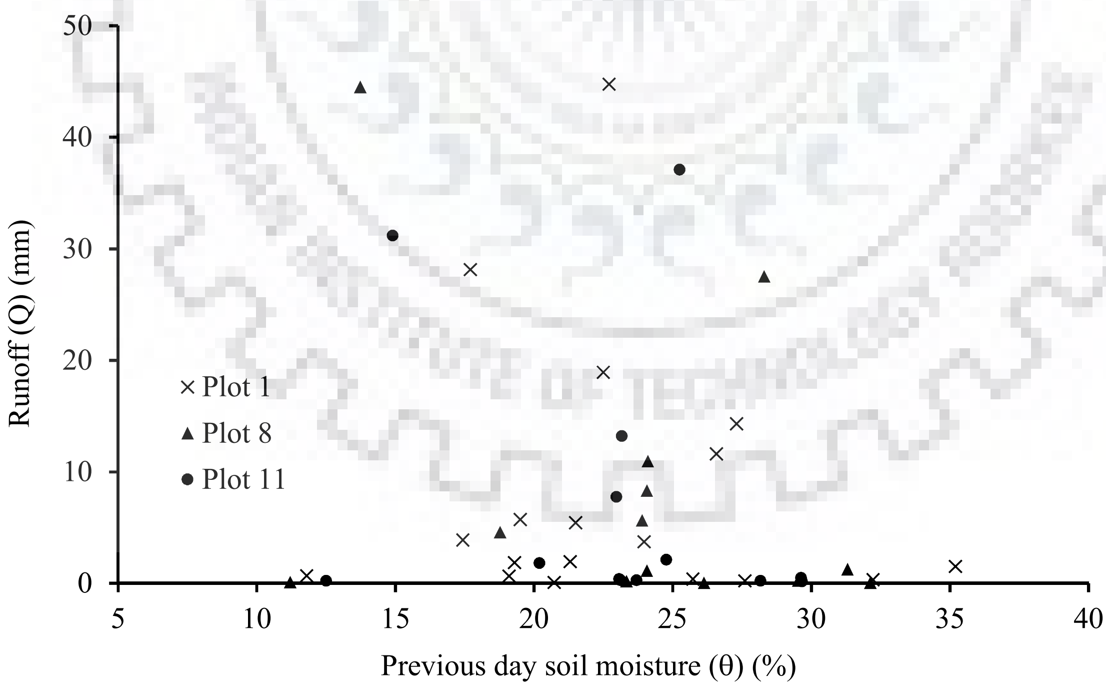

Figure 4.7 Plot showing relationship of runoff depth (Q) with previous day soil moisture (θ) for plot nos. 1, 8 and 11

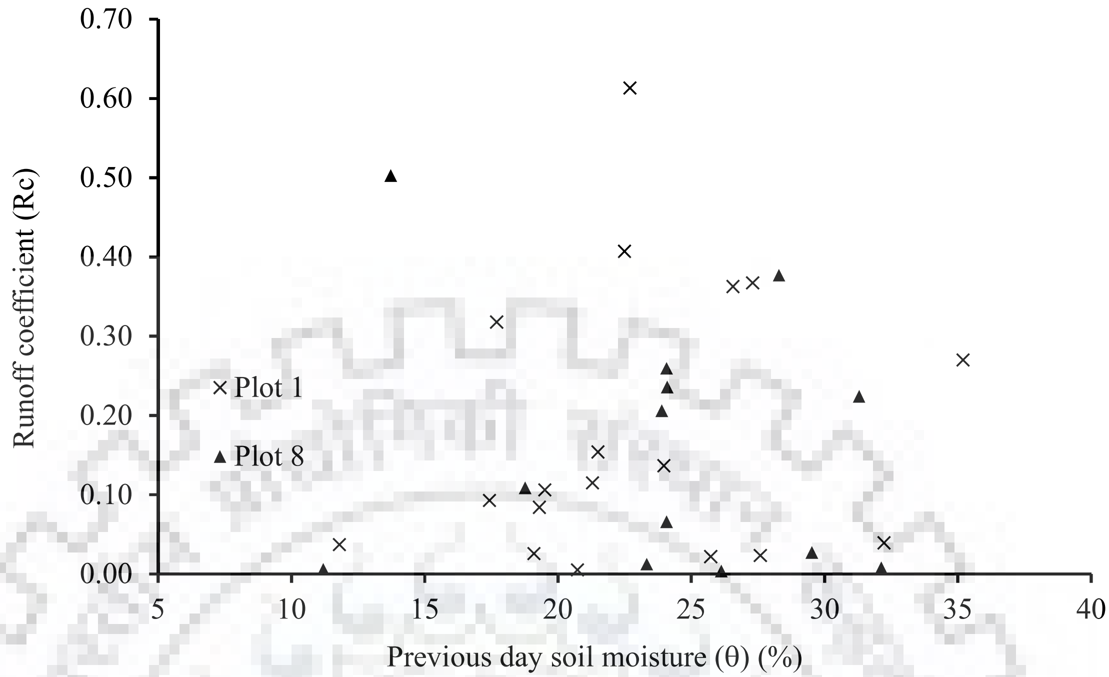

Figure 4.8 Plot showing relationship of runoff coefficient (Rc) with previous day soil moisture (θ) for plot nos. 1 and 8

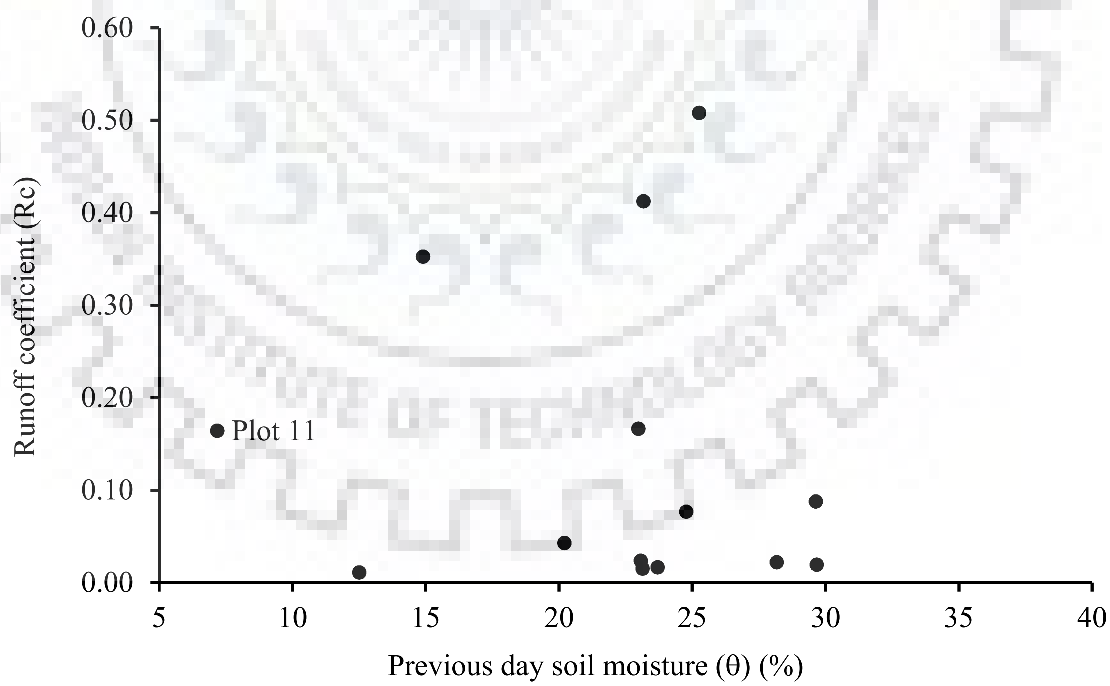

Figure 4.9 Plot showing relationship of runoff coefficient (Rc) with previous day soil moisture (θ) for plot no. 11

Table 4.2 Rainfall threshold for runoff initiation (I, mm) and coefficients i.e. slope (x) and intercept (y) of linear regression (Q=xP+y) of the rainfall (P)–runoff (Q) curve.

Plot No.	n	R^2	x (m/m)	(-) y (mm)	I (mm)
1	38	0.728	0.375	2.798	7.50
2	38	0.661	0.383	3.051	7.90
3	38	0.755	0.406	2.849	6.80
4	33	0.735	0.319	2.183	6.70
5	33	0.730	0.327	1.925	6.00
6	33	0.692	0.250	1.181	7.60
7	33	0.904	0.450	2.968	6.60
8	33	0.864	0.413	3.009	7.20
9	33	0.891	0.515	3.457	6.20
10	33	0.790	0.449	3.174	6.80
11	33	0.801	0.372	2.677	7.20
12	33	0.784	0.380	2.563	6.60
13	26	0.883	0.259	2.239	9.00
14	26	0.747	0.317	2.002	6.60
15	26	0.791	0.279	1.994	7.40
16	24	0.767	0.323	3.032	9.60
17	24	0.852	0.281	2.751	10.00
18	24	0.777	0.420	4.056	9.50
19	24	0.666	0.148	0.913	6.20
20	24	0.769	0.245	1.833	7.60
21	24	0.708	0.313	2.512	8.10
22	26	0.716	0.186	1.084	6.00
23	24	0.476	0.187	1.036	5.60
24	26	0.593	0.197	1.088	5.60
25	11	0.739	0.492	0.442	1.80
26	11	0.783	0.458	2.412	5.00
27	11	0.687	0.396	2.200	5.20

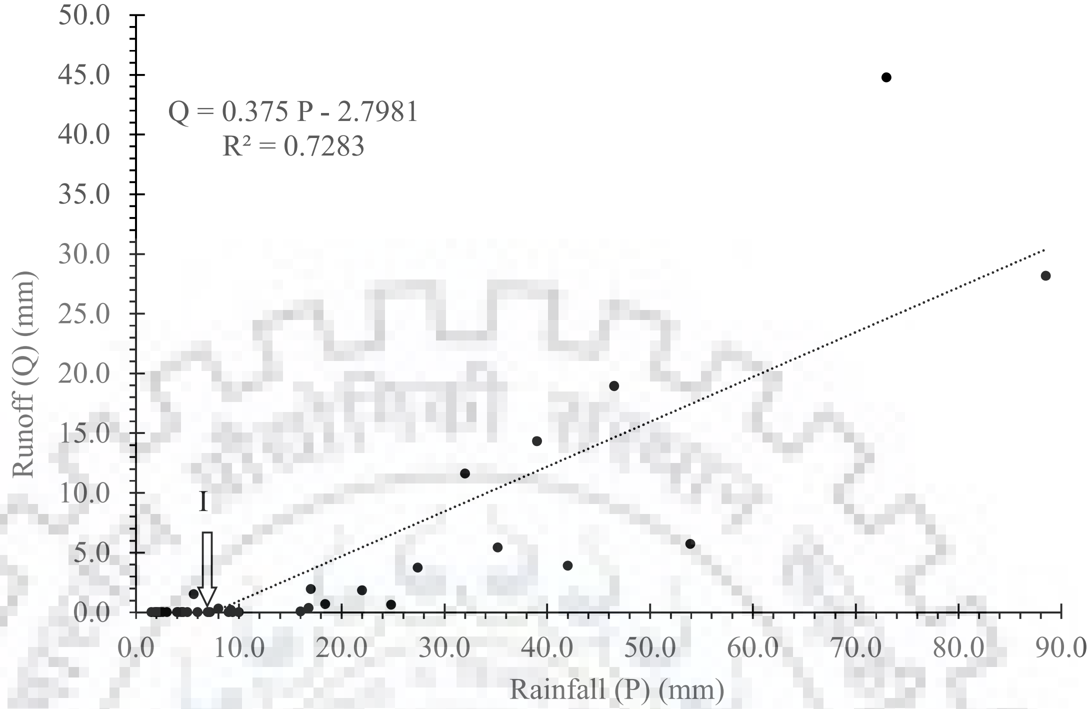

Figure 4.10 Plot showing value of I (mm) from the relationship of runoff depth (Q) with rainfall (P) for plot no. 1

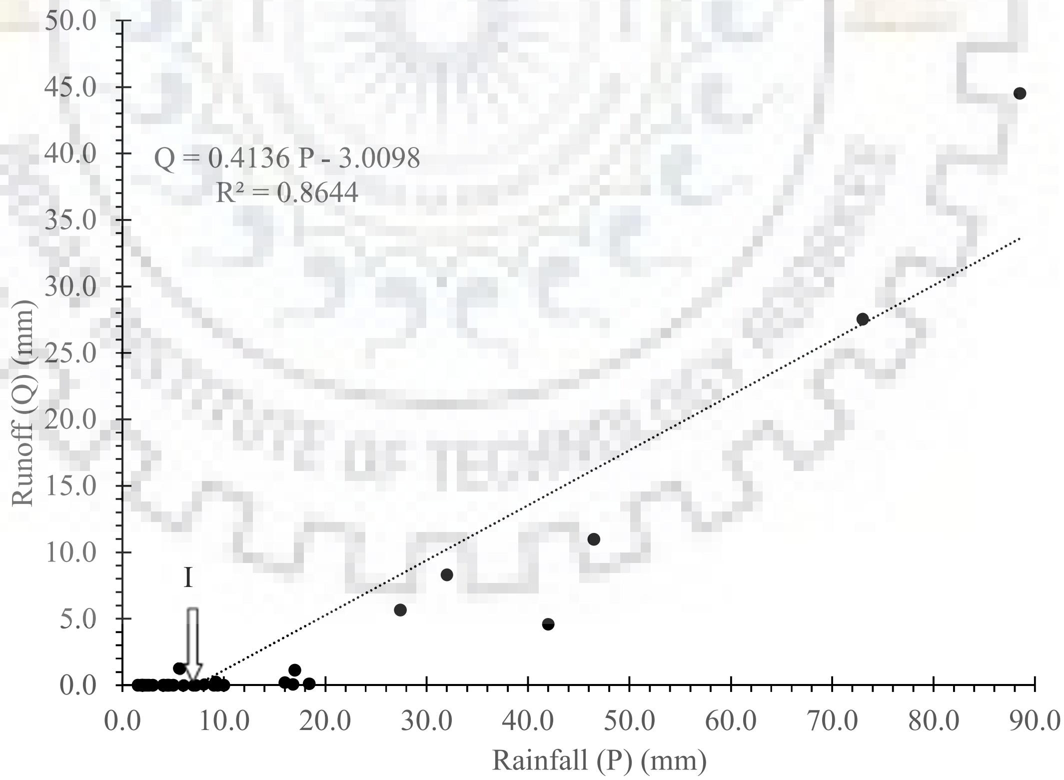

Figure 4.11 Plot showing value of I (mm) from the relationship of runoff depth (Q) with rainfall (P) for plot no. 8

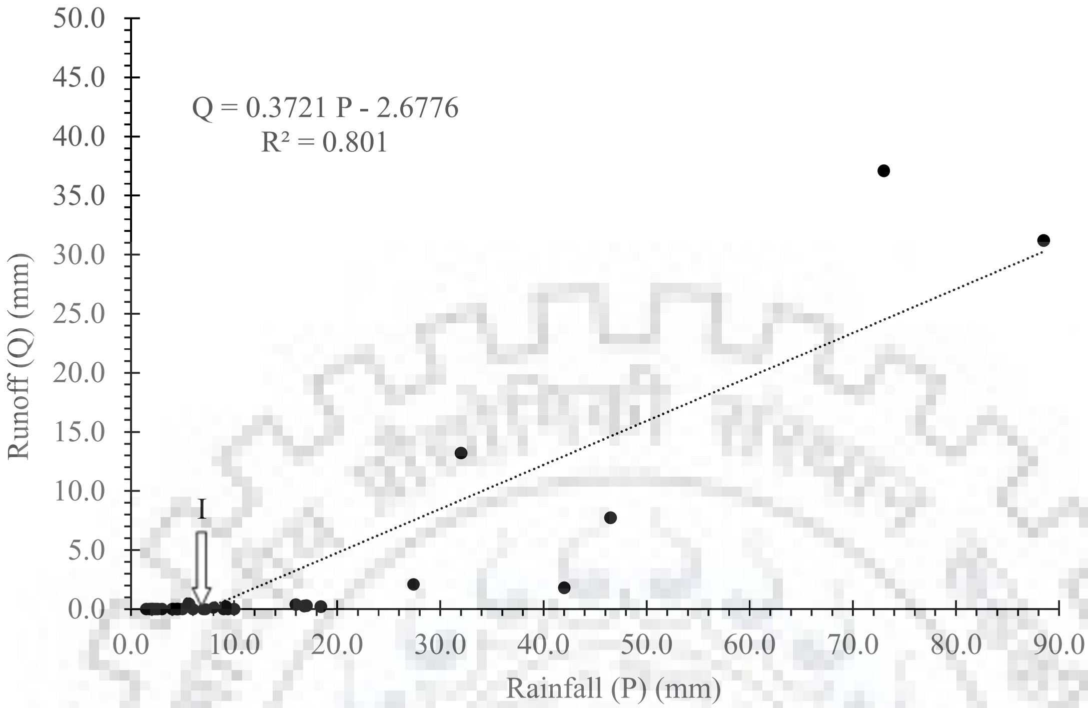

Figure 4.12 Plot showing value of I (mm) from the relationship of runoff depth (Q) with rainfall (P) for plot no. 11

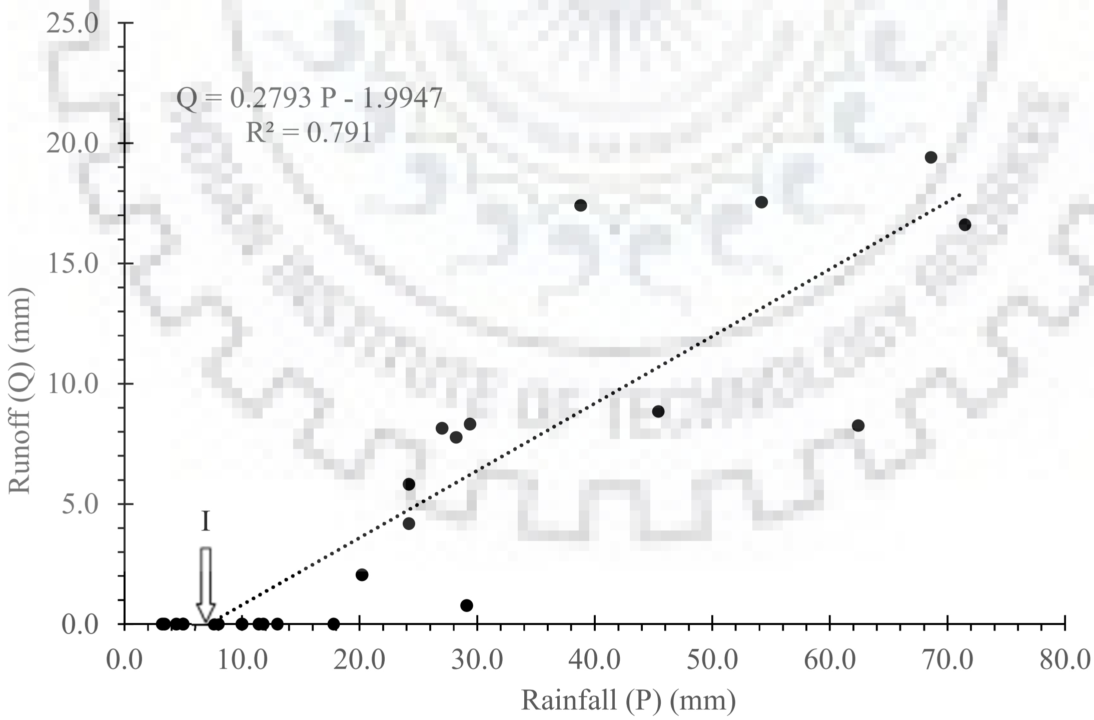

Figure 4.13 Plot showing value of I (mm) from the relationship of runoff depth (Q) with rainfall (P) for plot no. 15

4.1.3 Variation of mean runoff coefficient (Rc_m)

As seen from the above, the concept of I is also supported by response of runoff to rainfall, i.e. runoff coefficient which followed the similar pattern as does I. As can be seen from Table 4.1, the mean runoff coefficient (Rc_m) as calculated by Equation 3.10 was higher for the plots having HSGs C followed by B and A. This pattern for Rc_m was followed by nearly all the plots with few exceptions (i.e. plots 12 and 21). Rc_m of the plots ranged from 0.093 to 0.473.

Runoff coefficients (Rc) for individual rainfall events also varied considerably from less than 0.005 to over 0.60, depending on the nature of the event and plot type. The Kolmogorov–Smirnov test revealed event wise Rc for all the individual plots not to be normally distributed. The non-parametric Kruskal–Wallis test revealed statistical significance difference between events Rc of all 27 study plots.

4.1.4 Effect of land use, infiltration capacity, and plot slope on Q and CN

The effect of land use, infiltration capacity, and slope on Q (or Rc) was also tested individually for their significance. To this end, plots located in the same land use, HSG, and slope were grouped separately for checking their significance among studied variables. Since the data distribution fails to pass the normality test for the entire three individual groups (i.e. land use, HSG, and slope), non-parametric Kruskal–Wallis test was used to test significance level and the results are shown in Table 4.3. The test revealed that land uses did not show any significant difference in Rc except sugarcane which produced significantly ($p < 0.05$) higher Rc than blackgram and fallow land uses. In case of HSGs, however, HSG C had significantly higher Rc than did B and A, but the last ones did not differ from each other. In addition, slope did not show any effect on Rc as all three groups of slopes were insignificantly different from each other. Thus, Rc (or Q) is more significantly influenced by infiltration capacity (fc) of soil rather than land uses or slopes. The graphical representation of relationship between mean runoff (Q_m) of the plot against corresponding fc is shown in Figure 4.14. As seen from this figure, Q_m produced at the study plots significantly (R^2=0.269; $p < 0.01$) influenced by soil permeability described by plots soil fc. With an increase in fc, Q_m decreased logarithmically, and vice versa. Similarly, graphical representation of relationship between mean runoff coefficient (Rc_m) of the plot against corresponding fc is shown in Figure 4.15. Similar to the Figure 4.14, the correlation (R^2=0.214; $p < 0.05$) between Rc_m and fc is also significant; and with an increase in fc, Rc_m also decreased logarithmically, and vice versa

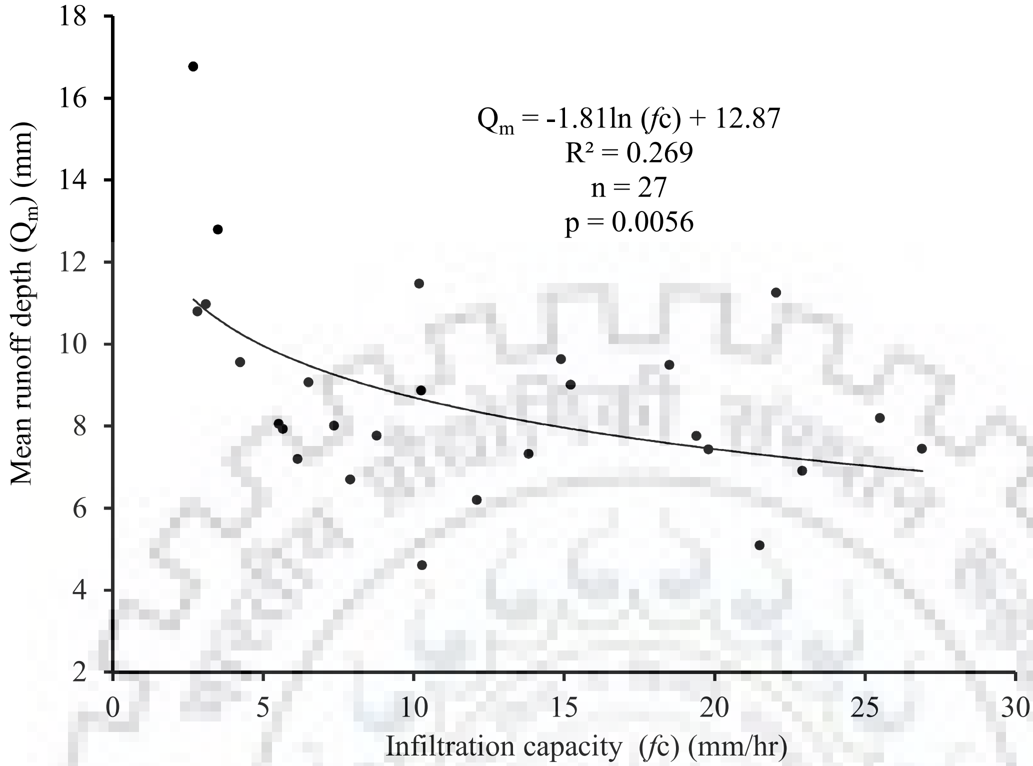

Figure 4.14 Relationship of mean runoff depth (Q_m) with Infiltration capacity (fc) of soil for all 27 agricultural plots data.

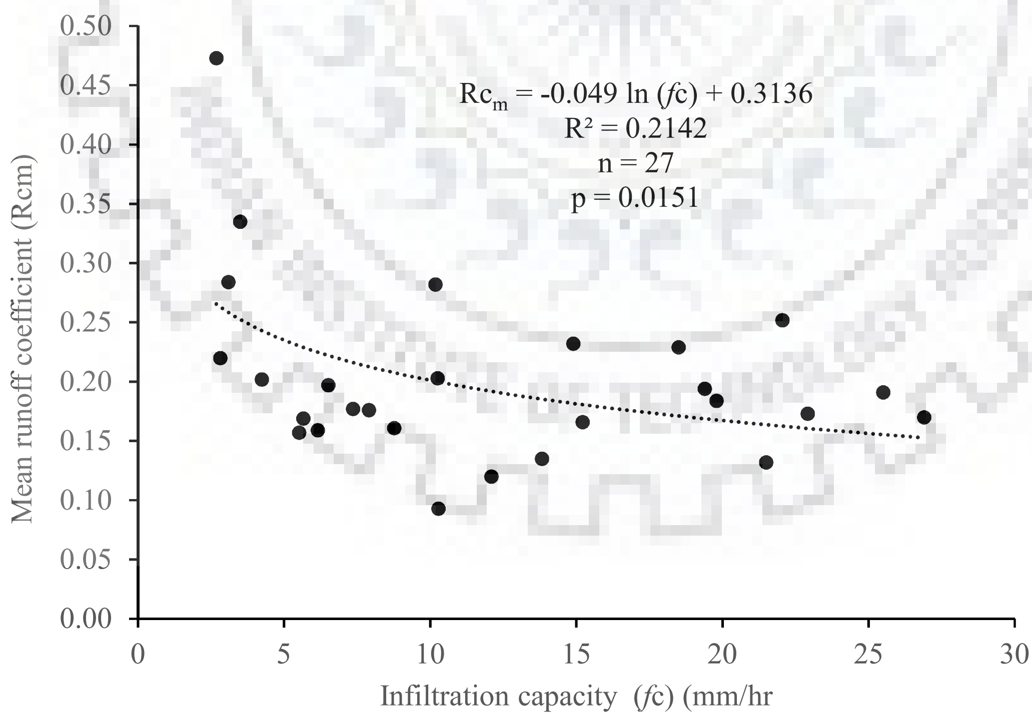

Figure 4.15 Relationship of mean runoff coefficient (Rc_m) with Infiltration capacity (fc) of soil for all 27 agricultural plots data.

The effect of land use, *f*c, and slope on event-wise CNs was also studied using similar analysis (or tests) as discussed above for Rc. Here, standard SCS Equations 3.8 and 3.9 were employed for estimating the event wise CNs from observed P-Q event. As seen from Table 4.3, land uses did not show any significant difference in CNs except sugarcane which produced significantly ($p < 0.05$) higher CNs than blackgram and fallow land uses. Furthermore, slope also did not show any effect on CNs as all three groups (i.e. 5, 3, and 1%) of slope were statistically insignificant. In the present study, CNs are seen to be influenced by *f*c of soil because all three groups of soil (i.e. A, B and C) exhibited significantly different CNs.

As already analyzed that *f*c is the main explanatory variable for Q-production in the study plots. The graphical representation of relationship of plot representative CN (at AMC-2) with *f*c is shown in Figure 4.16. In this Figure, the plots representative CN (AMC-2) was calculated employing least square fit technique i.e. Equation 3.11. As seen, an inverse relationship between CN and *f*c for all 27 study plots was detected with significant correlation ($R^2 = 0.461$, $p<0.01$). The results from this analysis support the applicability of NEH-4 tables where CNs decline with *f*c (or HSG).

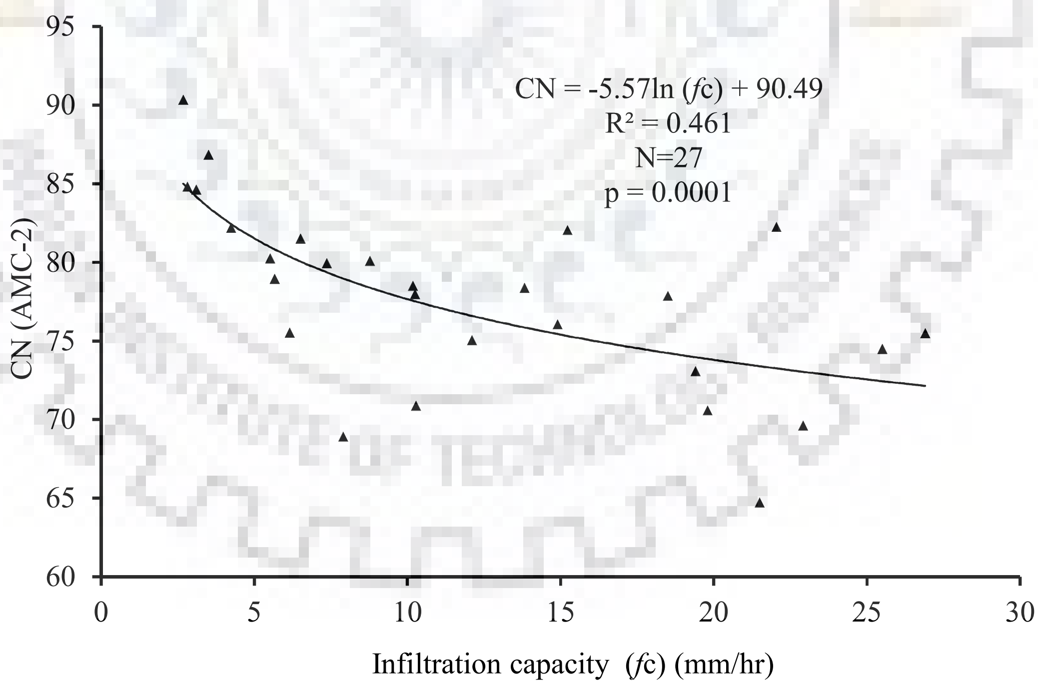

Figure 4.16 Relationship of Curve Number (CN) with Infiltration capacity (*f*c) of soil for all 27 agricultural plots data

Table 4.3 Mean event runoff coefficient (Rc) and CNs for the groups of different land uses, HSGs and slopes

Land uses group				HSG group				Slope group			
Land use type	Rc	CN	n	HSG*	Rc	CN	n	Slope (%)	Rc	CN	n
Sugarcane	0.245 a	83.66 a	126	A	0.178 a	80.26 a	210	5	0.200 a	81.99 a	115
Black gram	0.170 bc	80.99 bc	72	B	0.179 a	82.99 b	87	3	0.194 a	81.88 a	113
Maize	0.200 bca	82.40 bca	72	C	0.323 b	88.00 c	46	1	0.195 a	82.09 a	115
Fallow	0.151c	79.67 c	73								

Within one group, variables with no letter (alphabet, a, b, c) in common have significantly different Rc or CN at the 0.05 significance level (based on the Kruskal–Wallis test).

* HSGs are mainly determined by infiltration capacity: A > 7.26 mm/hr; 3.81 mm/hr < B < 7.26 mm/hr; 1.27 mm/hr < C < 3.81 mm/hr; D < 1.27 mm/hr.

4.2 OBSERVED P-Q DATA-BASED CN AND THEIR COMPARISON WITH TABULATED CN

4.2.1 Observed P-Q data-based CN estimation

In the present study, eight different CNs estimation methods from observed P-Q data have used for analysis, and the results of estimated CNs are shown in Table 4.4. Here notable point is that the observed P–Q data of 36 plots have been used for comparing the CNs estimated by methods M1 through M8. As seen, the CNs estimated by least squares fit (M2) method range from 45.12 (plot 35) to 95.30 (plot 28). The CNs estimated by traditionally recommended NEH-4 median (M5) method range from 72.26 (plot 34) to 95.55 (plot 28). In general, the CNs estimated by Geometric-mean (M3) method are usually larger (17 of 36 plots) followed by S-probability (M8) (15 of 36 plots). Based on overall mean (mean of representative CNs of 36 plot), M2 was found to estimate the lowest CNs among all methods. In contract, M8 method found to estimate the larger CNs. The multiple comparison results of CNs estimated by all the eight methods is shown in Table 4.5. Based on the Kruskal−Wallis test analysis, mix results were obtained. There was no single method which has produced significantly higher (or lower) CNs than other. Method M3 produced significantly ($p < 0.05$) higher CNs than M2 and M4, but it was statistically insignificant with others (i.e. M1, M5, M6, M7, M8). Similarly, M2 produced significantly lower CNs than other methods except M4. The CNs estimated by M1, M3, M5, M6, M7 and M8 were statistically insignificant among each other.

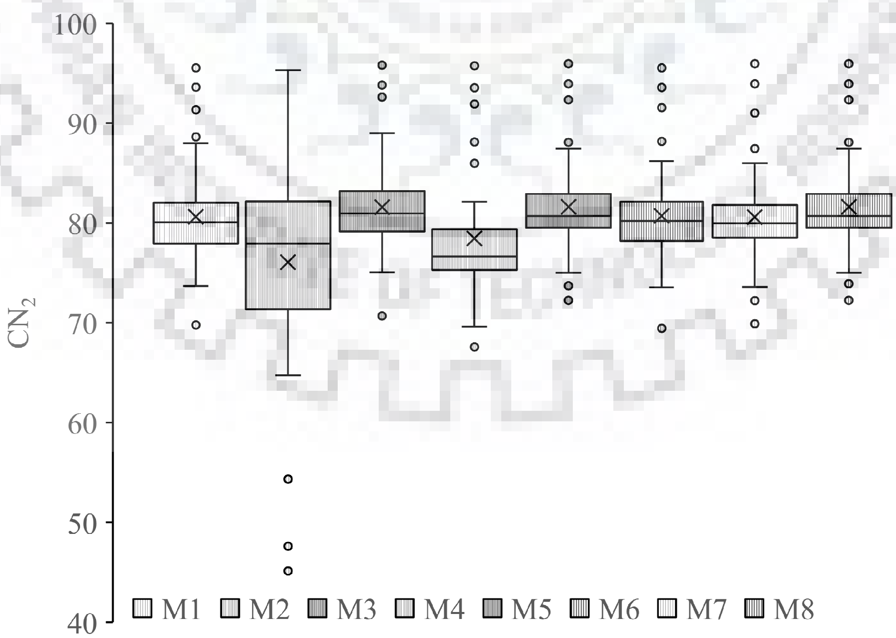

Figure 4.17 Box plot showing the CN estimated by methods M1-M8.

Table 4.4 Estimated curve numbers using the eight different methods for the 36 agricultural plots of various characteristics.

Plot No.	n	Curve Number (AMC-2) estimation method							
		M1	M2	M3	M4	M5	M6	M7	M8
1	15	80.61	79.93	81.42	77.77	81.24	80.79	81.24	81.24
2	15	79.47	80.09	80.75	76.00	79.88	79.74	79.71	79.88
3	15	81.27	81.51	82.69	76.39	81.09	81.60	81.37	81.09
4	10	78.49	75.05	79.15	75.97	78.08	78.58	79.06	78.08
5	10	80.10	75.52	81.13	75.24	79.21	80.19	79.07	79.21
6	10	74.64	70.87	75.22	72.24	77.75	74.64	73.60	77.75
7	10	82.10	82.19	82.73	76.10	80.88	82.18	81.86	80.88
8	10	80.31	80.24	80.61	75.62	79.77	80.33	79.22	79.77
9	10	83.46	84.81	84.14	77.95	81.49	82.44	84.13	81.49
10	10	81.12	82.06	81.92	76.65	79.77	81.30	81.65	79.77
11	10	78.87	78.38	79.59	75.23	79.16	79.02	79.72	79.16
12	10	79.26	78.95	80.49	75.36	80.28	79.47	80.28	80.28
13	13	79.38	74.49	80.18	79.05	79.83	79.46	80.10	79.83
14	13	82.71	78.50	84.27	82.13	83.65	82.96	83.76	83.65
15	13	81.10	76.05	82.21	80.88	84.48	81.25	80.88	84.48
16	11	80.17	77.97	81.14	78.01	81.52	80.21	79.88	81.52
17	11	78.79	75.49	79.53	76.35	80.02	78.87	78.47	80.02
18	11	81.92	82.26	83.34	79.00	82.47	82.04	81.50	82.47
19	11	76.53	64.73	77.59	76.15	79.44	80.98	79.65	79.44
20	11	80.06	73.07	81.17	79.44	81.72	80.20	80.94	81.72
21	11	80.78	77.88	82.41	78.76	79.65	80.98	79.65	79.65
22	13	77.89	69.61	79.15	77.76	83.07	78.01	80.01	83.07
23	11	77.94	68.90	79.64	74.19	81.66	73.81	72.75	81.66
24	13	78.34	70.59	79.62	78.10	81.42	78.45	78.64	81.42
25	10	91.36	90.33	92.60	91.92	92.35	91.55	91.02	92.35
26	10	87.99	86.84	88.75	88.11	88.10	88.17	87.97	88.10
27	10	85.95	84.62	86.83	85.97	86.29	86.20	86.00	86.29
28	4	95.55	95.30	95.81	95.76	95.95	95.55	95.96	95.95

Table 4.4 (Continued)

Plot No.	n	Curve Number (AMC-2) estimation method							
		M1	M2	M3	M4	M5	M6	M7	M8
29	4	93.60	93.49	93.81	93.56	93.95	93.59	93.95	93.95
30	4	88.63	88.89	89.01	88.23	87.44	88.63	87.44	87.44
31	5	77.96	66.70	79.11	76.61	79.80	78.12	77.22	79.80
32	5	74.25	73.57	75.37	69.62	75.28	74.38	73.82	75.28
33	5	74.44	47.61	75.41	74.05	75.00	74.48	75.00	75.00
34	5	69.79	54.35	70.70	67.58	72.26	69.46	69.91	72.26
35	5	73.68	45.13	75.04	70.11	80.55	73.55	72.23	80.55
36	40	74.05	72.87	75.09	72.23	73.69	74.15	73.90	73.90

Table 4.5 Comparison of CN determination methods based on the Kruskal–Wallis test

Method	CN	n
M1	80.63 a	36
M2	76.08 b	36
M3	81.60 a	36
M4	78.45 c, b	36
M5	81.62 a	36
M6	80.70 a	36
M7	80.60 a	36
M8	81.62 a	36

Note: variables with no letter (alphabet, a, b, c) in common have significantly different CN at the 0.05 significance level (based on the Kruskal–Wallis test), (n is the number of rainfall events).

4.2.2 Performance evaluation of M1-M8 method in runoff estimation

In order to judge the runoff estimation accuracy of CNs estimated by various methods used in this study, the runoff was estimated for the 1-24 plots datasets. The plots 25-36 were excluded from the analysis due unavailability of P_5 data. The standard SCS-CN procedure was followed to estimate the runoff. The box and whisker plots for plot wise E, RMSE, e and d are shown in Figures 4.18-4.21 respectively.

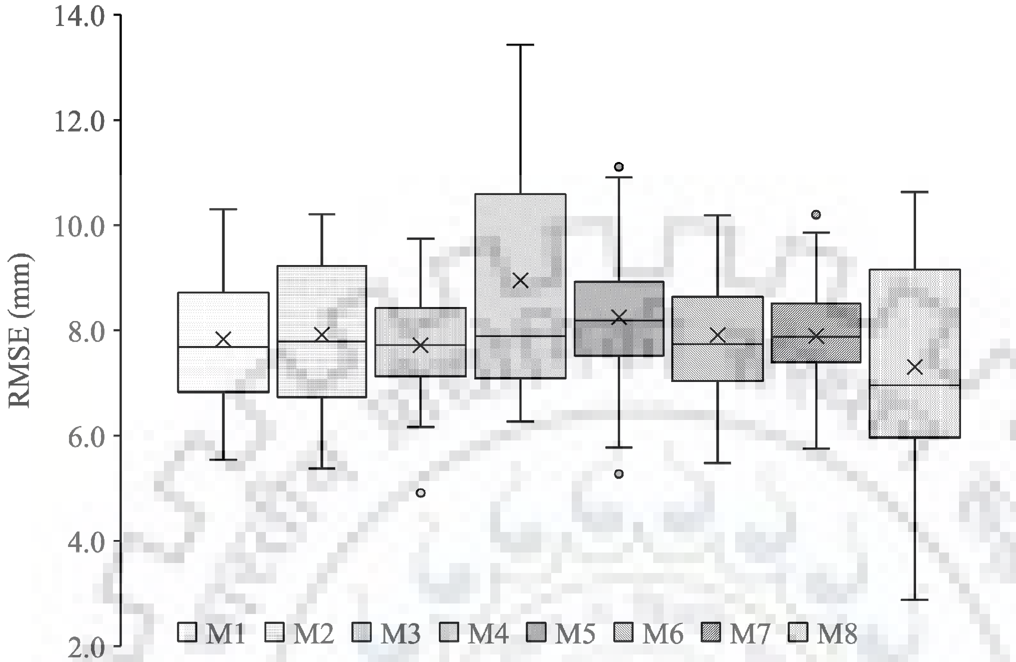

Figure 4.18 Box and whisker plot showing the RMSE obtained by methods M1-M8

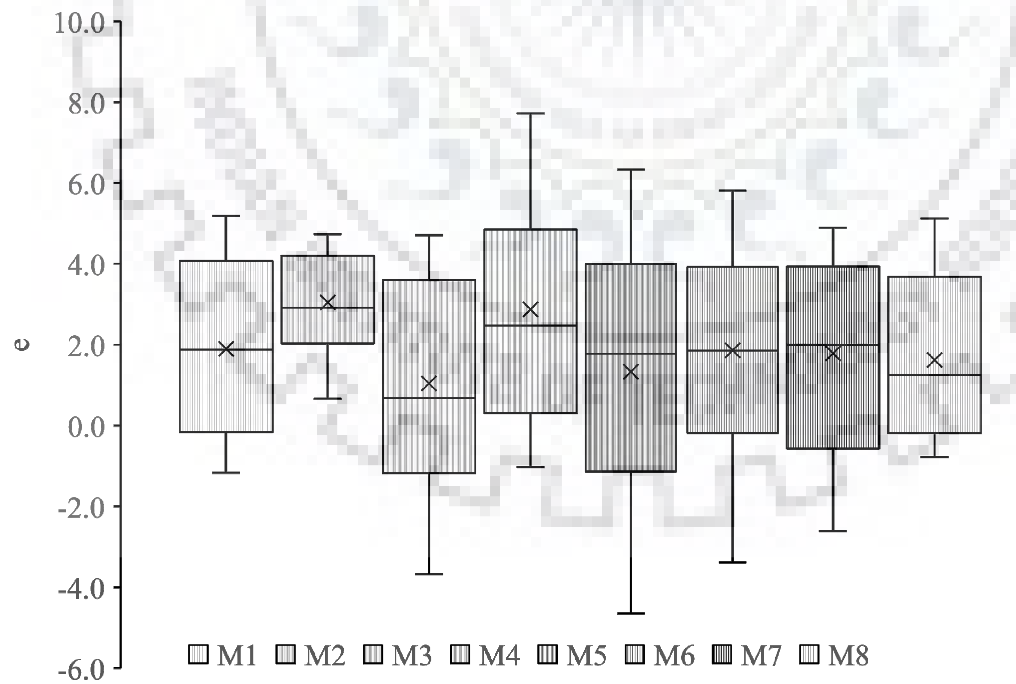

Figure 4.19 Box and whisker plot showing the bias (e) obtained by methods M1-M8

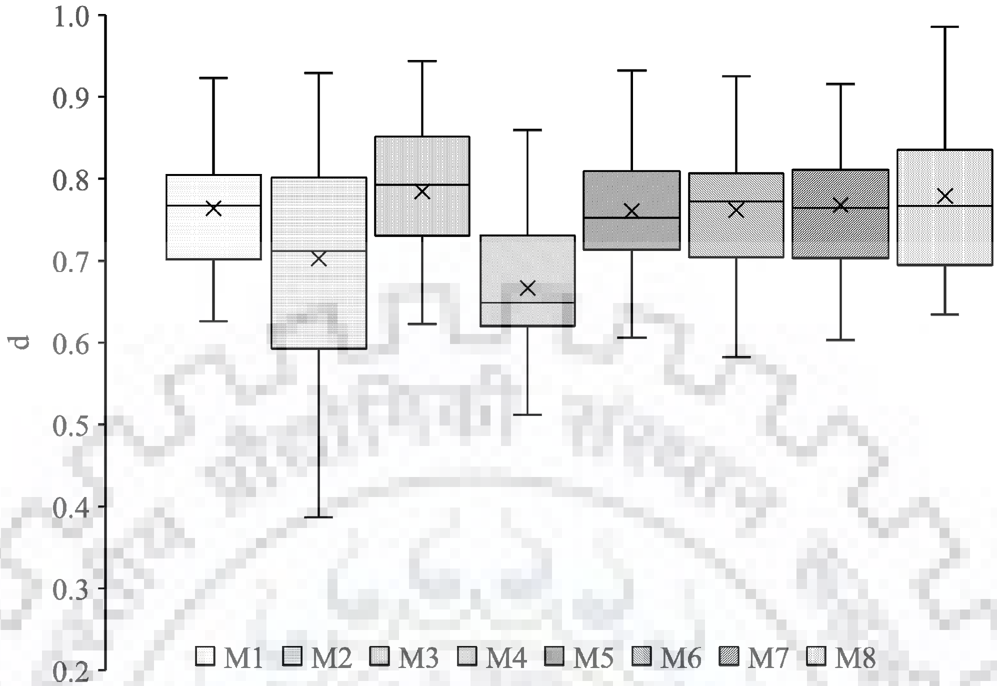

Figure 4.20 Box and whisker plot showing the d obtained by methods M1-M8

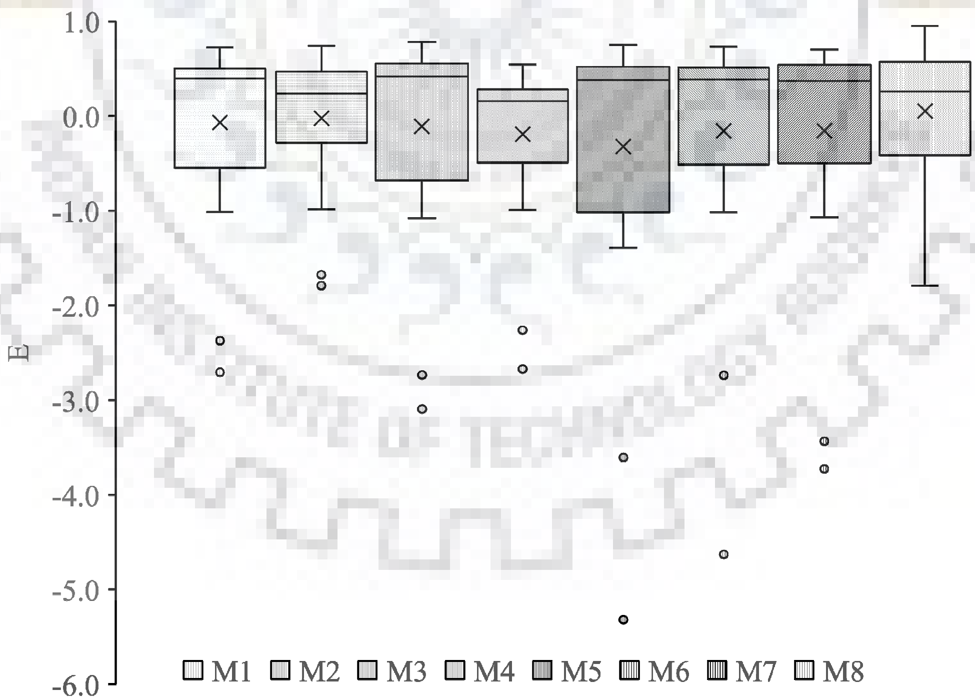

Figure 4.21 Box and whisker plot showing the E obtained by methods M1-M8

Table 4.6 shows the mean values of E, RMSE, e and d from all the 24 plots for the runoff estimation using the CNs estimated by M1-M8 methods. Considering the cumulative mean value of RMSE as a yardstick of evaluation, the performance of eight method was as follows:

M8 > M3 > M1 > M7 > M6 > M2 > M5 > M4.

For further analyses based on the mean values of d, the M3 was found to perform superior followed by M8. Similarly, based on mean values of E, M8 performance was good whereas M5 performed poorest. The model performance based on E was as follows:

M8 > M2 > M1 > M3 > M7 > M6 > M4 > M5.

Table 4.6. Comparison of runoff estimation using eight different curve number determination methods for 24 plots datasets.

	M1	M2	M3	M4	M5	M6	M7	M8
	RMSE (mm)							
Maximum	10.303	10.211	9.746	13.429	11.106	10.189	10.200	10.631
Mean	7.834	7.915	7.716	8.953	8.247	7.909	7.895	7.307
Minimum	5.545	5.377	4.911	6.269	5.276	5.483	5.759	2.880
	Index of agreement (d)							
Maximum	0.923	0.929	0.944	0.860	0.932	0.925	0.916	0.986
Mean	0.764	0.703	0.784	0.667	0.761	0.762	0.761	0.779
Minimum	0.626	0.387	0.623	0.512	0.606	0.582	0.603	0.635
	Bias (mm)							
Maximum	5.186	4.733	4.713	7.727	6.333	5.813	4.897	5.130
Mean	1.896	3.043	1.041	2.873	1.328	1.856	1.783	1.617
Minimum	-1.162	0.666	-3.674	-1.021	-4.643	-3.387	-2.606	-0.779
	E							
Maximum	0.724	0.741	0.784	0.545	0.750	0.730	0.703	0.950
Mean	-0.068	-0.024	-0.111	-0.195	-0.324	-0.159	-0.158	0.052
Minimum	-2.705	-1.791	-3.094	-2.671	-5.319	-4.628	-3.726	-1.791

As shown in Table 4.6, the variation in the mean bias values by different methods was varies from 1.041 mm (for M3) to 3.043 (for M2). The performance of different methods based on Bias criteria can be described as:

M3 > M5 > M8 > M7 > M6 > M1 > M4 > M2.

The results from present analysis show that there are no single methods which do have performed good based on all the four goodness of fit criteria. However, either M3 or M8 can be considered as good among all based on individual goodness of fit criteria.

For evaluating the overall performance, the methods were ranked based on the mean statistics viz. d, RMSE, Bias and E. To this end, a rank of 1-8 was assigned to show the RMSE, Bias from lowest to highest, and d and E from highest to lowest. After assigning of ranks, corresponding marks of 8 to 1 are given to each index. For example, a method having the minimum RMSE, Bias, and maximum d, E will be ranked 1. The method corresponding to rank 1 will be achieved to score 8 marks. Similarly, the method corresponding to rank 2 will be achieved to score 7 marks and so on. The overall performance of method was judged based on the total marks gained by method using all four statistics. The first rank will be given to the method scoring highest marks whereas last rank (i.e. eight) will be given to method scoring lowest marks. Table 4.7 shows the ranks and marks achieved by all methods for their respective performance indices. As seen from this table, M8 performed best followed by M3. Based on overall score the methods performance can be described as follows:

M8 > M3 > M1 > M7 > M6 > M2 > M5 > M4

As can be seen from above analysis that either M8 or M3 can be considered as best performing methods in the study region. The results from present study contradicts with the results of Sharda and Ali (2008) who have found respectively log normal frequency (M4) and S-probability (M8) methods as best and least performing ones in Rajasthan, India. Contrary to Ali and Sharda (2008) findings, log normal frequency method performance was least among all methods tested in the present study. On the other hand, the present study results could be comparable with Tedla et al. (2012) as geometric mean (M3) method was the best performing method in the study conducted by these researches.

4.2.3 Comparison between Handbook table and observed P-Q data-based Curve number

One of the aims of the present study was to investigate the applicability of NEH-4 CN values to Indian watersheds, which are otherwise based on a large P-Q dataset of a number of small US watersheds. In this study, P-Q data are derived from 27 plots of the same size and situated at one location (Roorkee experimental site), i.e. the same climatic condition. The NEH-4 curve numbers (CN_{HT}) are compared with those due to both natural and ordered P–Q datasets observed on 27 plots. The CN_{HT} and P-Q based CNs i.e. CN_m, CN_{LSn}, CN_{LSo}, CN_{LSMn}, CN_{LSMo}

Table 4.7 Performance evaluation of models based on ranks (scores)

Method	RMSE (mm)	Rank (score)	d	Rank (score)	Bias (mm)	Rank (score)	NSE	Rank (score)	Total score	Overall Rank
	Performance indices and their ranks (scores)									
M1	7.834	3 (6)	0.764	3 (6)	1.896	6 (3)	-0.068	3 (6)	21	3
M2	7.915	6 (3)	0.702	7 (2)	3.043	8 (1)	-0.024	2 (7)	13	6
M3	**7.716**	**2 (7)**	**0.784**	**1(8)**	**1.041**	**1 (8)**	**-0.111**	**4 (5)**	**28**	**2**
M4	8.953	8 (1)	0.667	8 (1)	2.873	7 (2)	-0.195	7 (2)	6	8
M5	8.247	7 (2)	0.761	6 (3)	1.328	2 (7)	-0.324	8 (1)	13	7
M6	7.909	5 (4)	0.761	4 (5)	1.856	5 (4)	-0.159	6 (3)	16	5
M7	7.895	4 (5)	0.761	5 (4)	1.783	4 (5)	-0.158	5 (4)	18	4
M8	**7.307**	**1 (8)**	**0.779**	**2 (7)**	**1.617**	**3 (6)**	**0.052**	**1 (8)**	**29**	**1**

estimated for 27 plots are shown in Table 4.8. As seen, CN_{HT} ranged from 58 (plots 19, 20, and 21) to 88 (plots 25, 26, and 27). The optimized values of CN_{LSMn} ranged respectively from 64.73 (plot 19) to 90.33 (plot 25), and CN_{LSMo} from 67.47 to 90.59 for ordered dataset. Whereas the optimized values of CN_{LSn} ranged respectively from 38.72 (plot 19) to 85.36 (plot 25), and CN_{LSo} from 42.16 to 87.12 (plot 10) for ordered dataset. Similarly, CN_m were ranged from 77.75 to 92.35. The box plot of these CNs is shown in Figure 4.22. As seen from this figure, the CN_{LSMn}, CN_{LSMo} and CN_m values were higher than CN_{HT}, consistent with that reported by Stewart et al. (2012).

The Comparison of CN_{HT} with CN_m, CN_{LSn}, CN_{LSo}, CN_{LSMn}, CN_{LSMo} are shown in Figures 4.23-4.27 respectively. From Figure 4.23, it is seen that the comparison between CN_{HT} and CN_m is less than satisfactory. Furthermore, CN_m obtained by traditional median method assume high values compared to CN_{HT} and the discrepancy increases for CNs below 75. Most of the CN_m values (24 out of 27) were greater than the CN_{HT} values, consistent with those reported in literature (D'Asaro et al. 2014; Hawkins and Ward 1998). The group of CN_{HT} lower than 80 was found to observed high amount of bias (e = -11.38 CN) as compare to (e =0.89 CN) group of CN_{HT} higher than 80.

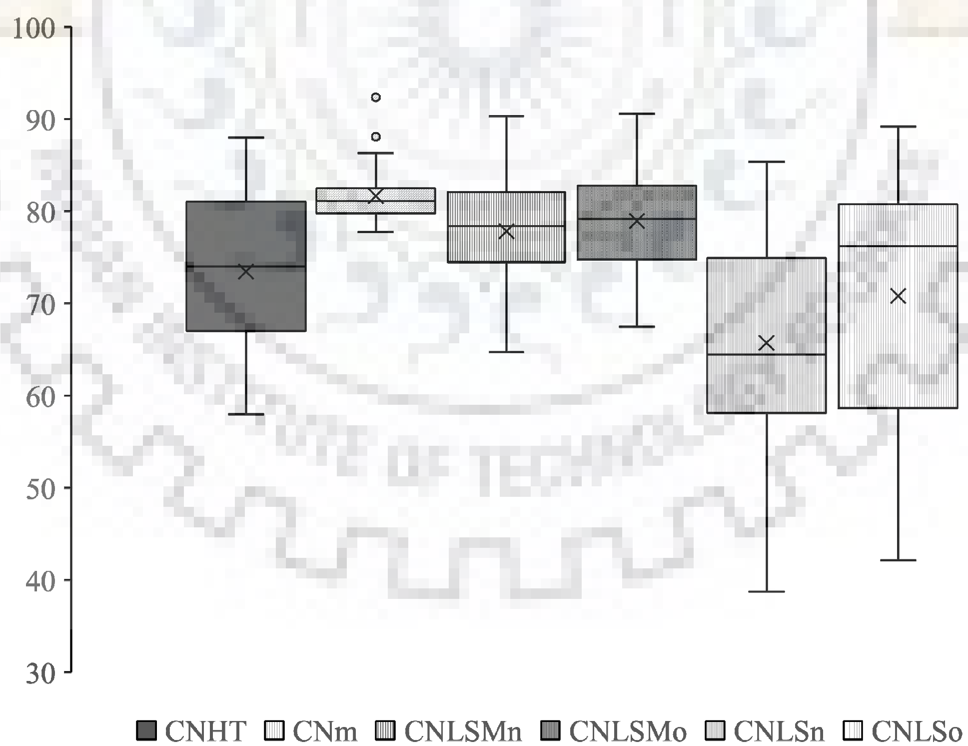

Figure 4.22 Box and whisker plot showing the comparison among tabulated and observed P-Q data based CNs

Table 4.8 Summary of runoff plot characteristics and CN values derived using NEH-4 median, Least-Squares fit method (LSM) and Handbook tables (Used partial dataset excluding P<15 mm)

Plot No.	Land use	n	NEH-4 Table	NEH-4 method (natural data, λ=0.20)	LSM (λ=0.20)		LSM (Optimized λ)			
					Natural	Ordered	Natural data		Ordered data	
			CN_{HT}	CN_m	CN_{LSMn}	CN_{LSMo}	CN_{LSn}	λ	CN_{LSo}	λ
1	Sugarcane	15	81	81.24	79.93	81.01	70.79	0.0334	81.87	0.2276
2	Sugarcane	15	72	79.88	80.09	81.41	77.00	0.1244	89.17	0.6590
3	Sugarcane	15	81	81.09	81.51	82.75	70.30	0.0002	80.23	0.1267
4	Fallow	10	76	78.08	75.05	76.16	62.61	0.0204	80.74	0.3513
5	Fallow	10	85	79.21	75.52	76.99	59.91	0.000	66.61	0.0245
6	Fallow	10	76	77.75	70.87	71.94	60.86	0.0631	76.63	0.3174
7	Maize	10	78	80.88	82.19	82.46	74.91	0.0314	76.17	0.0455
8	Maize	10	78	79.77	80.24	80.39	80.49	0.2079	80.98	0.2192
9	Maize	10	85	81.49	84.81	85.04	81.89	0.0999	83.60	0.1443
10	Blackgram	10	66	79.77	82.06	82.83	79.07	0.1141	87.13	0.4213
11	Blackgram	10	66	79.16	78.38	79.16	73.13	0.0879	79.09	0.1966
12	Blackgram	10	77	80.28	78.95	80.01	69.93	0.0328	77.81	0.1412

Table 4.8 (Continued)

Plot No.	Land use	n	NEH-4 Table	NEH-4 method (natural data, λ=0.20)	LSM (λ=0.20)		LSM (Optimized λ)			
					Natural	Ordered	Natural data		Ordered data	
			CN_{HT}	CN_m	CN_{LSMn}	CN_{LSMo}	CN_{LSn}	λ	CN_{LSo}	λ
13	Sugarcane	13	67	79.83	74.49	74.74	56.94	0.0003	57.21	0.0000
14	Sugarcane	13	67	83.65	78.5	79.72	64.47	0.0000	67.69	0.0000
15	Sugarcane	13	67	84.48	76.05	77.10	61.23	0.0002	62.22	0.0000
16	Maize	11	67	81.52	77.97	78.59	62.39	0.0000	64.06	0.0000
17	Maize	11	67	80.02	75.49	75.94	58.13	0.0001	58.65	0.0001
18	Maize	11	67	82.47	82.26	82.92	70.93	0.0000	75.77	0.0415
19	Blackgram	11	58	79.44	64.73	67.47	38.72	0.0000	42.16	0.0000
20	Blackgram	11	58	81.72	73.07	74.79	55.95	0.0000	56.11	0.0000
21	Blackgram	11	58	79.65	77.88	78.96	61.92	0.0000	64.30	0.0000
22	Fallow	13	74	83.07	69.61	71.43	46.21	0.0000	51.12	0.0001
23	Fallow	11	74	81.66	68.90	72.23	45.80	0.0000	55.11	0.0001
24	Fallow	13	74	81.42	70.59	73.76	51.79	0.0000	54.66	0.0001
25	Sugarcane	10	88	92.35	90.33	90.59	85.36	0.0000	85.97	0.0000
26	Sugarcane	10	88	88.10	86.84	87.19	79.03	0.0000	79.88	0.0000

Table 4.8 (Continued)

Plot No.	Land use	n	NEH-4 Table	NEH-4 method (natural data, λ=0.20)	LSM (λ=0.20)		LSM (Optimized λ)			
					Natural	Ordered	Natural data		Ordered data	
			CN_{HT}	CN_m	CN_{LSMn}	CN_{LSMo}	CN_{LSn}	λ	CN_{LSo}	λ
27	Sugarcane	10	88	86.29	84.62	85.27	74.56	0.0000	76.17	0.0000
	Statistics									
	Mean		73.44	81.64	77.83	78.92	65.72	0.0302	70.78	0.1080
	Median		74.00	81.09	78.38	79.16	64.47	0.0001	76.17	0.0001
	Standard deviation		9.12	3.17	5.85	5.27	11.93	0.0527	12.68	0.1665
	Maximum		88.00	92.35	90.33	90.59	85.39	0.2079	89.17	0.6590
	Minimum		58.00	77.75	64.73	67.47	38.72	0.0000	42.16	0.0000
	Skewness		0.00	1.90	-0.15	0.00	-0.41	2.0189	-0.51	1.8609

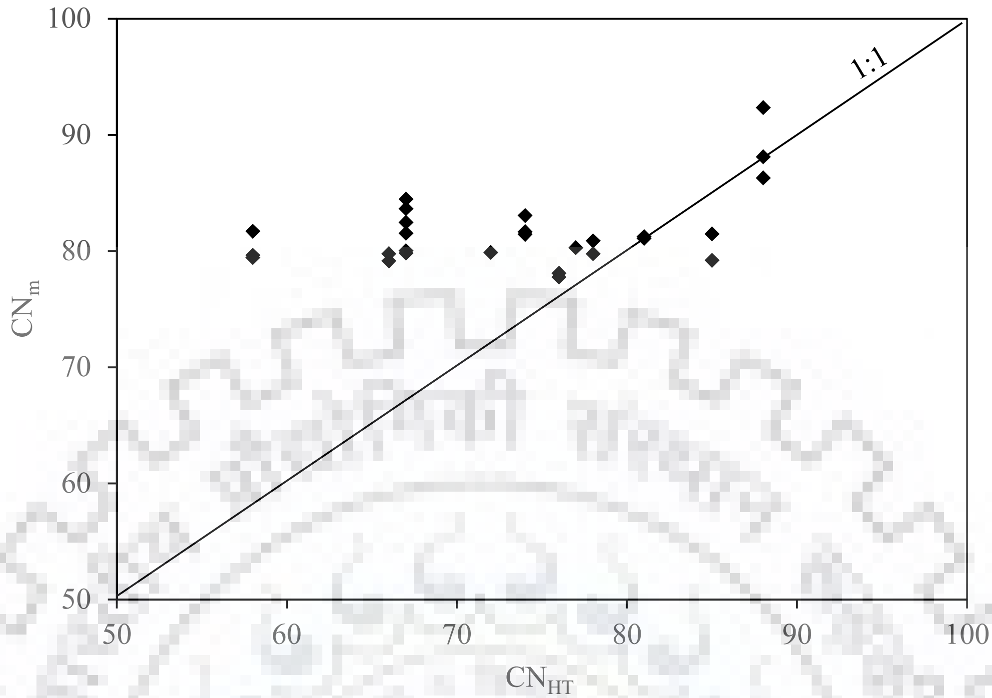

Figure 4.23 CN Plot for comparison between CN_m and CN_{HT}

As shown in Figures 4.24 and 4.25, the comparison between CN_{HT} and CN_{LS} is also poor for both natural and ordered datasets. In general, CN_{HT} values are higher than CN_{LS} and the difference is larger for CN values varying from 68-78.

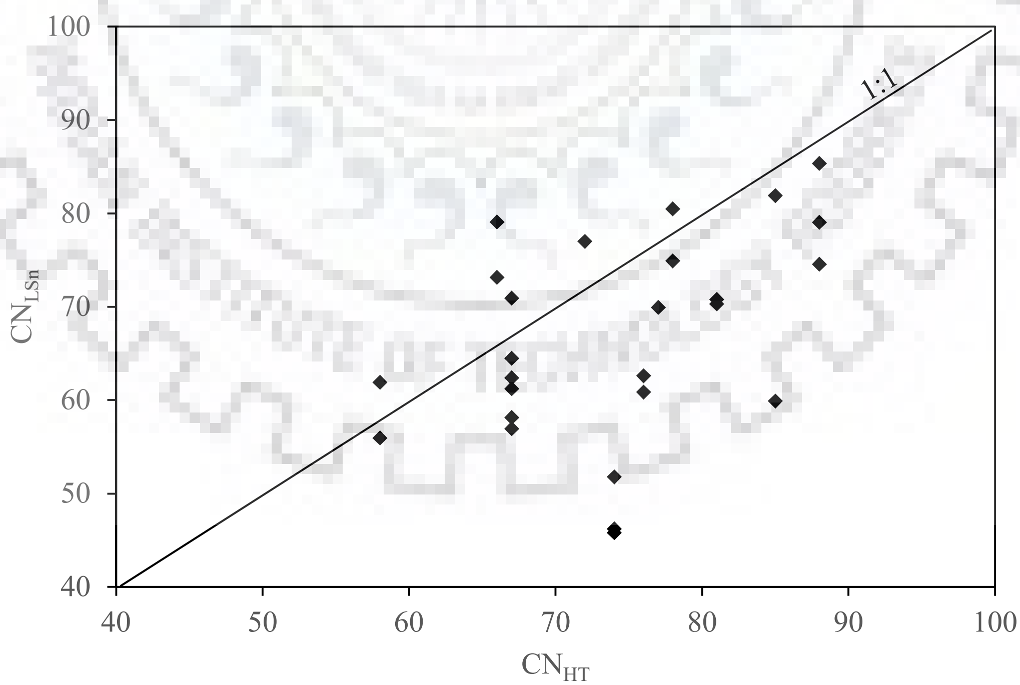

Figure 4.24 CN Plot for comparison between CN_{LSn} and CN_{HT}

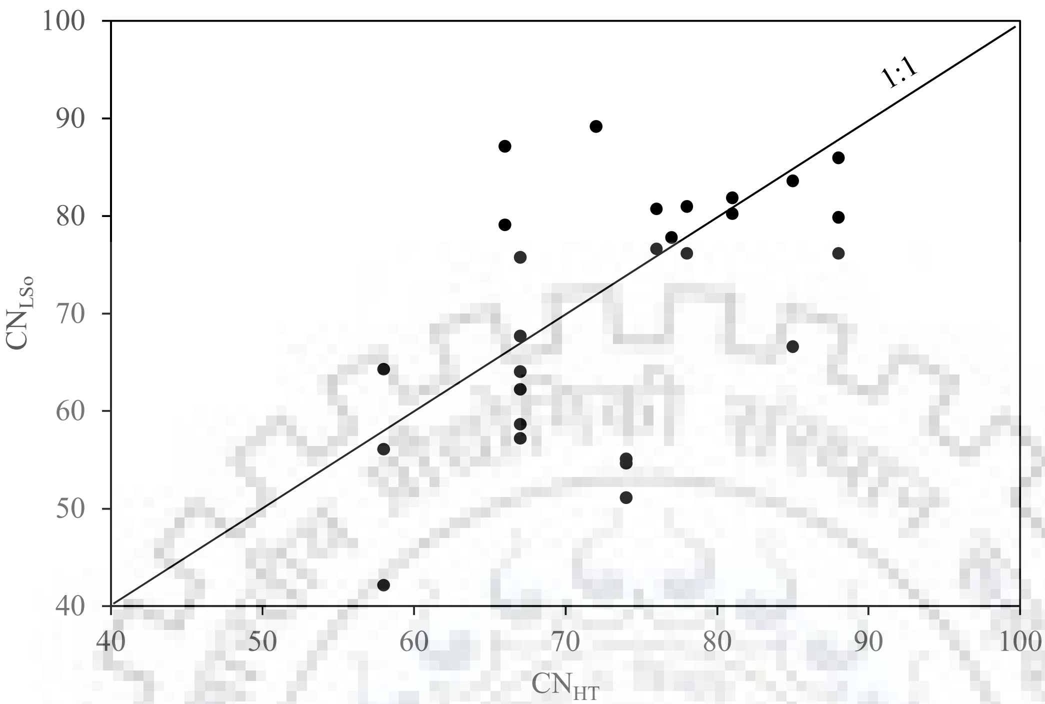

Figure 4.25 CN Plot for comparison between CN_{LSo} and CN_{HT}

The comparison of CN_{HT} with CN_{LSMn} and CN_{LSMo} are given in Figures 4.26 and 4.27 respectively. As in Figure 4.26, CN_{HT} and CN_{LSMn} do not compare well, for 17 out of 27 CN_{LSMn}–values are higher than CN_{HT}; both exhibiting greater difference for values lower than 75, consistent with that reported by Stewart et al. (2012). However, the difference diminishes with increasing values. The group of CN_{HT} lower than 75 shows a higher PBIAS (=-12.84%) than the group of CN_{HT} higher than 75 (=1.03%). Overall, pair–wise comparison showed a significant difference ($p<0.05$) to exist between CN_{HT} and CN_{LSMn} means. Such an inference is consistent with the general notion that the existing SCS–CN method performs better for high P–Q (or CN) events.

From Figure 4.27, CN_{HT} with CN_{LSMo} compare similarly as in Figure 4.26. However, PBIAS of the group of CN_{HT} lower than 75 is -14.87% compared to 0.12% for the group higher than 75.

Figures 4.28 and 4.29a & 4.29b show a plot of CN_m with CN_{LS} and CN_{LSM} for both natural and ordered P-Q datasets. The difference is noticeable between CN_m and CN_{LSM} (or CN_{LS}) for lower CN values. As shown in Table 4.8 and Figures 4.28 and 4.29, CN_m are higher than that of both CN_{LSM} and CN_{LS}, consistent with those reported in literature (D’Asaro and Grillone 2012; D’Asaro et al. 2014; Stewart et al. 2012).

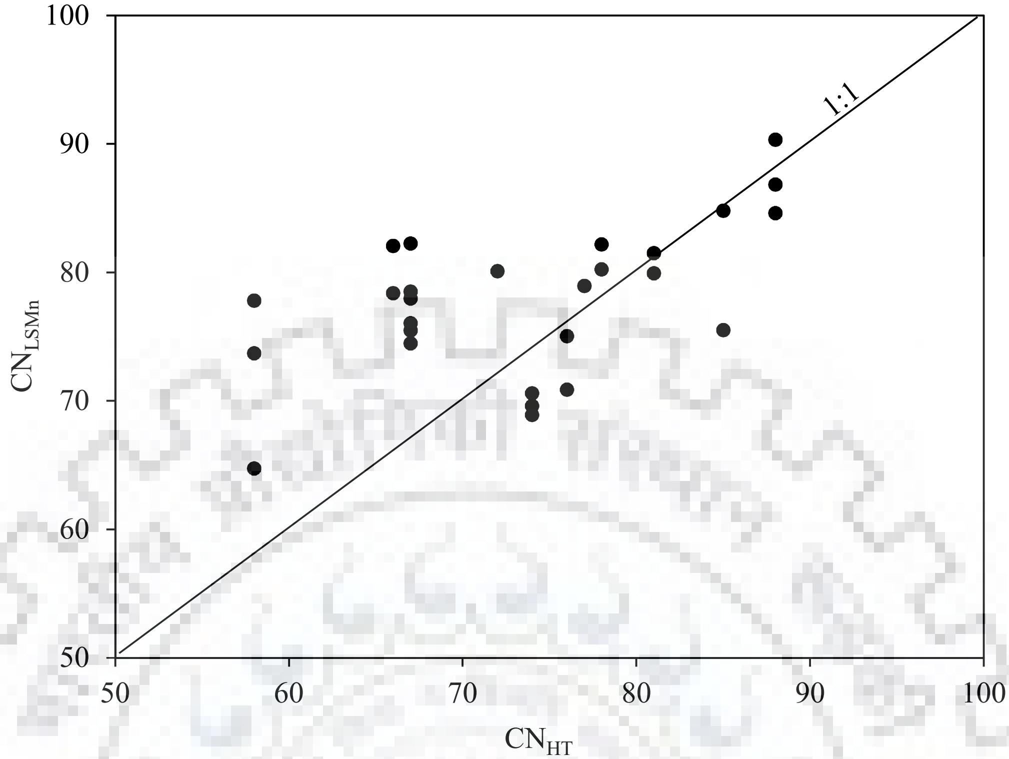

Figure 4.26 CN comparison plot for CN_{LSMn} vs CN_{HT}

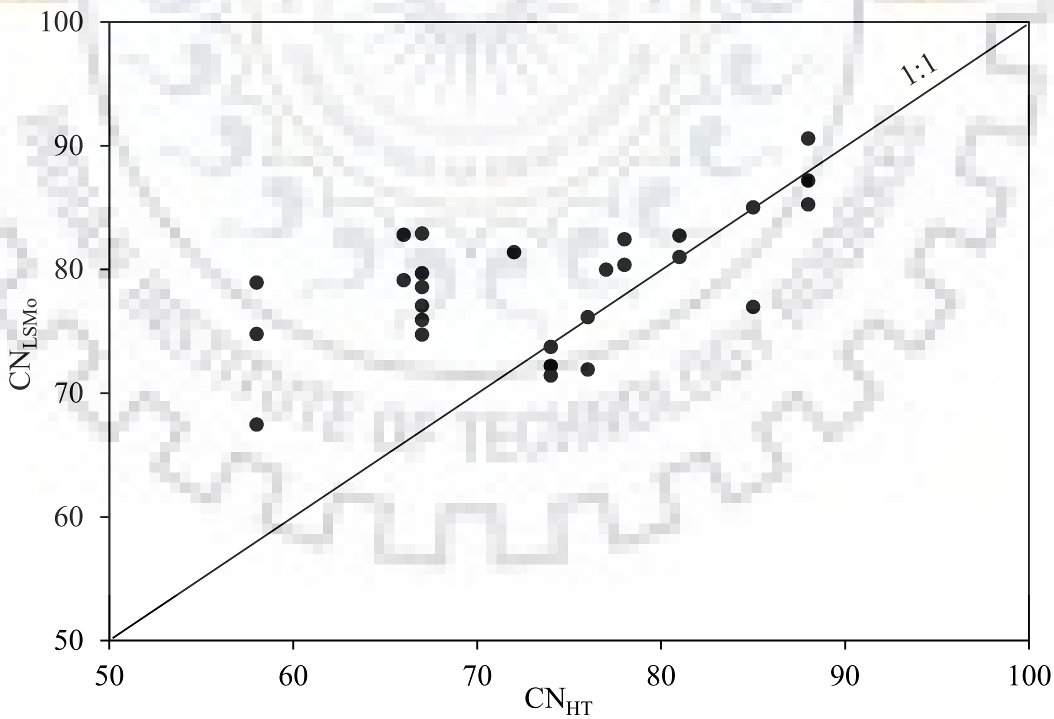

Figure 4.27 CN comparison plot for CN_{LSMo} vs CN_{HT}

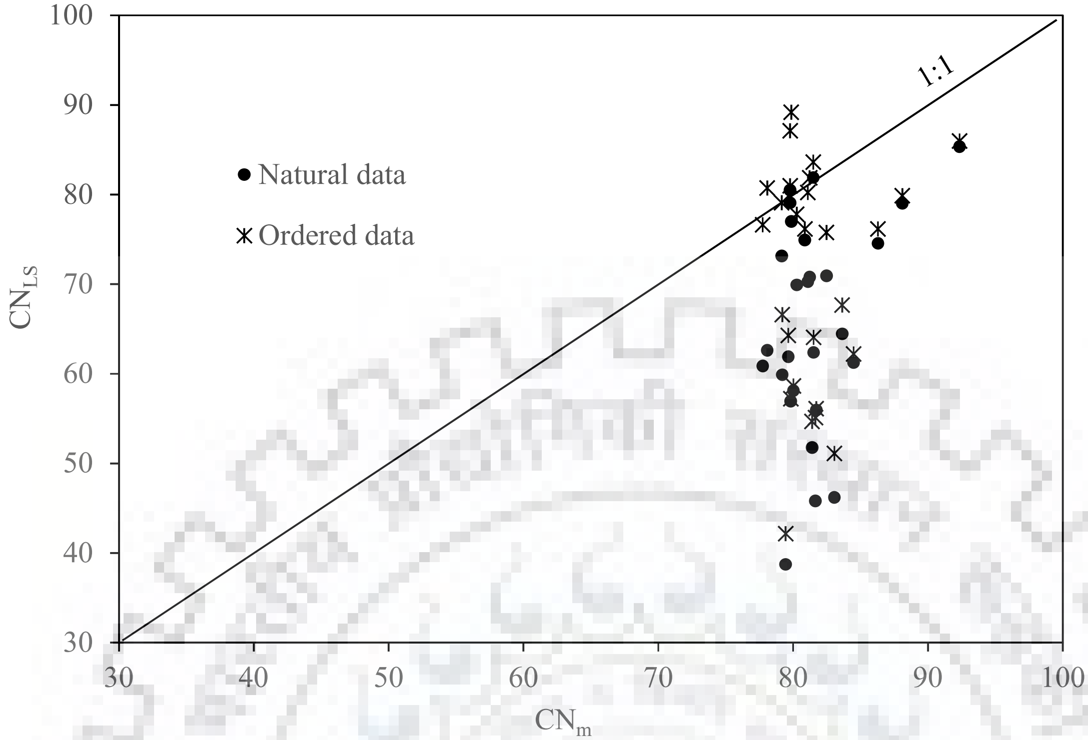

Figure 4.28 CN comparison plot for CN_{LS} vs CN_m

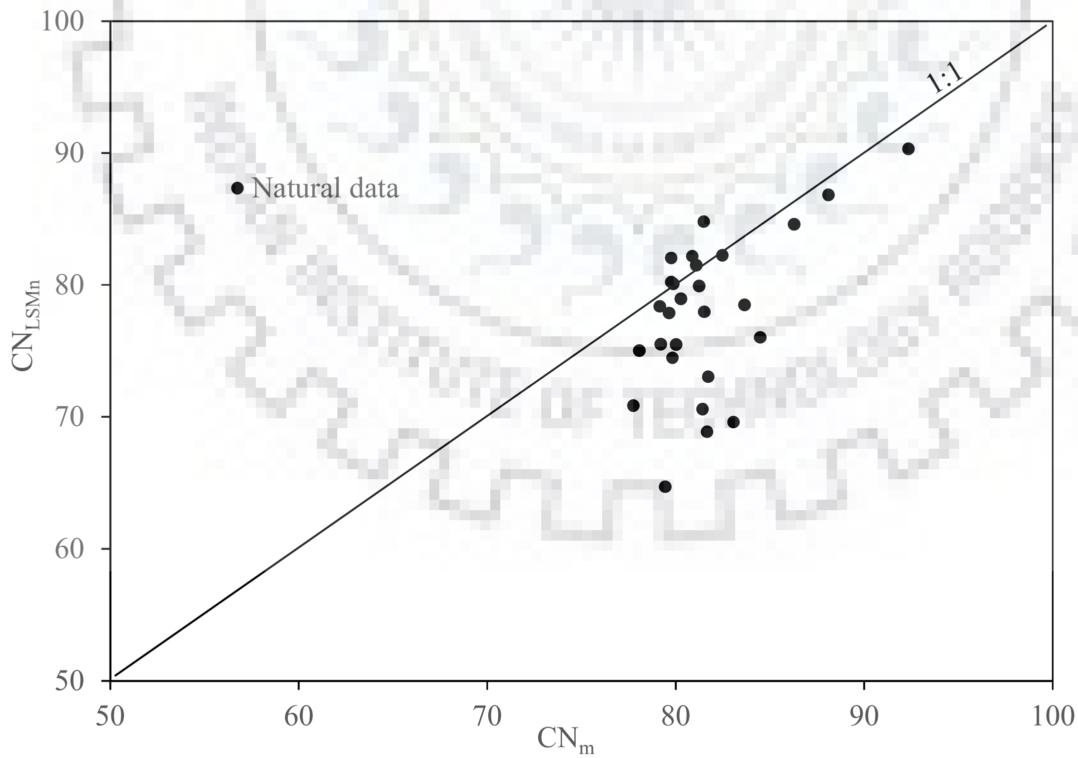

Figure 4.29a CN comparison plot of CN_{LSM} vs CN_m for natural datasets

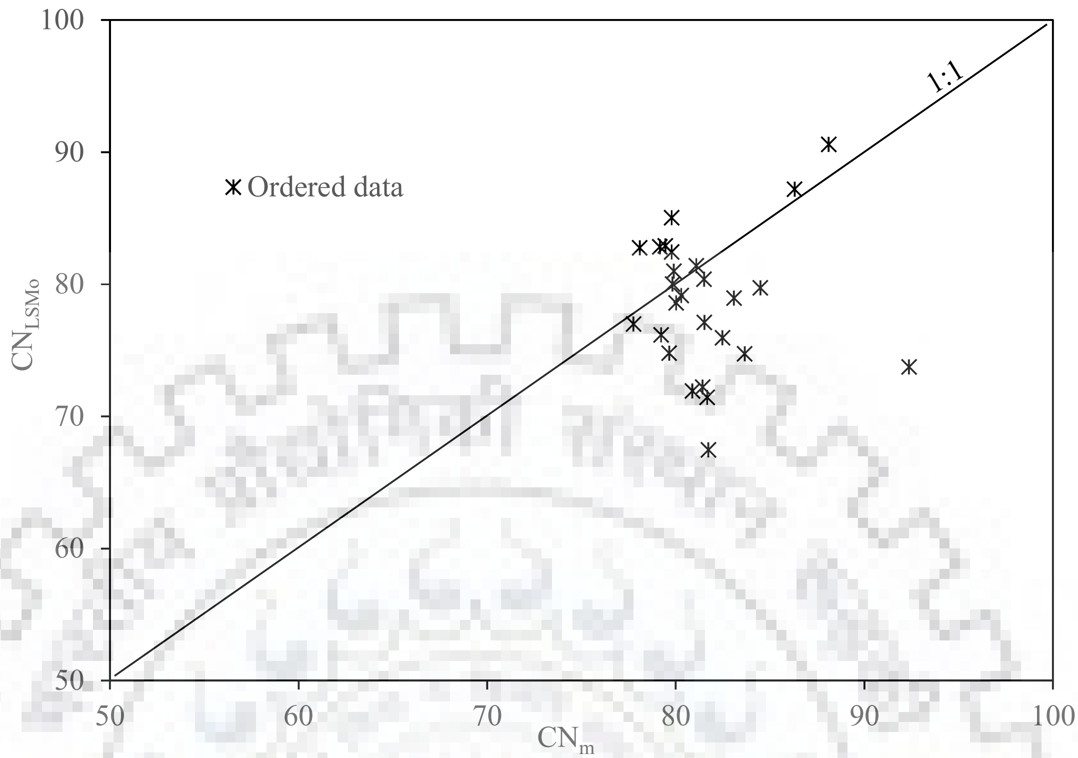

Figure 4.29b CN comparison plot of CN_{LSM} vs CN_m for ordered datasets

To check the accuracy of CNs in estimation of runoff from the studied agricultural plots, runoff was estimated by using all the four sets of CNs, viz., CN_{HT}, CN_m, CN_{LSMn} and CN_{LSMo} for the data of 24 plots (plots 1–24 of Table 4.8). In order to estimate the runoff, it is required to correct the AMC of CNs based on P_5 values. Therefore, plot nos. 25–27 were excluded from comparison due to unavailability of their corresponding P_5 data. The AMC correction formulae as given in Equations 3.12 & 3.13 have been used for estimating the CN_1 and CN_3 from CN_{HT}, CN_m, CN_{LSMn} and CN_{LSMo}. Here notable point is that CN_{LSn} and CN_{LSo} were excluded from this analysis because there are no formulae available for estimating the CN_1 and CN_3 from CN_2 for λ value other than 0.2.

Table 4.9a and 4.9b shows the performance statistic along with the resulting RMSE, R^2 and E values, used to test the accuracy of all four sets of CNs in runoff estimation. As seen from this table, CN_{HT} values derived from plot characteristics do not estimate the runoff from these plots as accurately as do the other CNs. As seen from these tables, both E and R^2 show the estimated runoff based on all four CNs to be poorly matching (except for a few plots) the observed runoff. In general, CN_{LSMo} performed the best of all, and CN_m better than CN_{HT}.

Table 4.9a Performance statistic for runoff estimation using CN_{HT} and CN_m

Plot No.	NEH-4 Table (λ=0.20)				NEH-4 method (natural data, λ=0.20)		
	CN_{HT}	R^2	E	RMSE (mm)	CN_m	E	RMSE (mm)
1	81	0.543	0.451	8.631	79.93	0.465	8.518
2	72	0.154	-0.042	13.029	80.09	0.371	10.126
3	81	0.505	0.365	9.708	81.51	0.373	9.649
4	76	0.597	0.357	8.875	75.05	0.439	8.290
5	85	0.601	0.551	7.429	75.52	0.387	8.679
6	76	0.641	0.496	6.454	70.87	0.596	5.780
7	78	0.805	0.321	10.935	82.19	0.544	8.966
8	78	0.921	0.474	9.307	80.24	0.606	8.062
9	85	0.884	0.751	7.680	84.81	0.499	10.909
10	66	0.025	-0.264	16.483	82.06	0.426	11.106
11	66	0.013	-0.231	13.397	78.38	0.530	8.276
12	77	0.660	0.305	10.284	78.95	0.526	8.499
13	67	0.001	-1.296	8.240	74.49	-1.047	7.779
14	67	0.092	-1.120	9.828	78.5	-0.195	7.377
15	67	0.030	-1.157	8.710	76.05	-1.193	8.784
16	67	0.056	-0.349	9.536	77.97	0.421	6.157
17	67	0.023	-0.504	8.204	75.49	0.011	6.553
18	67	0.134	-0.263	12.027	82.26	0.750	5.276
19	58	0.040	-1.376	5.484	64.73	-3.604	7.448
20	58	0.001	-1.160	8.189	73.07	-1.054	7.802
21	58	0.000	-0.752	10.503	77.88	0.015	7.740
22	74	0.135	-2.033	6.990	69.61	-3.319	10.089
23	74	0.290	-0.146	6.340	68.9	-0.929	8.100
24	74	0.390	-0.305	5.879	70.59	-1.390	7.956
Mean		0.314	-0.289	9.256		-0.241	8.247

Table 4.9b Performance statistic for runoff estimation using CN_{LSMn} and CN_{LSMo}

Plot No.	LSM (Natural data, λ=0.20)				LSM (Ordered data, λ=0.20)			
	CN_{LSMn}	R^2	E	RMSE (mm)	CN_{LSMo}	R^2	E	RMSE (mm)
1	79.93	0.514	0.387	9.123	81.01	0.543	0.452	8.625
2	80.09	0.470	0.382	10.035	81.41	0.518	0.451	9.456
3	81.51	0.520	0.400	9.442	82.75	0.550	0.474	8.837
4	75.05	0.564	0.296	9.283	76.16	0.602	0.367	8.805
5	75.52	0.414	0.172	10.081	76.99	0.638	0.560	7.355
6	70.87	0.313	0.152	8.372	71.94	0.437	0.226	7.999
7	82.19	0.868	0.643	7.925	82.46	0.872	0.663	7.700
8	80.24	0.943	0.640	7.706	80.39	0.943	0.651	7.589
9	84.81	0.883	0.739	7.869	85.04	0.884	0.754	7.637
10	82.06	0.759	0.573	9.578	82.83	0.766	0.622	9.040
11	78.38	0.767	0.477	8.728	79.16	0.778	0.530	8.275
12	78.95	0.701	0.437	9.256	80.01	0.718	0.508	8.658
13	74.49	0.141	-0.984	7.659	74.74	0.316	-0.577	6.829
14	78.5	0.451	-0.181	7.336	79.72	0.481	-0.121	7.145
15	76.05	0.274	-0.598	7.498	77.10	0.304	-0.557	7.401
16	77.97	0.490	0.336	6.688	78.59	0.612	0.598	4.252
17	75.49	0.313	-0.038	6.816	75.94	0.331	-0.019	6.754
18	82.26	0.779	0.748	5.377	82.92	0.795	0.775	5.077
19	64.73	0.000	-1.548	5.680	67.47	0.060	-1.356	5.461
20	73.07	0.110	-0.813	7.503	74.79	0.165	-0.743	7.357
21	77.88	0.310	-0.032	8.061	78.96	0.346	0.021	7.851
22	69.61	0.047	-1.791	6.705	71.43	0.081	-1.848	6.773
23	68.9	0.154	-0.224	6.553	72.23	0.177	-0.378	6.953
24	70.59	0.315	-0.288	5.839	73.76	0.386	-0.386	5.860
mean		0.463	-0.005	7.880	-	0.513	0.069	7.404

The reason for CN_{HT} to have performed most poorly is that these are the generalized values derived from small watersheds of United States for high magnitude P-Q events (or high CN values). As seen from Tables 4.9a and 4.9b, for 15 out of 24 plots, a simple mean of the observed runoff was a better estimate (due to negative E values) than that due to CN_{HT}. CN_{HT} estimates reasonably correlated (E > 0.50) with observed runoff for only two plots. Similarly, the mean of observed runoff series was a better estimate for 8 out of 24 plots than that due to CN_{LSn} or CN_{LSMo}. The runoff estimated by CN_{LSMn} and CN_{LSMo} was reasonably close (E > 0.50) to the observed for 5 and 9 plots, respectively.

From Figures 4.23 & 4.26–4.27, and Tables 4.9a & 4.9b, it is evident that the general agreement between CN_{HT} and CN_m, CN_{LSMn} or CN_{LSMo} is poor, consistent with that reported elsewhere (D'Asaro et al. 2014; Fennessey 2000; Feyereisen et al. 2008; Hawkins 1984; Hawkins and Ward 1998; Sartori et al. 2011; Stewart et al. 2012; Titmarsh et al. 1989, 1995, 1996; Tedela et al. 2012; Taguas et al. 2015). As an alternative to CN_{HT}, the best CN-values based on the highest R^2, E (or lowest RMSE) as given in Tables 4.9a & 4.9b are suggested for each of 24 plots. As seen, CN_{LSMo} ranked first for 20 out of 24 plots whereas each of CN_{HT} and CN_{LSMn} ranked first on only 2 plots. Therefore, CN_{LSMo} are suggested as a preference over CN_{HT} for use in areas with similar plot characteristics and climatic conditions.

4.2.4 Relationship between ordered (i.e. CN_{LSMo}) and natural (i.e. CN_{LSMn}) data CNs

The graphical representation between ordered CNs (i.e. CN_{LSMo}) and natural data CNs (i.e. CN_{LSMn}) is given in Figure 4.30. As expected, CN values derived from ordered data (CN_{LSMo}) are higher than CN values derived from natural data (CN_{LSMn}). From this figure, CN_{LSMo} values are seen to be higher than CN_{LSMn}, consistent with that reported elsewhere (Ajmal et al. 2015a; D'Asaro and Grillone 2012; D'Asaro et al. 2014; Hawkins et al. 2009; Stewart et al. 2012). It is for obvious reasons that the former CN values derived from frequency matched P and Q data will always be higher than the latter ones derived from natural data as Q corresponding to a P of certain frequency will always be higher than or equal to the observed Q. CN values derived for individual plots using ordered dataset differ from 0.15 to 3.22 CN compared with those derived from natural data. The trend between CN_{LSMo} and CN_{LSMn} allow a conversion as given in Equation 4.1:

$$CN_{LSMo} = 0.005\,(CN_{LSMn})^2 + 0.182\,CN_{LSMn} + 36.83;\ R^2 = 0.990;\ SE = 0.552\ CN \qquad (4.1)$$

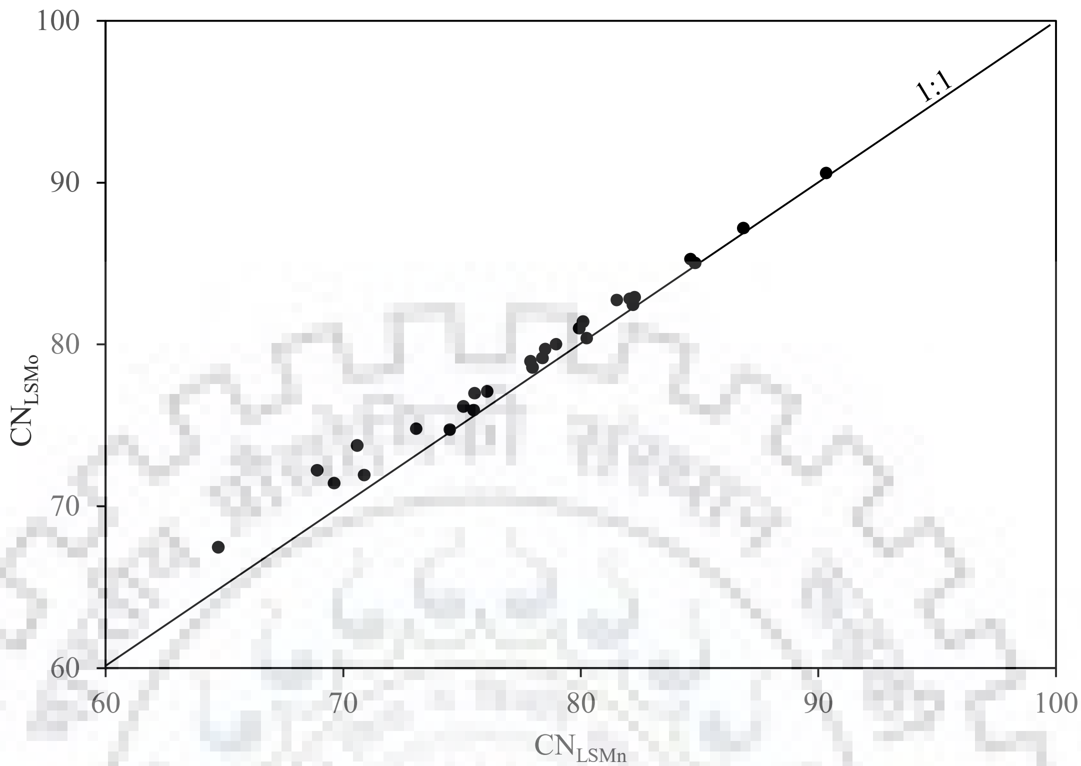

Figure 4.30 CN plot for CN_{LSMo} vs CN_{LSMn}

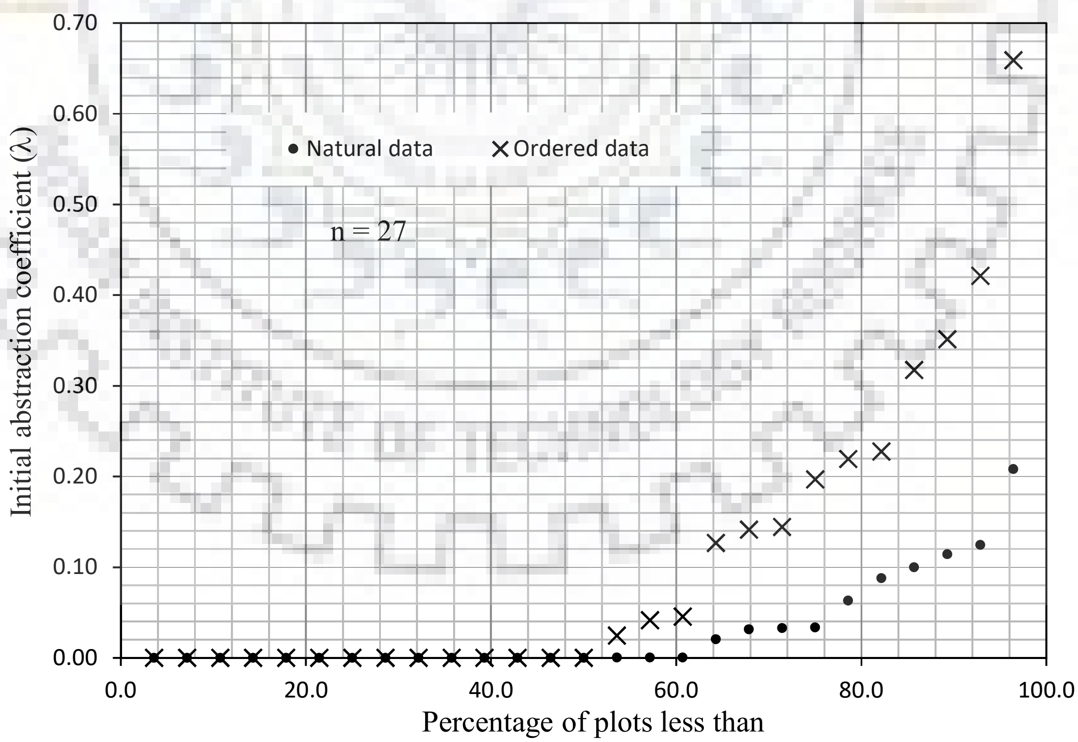

Figure 4.31 Cumulative frequency distribution of model fitted λ-values for 27 plot-datasets

4.3 DERIVATION OF INITIAL ABSTRACTION RATIO (λ) VALUES

The optimized λ-values derived for different P-Q (both ordered and natural) data sets observed at 27 runoff plots are shown in Table 4.8. As seen, the optimized λ–values derived for both natural (ranging from 0 to 0.208) and ordered (ranging from 0 to 0.659) P–Q datasets are seen to vary widely from plot to plot with 0 as the most frequent value. The cumulative frequency distribution of λ-values for both datasets given in Figure 4.31 shows that λ values are larger for ordered data, the distribution is skewed, and most λ-values (out of 27, 26 for natural and 21 for ordered P–Q datasets) are less than the standard λ=0.2 value.

The mean and median λ-values are 0.030 & 0 for natural, and 0.108 & 0 for ordered data, quite different from standard λ = 0.20, but consistent with the results of other studies carried out elsewhere (Ajmal et al. 2015a; Baltas et al. 2007; D'Asaro and Grillone 2012; D'Asaro et al. 2014; Elhakeem and Papanicolaou 2009; Fu et al. 2011; Hawkins and Khojeini 2000; Hawkins et al. 2002; Menberu et al. 2015; Shi et al. 2009; Yuan et al. 2014; Zhou and Lei 2011).

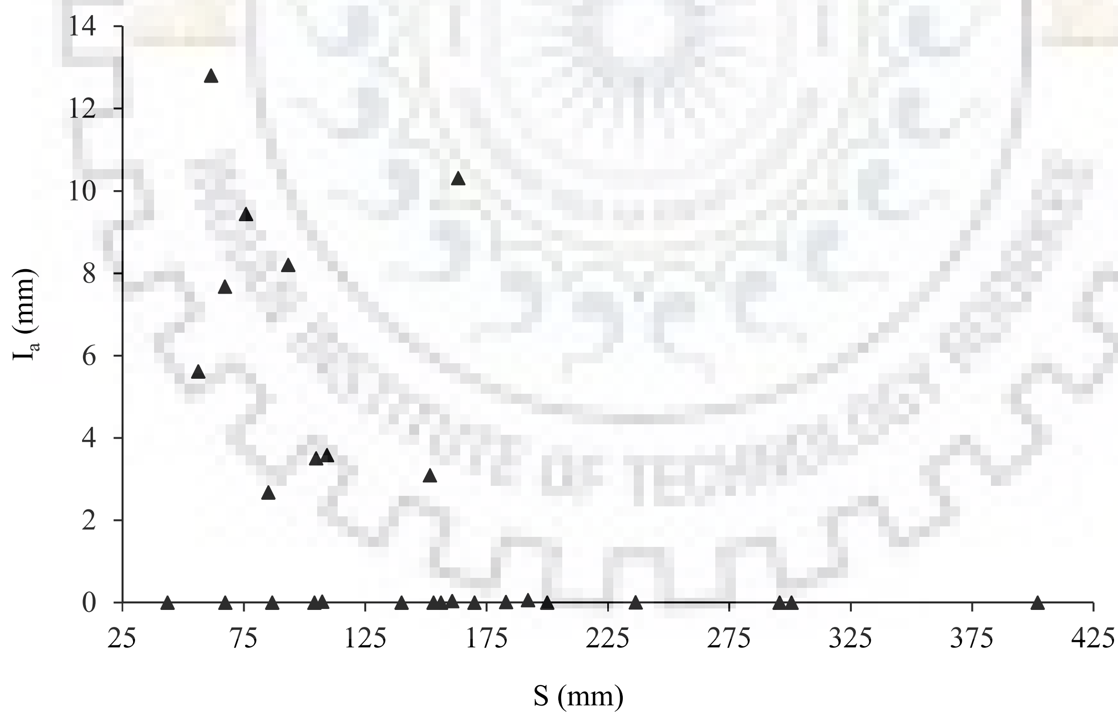

Figure 4.32 Relationship between I_a and S for 27 plots natural occurred P-Q datasets

In addition, the existence of I_a-S relationship for different plots was also investigated using the whole data of 27 plots. In contrast to the existing notion, I_a when plotted against S (Figures 4.32 and 4.33) exhibited no correlation for both natural and ordered datasets, consistent with the findings of Jiang (2001).

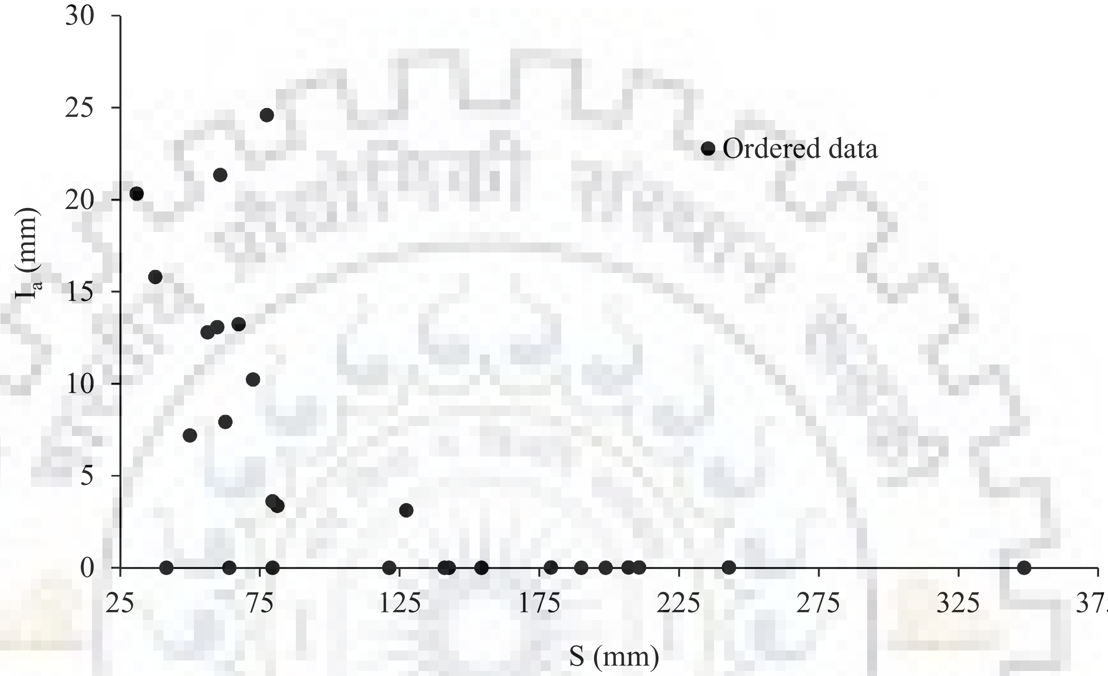

Figure 4.33 Relationship between I_a and S for 27 plots ordered P-Q datasets

4.3.1 Performance evaluation of the λ based Proposed Model

Table 4.10 shows the performance indices (viz., R^2, E, RMSE, n_t and PBIAS) for fitting of Equation 3.5 with $\lambda = 0.2$ (existing SCS-CN method i.e. $M_{0.2}$) and $\lambda = 0.03$ (proposed method i.e. $M_{0.03}$). As seen from the table, the runoff estimates with λ=0.03 ($M_{0.03}$) provides larger E and lower RMSE for 26 out of 27 plots than those due to λ=0.2 ($M_{0.2}$). Based on E, performance of the existing SCS–CN method ($M_{\lambda=0.2}$) is seen to be unsatisfactory, satisfactory, good, and very good on the data of 12, 5, 3, and 7 plots out of 27 plots, respectively. On the other hand, the performance of the proposed method ($M_{0.03}$) is unsatisfactory, satisfactory, good, and very good on 8, 5, 5 and 9 plots out of 27 plots, respectively. Based on the mean values of E, $M_{0.03}$ performed satisfactorily (E = 0.565) compared to $M_{0.2}$ (E = 0.392).

The positive PBIAS values resulting for both the methods indicate that the existing SCS–CN method (i.e. $M_{0.2}$) underestimated the average runoff. However, these values for

Table 4.10 Performance statistic for runoff estimation using Equation 3.5 with λ = 0.2 (model $M_{0.2}$) and λ = 0.03 (model $M_{0.03}$) (Used all runoff producing events)

Plot No.	n	Existing SCS-CN method (λ=0.20) (model $M_{0.2}$)						Proposed method (λ=0.03) (model $M_{0.03}$)						
		CN	R^2	E	n_t	PBIAS (%)	RMSE (mm)	CN	R^2	E	n_t	PBIAS (%)	RMSE (mm)	r^2 (%)
1	18	76.16	0.701	0.626	0.69	20.04	4.71	63.65	0.739	0.726	0.03	10.22	4.04	26.74
2	18	75.24	0.695	0.657	0.76	17.17	4.62	62.29	0.721	0.718	0.97	6.16	4.19	17.78
3	18	78.91	0.634	0.556	0.55	18.78	6.05	68.03	0.666	0.648	0.94	10.68	5.38	20.72
4	12	68.01	0.899	0.875	1.97	-0.78	2.00	51.67	0.985	0.979	0.74	11.52	0.83	83.20
5	12	67.09	0.507	0.341	0.29	23.46	4.44	51.13	0.731	0.627	6.16	33.18	3.34	43.40
6	12	65.25	0.941	0.890	2.17	-41.82	1.59	45.58	0.966	0.966	0.72	2.11	0.89	69.09
7	13	82.84	0.925	0.918	2.65	7.48	3.52	75.46	0.928	0.928	4.69	-1.47	3.29	12.20
8	13	80.84	0.969	0.969	4.97	1.20	2.10	72.66	0.960	0.952	2.91	-10.80	2.64	-54.84
9	13	82.80	0.936	0.928	2.88	8.55	3.27	75.41	0.941	0.941	3.76	-0.33	2.93	18.06
10	13	77.11	0.890	0.875	1.95	11.59	3.33	66.42	0.909	0.910	3.33	1.65	2.83	28.00
11	13	74.93	0.856	0.849	1.69	8.64	3.43	62.95	0.873	0.873	2.48	-0.73	3.14	15.89
12	13	74.91	0.766	0.738	1.04	17.17	4.48	63.00	0.792	0.788	1.93	8.37	4.03	19.08
13	13	74.49	0.808	0.509	0.49	21.91	3.81	60.85	0.810	0.724	1.27	11.09	2.86	43.79
14	13	78.50	0.407	-0.217	-0.06	23.26	7.45	67.44	0.419	0.096	0.98	17.33	6.42	25.72

Table 4.10 (continued)

Plot No.	n	Existing SCS-CN method (λ=0.20) (model $M_{0.2}$)						Proposed method (λ=0.03) (model $M_{0.03}$)						r^2 (%)
		CN	R^2	E	n_t	PBIAS (%)	RMSE (mm)	CN	R^2	E	n_t	PBIAS (%)	RMSE (mm)	
15	13	76.05	0.518	-0.015	0.03	24.58	5.98	63.41	0.532	0.299	0.09	16.08	4.97	30.94
16	11	77.97	0.612	0.468	0.46	16.72	5.80	66.46	0.624	0.598	0.24	7.63	5.13	24.44
17	11	75.49	0.804	0.679	0.85	18.97	3.73	62.45	0.812	0.796	0.65	6.47	2.98	36.45
18	11	82.26	0.657	0.608	0.68	8.48	6.61	73.69	0.661	0.655	1.32	2.93	6.20	11.99
19	11	67.48	0.415	-0.390	-0.11	45.43	4.44	50.26	0.480	0.136	0.79	25.33	3.50	37.84
20	11	73.70	0.489	-0.089	0.00	33.27	5.68	59.67	0.517	0.282	0.13	20.13	4.61	34.07
21	11	77.80	0.440	0.152	0.14	23.24	7.18	66.13	0.456	0.347	0.24	14.85	6.30	23.00
22	13	69.61	0.330	-0.718	-0.21	39.32	5.26	53.13	0.362	-0.151	0.30	24.22	4.31	33.00
23	11	69.63	0.127	-0.554	-0.16	46.94	7.11	53.76	0.161	-0.178	-0.03	29.67	6.19	24.20
24	13	70.59	0.155	-0.676	-0.20	38.47	6.66	54.49	0.189	-0.228	-0.03	25.20	5.70	26.73
25	11	90.36	0.675	0.484	0.46	7.84	6.57	86.50	0.678	0.554	-0.06	7.41	6.11	13.57
26	11	86.84	0.716	0.622	0.71	7.38	5.08	80.88	0.731	0.690	0.57	5.54	4.61	17.99
27	11	84.62	0.606	0.499	0.48	8.98	5.42	77.05	0.628	0.584	0.88	6.54	4.94	16.97
Mean		76.28	0.647	0.392	0.93	16.90	4.83	64.24	0.677	0.565	1.36	10.78	4.16	28.45

$M_{0.03}$ were much lower than those due to $M_{0.2}$, indicating an improvement in model performance. $M_{\lambda=0.2}$ performance was unsatisfactory, satisfactory, good, and very good on the data of 6, 10, 1, and 9 plots out of 27 plots, respectively. On the other hand, $M_{0.03}$ performance was unsatisfactory, satisfactory, good, and very good on 4, 4, 6 and 13 plots out of 27 plots, respectively.

Thus, based on the mean PBIAS values, $M_{0.03}$ performed good (=10.78) whereas M1 performed satisfactorily (=16.90). For further analysis based on nt, $M_{0.2}$ exhibited satisfactory or good performance on 11 plots out of 27 plots. The performance improved to 16 plots when used $M_{0.03}$. The improved $M_{0.03}$ model performance is also supported by the higher r^2-value. As shown in Figure 4.34, the significant improvement in E (or r^2) using $M_{0.03}$ model was observed in 26 out of the 27 study plots. On the contrary, the runoff predictions by $M_{0.03}$ model were debased ($r^2 \leq 0$) in only one plot. Overall, as seen from Table 4.10 and Figure 4.36, $M_{0.03}$ performed better than $M_{\lambda=0.2}$.

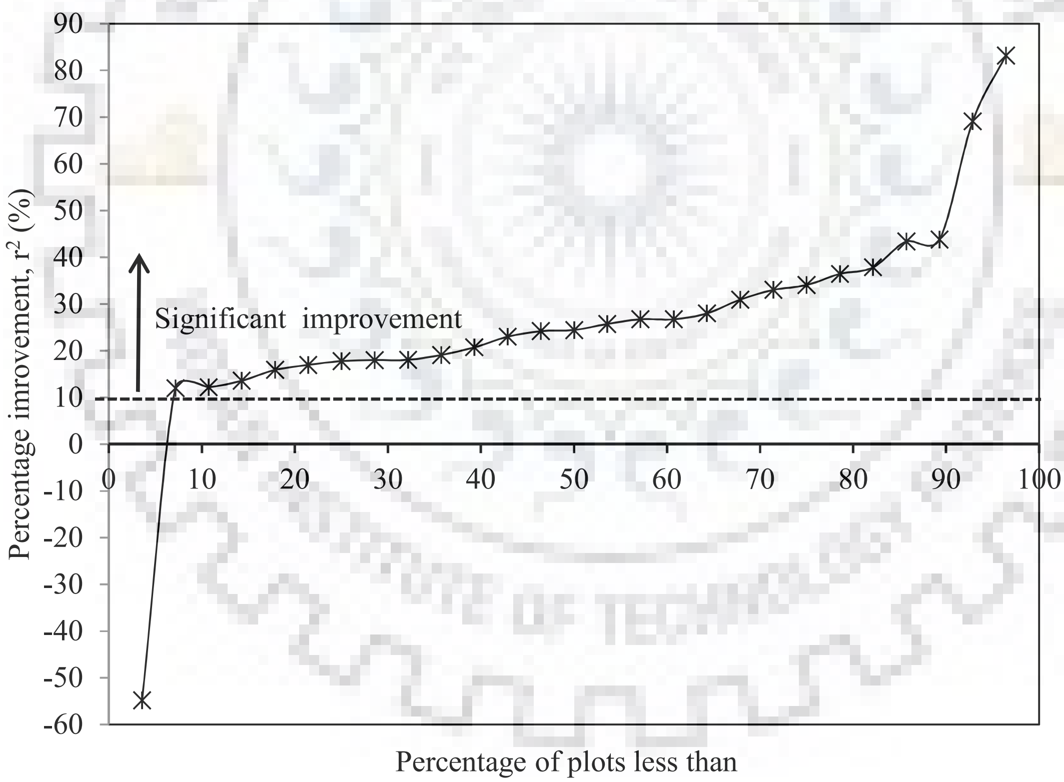

Figure 4.34 The cumulative frequency distribution of improvement in E using r^2 criteria

4.3.2 Sensitivity of CN and runoff to initial abstraction ratio (λ)

This sensitivity analysis was carried out using the data of only 5 plots. To this end, as shown in Figure 4.35, for a plot dataset and a given λ-value, S (or CN) was optimised using Equation

3.5. As seen, the rising trends are similar to each plot. In general, CN is seen to increase with λ. It is for the reason that for a given P-Q data, an increase in λ would require an increase in CN (or decrease in S) to obtain the same Q-value for a given P. Furthermore, variation in CN narrows down with increasing λ-values.

To indicate the most appropriate λ-value, variation of E with λ was plotted as shown in Figure 4.36. In general, E showed a decreasing trend with λ for all 5 plots, consistent with the findings of Woodward et al. (2004) and Yuan et al. (2014). It implies that low λ-value provides a better prediction of runoff, and vice versa. To show the sensitivity of λ to runoff (employing Equation 3.15), for a given CN=78.92 and P=30 mm, the estimated runoff increased by 165% when λ decreased (by 90%) from 0.2 to 0.02 consistent with the findings of Yuan et al. (2014) (Figure 4.37).

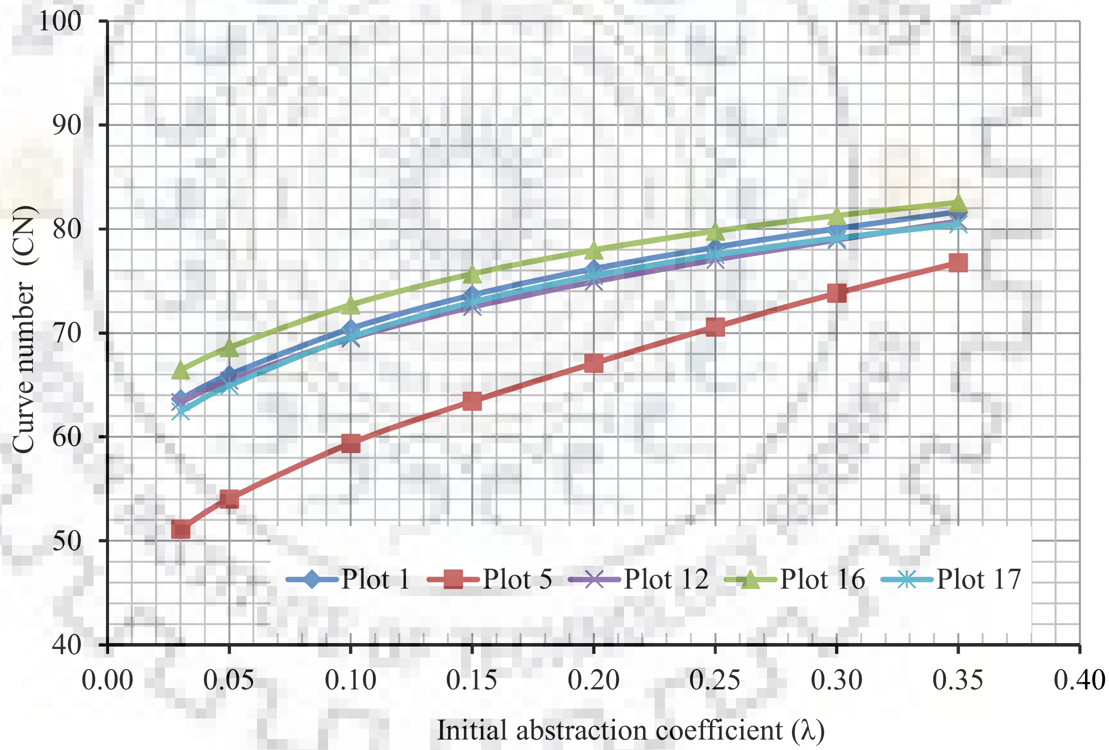

Figure 4.35 Variation in CNs (AMC-II) with λ for 5 plot-data

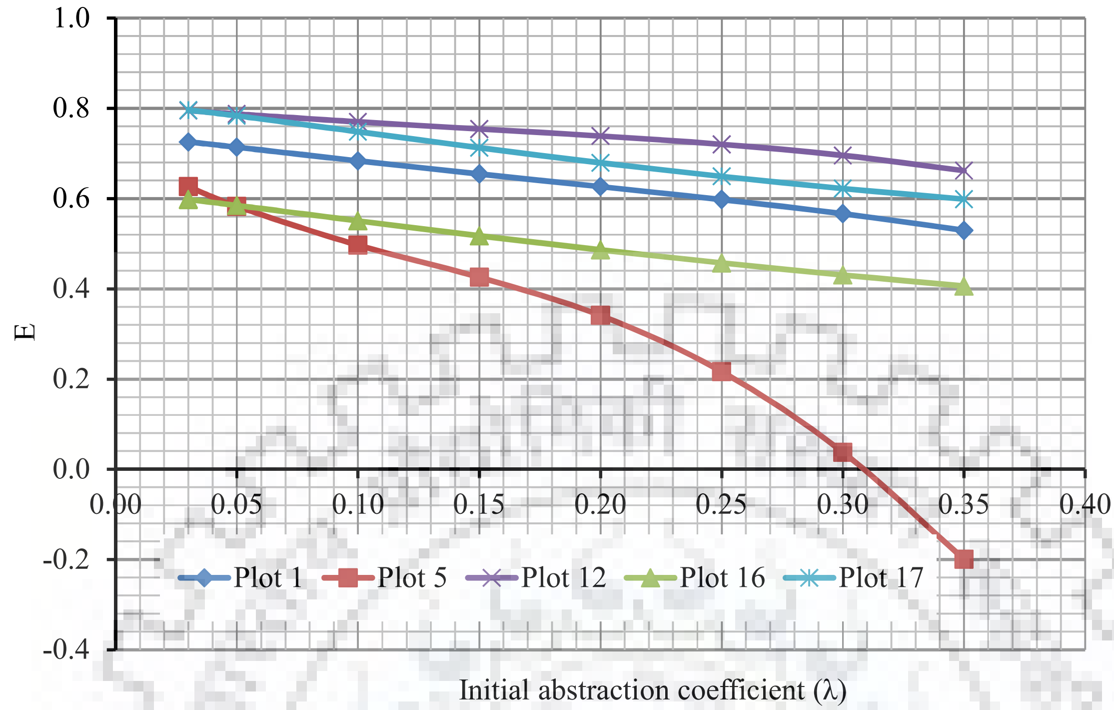

Figure 4.36 Variation in E with λ

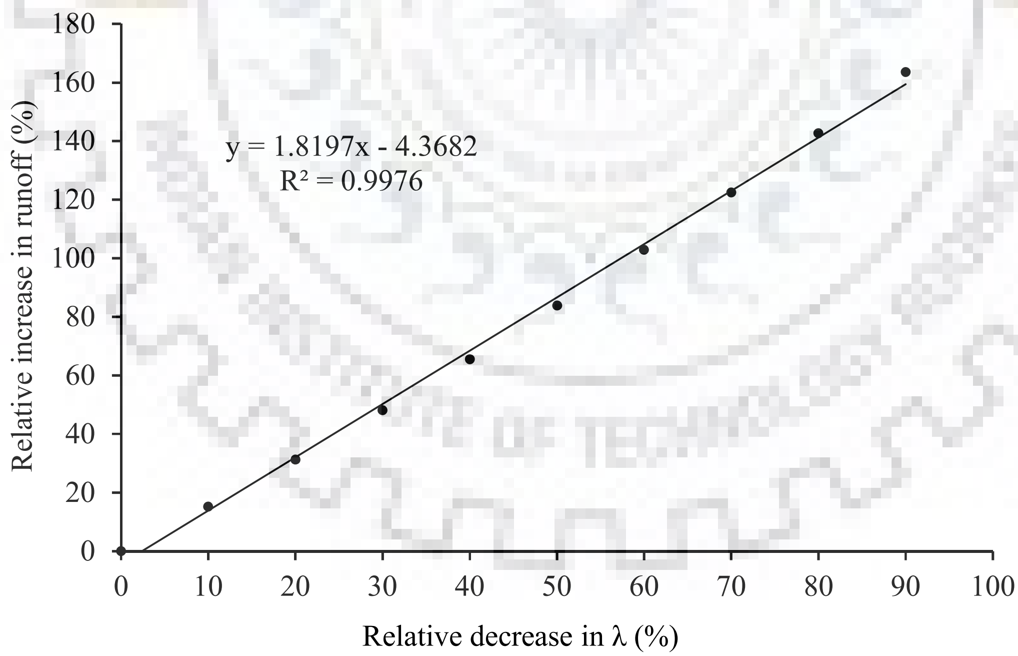

Figure 4.37 Relationship between relative increase in estimated runoff (%) vs relative decrease in λ (%)

4.3.3 Conjugate CN conversion from $CN_{0.2}$ to $CN_{0.03}$

It's commonly known that existing NEH-4 CNs are based on λ value equal to 0.2. Therefore, a transformation of CNs from λ = 0.2 to λ = 0.03 is imperative before using λ = 0.03 in runoff modeling. To this end, an empirical conversion equation based on direct least squares fitting of 27 plots natural data sets for converting CNs associated with λ = 0.2 ($CN_{0.2}$) to λ = 0.03 ($CN_{0.03}$) is proposed as follows (Figure 4.38):

$$S_{0.03} = 0.614\ (S_{0.2})^{1.248};\ R^2 = 0.9948;\ SE = 0.035\ mm \tag{4.2}$$

In Equation 4.2, maximum potential retention (S) is in mm and $S_{0.03} = S_{0.2}$ at 7.148 mm or $CN_{0.2}$ = 97.268. The plot of graphical representation of ratio of $S_{0.03}$ to $S_{0.2}$ (i.e. $S_{0.03}/S_{0.2}$) with mean ratio of Q to P (i.e. Rc_m) is given in Figure 4.39. From this figure, the $S_{0.03}/S_{0.2}$ ratio was seen to be inversely related to Rc_m.

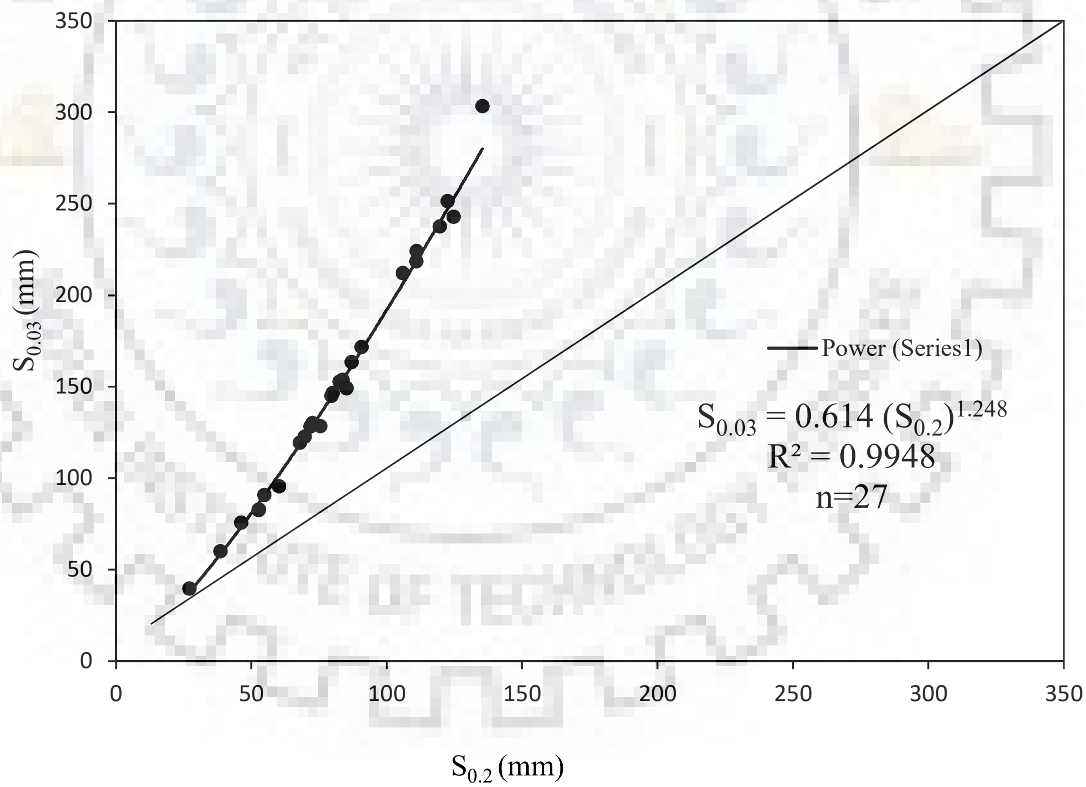

Figure 4.38 Plot of fitting between $S_{0.2}$ and $S_{0.03}$ for 27 agricultural plots data

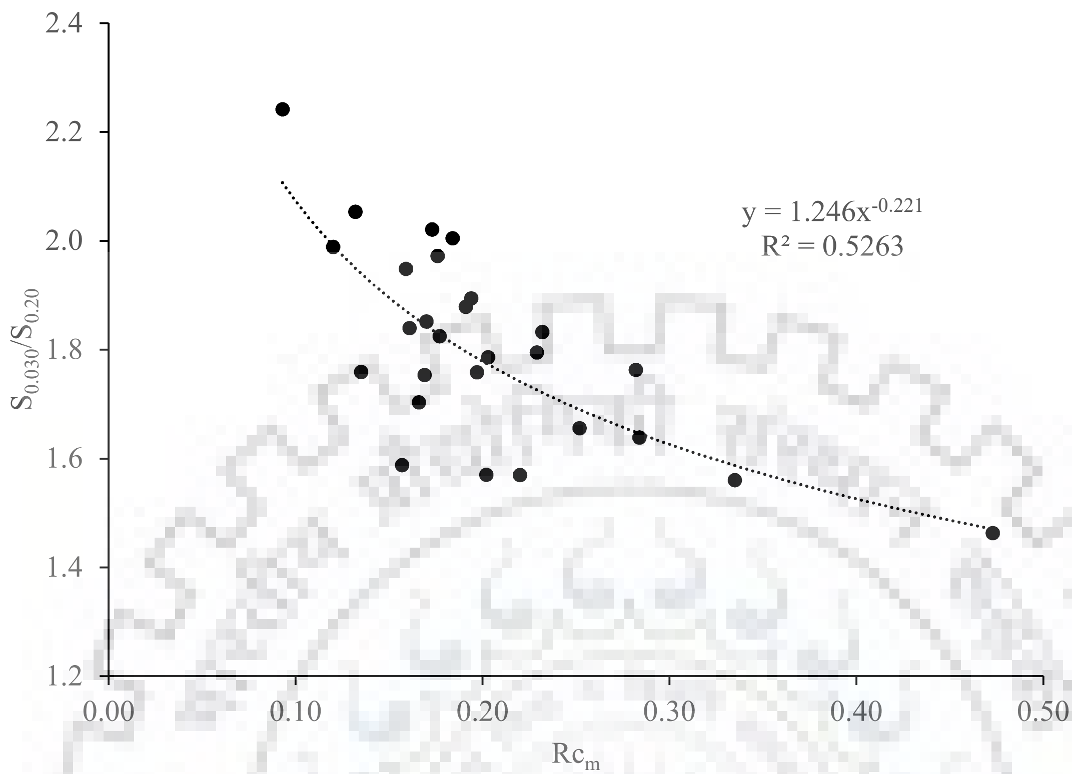

Figure 4.39 plot of ratio of $S_{0.03}$ to $S_{0.2}$ (i.e. $S_{0.03}/S_{0.2}$) vs Rc_m

The substitution of Equation 4.2 into definition of CN yields

$$CN_{0.03} = \frac{25400}{\left[254 + 0.614\left(\frac{25400}{CN_{0.2}} - 254\right)^{1.248}\right]} \tag{4.3}$$

The results of applicability of Equation 4.3 (or 4.2) for converting $CN_{0.2}$ to $CN_{0.03}$ are shown in Figure 4.40. Here, three different randomly chosen $CN_{0.2}$ values (88, 76, and 58) were converted to $CN_{0.03}$ values (83.22, 63.48, and 38.16, respectively) using purposed Equation 4.3. As seen in Figure 4.40, distinct differences in predicted runoff depths are seen with lower CN as compared to higher CN. Furthermore, a critical amount of rainfall ($P_{critical}$) was also seen for each pair of CN at which predicted runoff depths are equal. $P_{critical}$ is the rainfall below which runoff for $CN_{0.2}$ is smaller than that for $CN_{0.03}$, and above which predicted runoff for $CN_{0.2}$ is greater than that for $CN_{0.03}$.

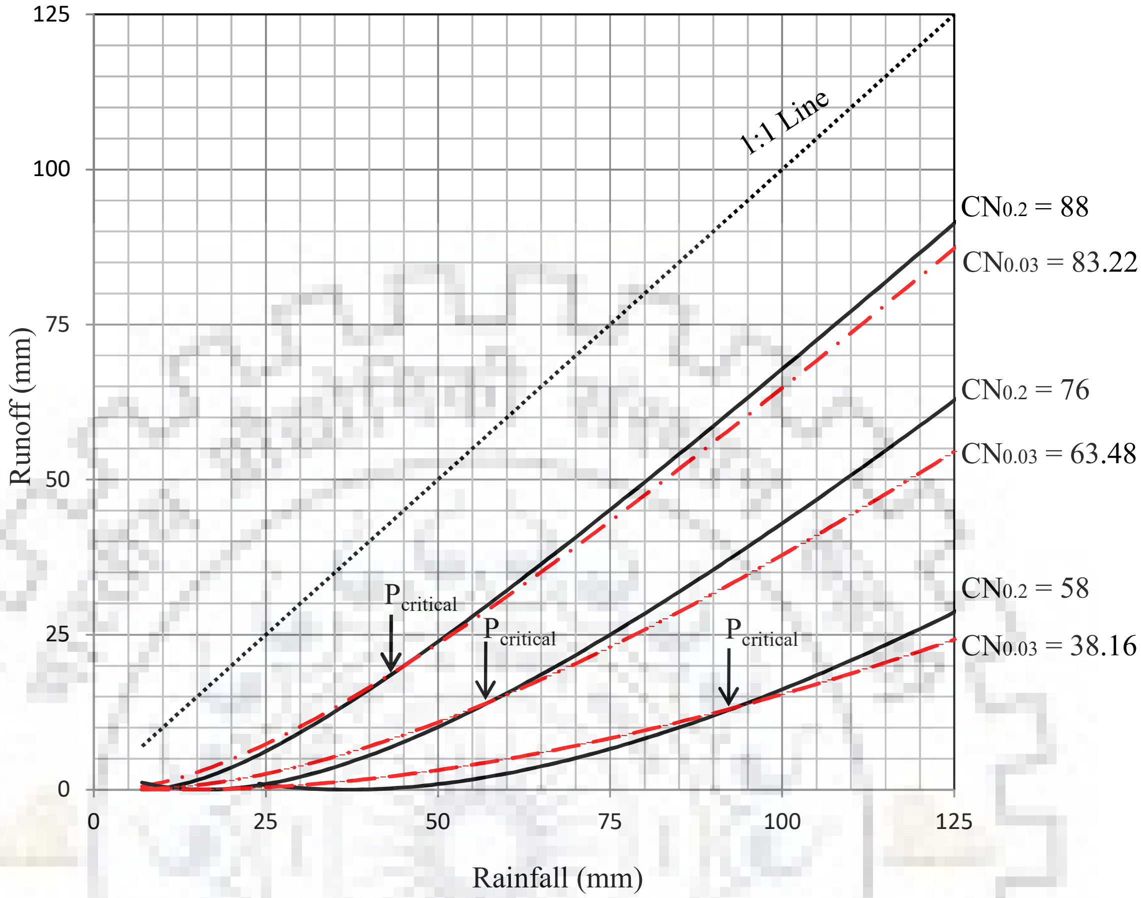

Figure 4.40 Rainfall and runoff for three pair of CNs associated with λ = 0.2 ($CN_{0.2}$) to λ = 0.03 ($CN_{0.03}$)

Lastly, the applicability of Equation 4.3 in prediction of runoff using NEH-4 tables Curve number (CN_{HT}) is also investigated. To this end, the estimated NEH-4 CNs (or $CN_{HT0.20}$) based on plot characteristics for all 27 plots were first converted to $CN_{HT0.03}$, and then employed for runoff estimation as shown in Table 4.11 along with R^2, E, and RMSE. As seen, $CN_{HT0.03}$ from Equation 4.3 estimates the runoff more accurately than did $CN_{HT0.20}$. As seen from this table, the proposed Equation 4.3 improve the mean R^2 and E from 0.314 to 0.529 and -0.289 to 0.017, respectively. The mean RMSE value was also improved from 9.256 mm to 8.259 mm. Here, it is noted that the RMSE variation (9.256–8.259 mm) might appear to be insignificant, it is however significant in volumetric terms, when the depth is multiplied by a large value of catchment area. Thus, it is clear from all the three goodness of fit indices that the proposed equation 4.3 improves the runoff estimation. Besides, the r^2-statistic (Figure 4.41) also shows the use of Equation 4.3 to have improved E in entirely 24 tested study plots. This improvement was, however, significant in 22 out of 24 study plots.

Table 4.11 Performance statistic for runoff estimation using CN_{HT} associated to λ=0.20 ($CN_{HT0.20}$) and λ=0.03 ($CN_{HT0.03}$)

Plot	CN_{HT} associated to λ=0.20				CN_{HT} associated to λ=0.03				r^2
No.	$CN_{HT0.20}$	R^2	E	RMSE (mm)	$CN_{HT0.03}$	R^2	E	RMSE (mm)	(%)
1	81	0.543	0.451	8.631	71.59	0.602	0.514	8.121	11.48
2	72	0.154	-0.042	13.029	57.28	0.465	0.143	11.187	17.75
3	81	0.505	0.365	9.708	71.59	0.579	0.448	9.054	13.07
4	76	0.597	0.357	8.875	63.48	0.706	0.476	8.010	18.51
5	85	0.601	0.551	7.429	78.23	0.623	0.615	6.880	14.25
6	76	0.641	0.496	6.454	63.48	0.710	0.595	5.783	19.64
7	78	0.805	0.321	10.935	66.69	0.895	0.424	10.075	15.17
8	78	0.921	0.474	9.307	66.69	0.958	0.545	8.663	13.50
9	85	0.884	0.751	7.680	78.23	0.902	0.759	7.569	3.21
10	66	0.025	-0.264	16.483	48.56	0.730	-0.041	14.957	17.64
11	66	0.013	-0.231	13.397	48.56	0.785	0.043	11.812	22.26
12	77	0.660	0.305	10.284	65.08	0.758	0.419	9.408	16.40
13	67	0.001	-1.296	8.240	49.96	0.207	-0.497	6.653	34.80
14	67	0.092	-1.120	9.828	49.96	0.413	-0.747	8.922	17.59
15	67	0.030	-1.157	8.710	49.96	0.304	-0.589	7.476	26.33
16	67	0.056	-0.349	9.536	49.96	0.441	0.034	8.071	28.39

Table 4.11 (continued)

Plot No.	CN_{HT} associated to λ=0.20				CN_{HT} associated to λ=0.03				r^2 (%)
	$CN_{HT0.20}$	R^2	E	RMSE (mm)	$CN_{HT0.03}$	R^2	E	RMSE (mm)	
17	67	0.023	-0.504	8.204	49.96	0.351	0.030	6.588	35.51
18	67	0.134	-0.263	12.027	49.96	0.591	-0.023	10.822	19.00
19	58	0.040	-1.376	5.484	38.16	0.300	-0.513	4.377	36.32
20	58	0.001	-1.160	8.189	38.16	0.135	-0.932	7.743	10.56
21	58	0.000	-0.752	10.503	38.16	0.170	-0.699	10.343	3.03
22	74	0.135	-2.033	6.990	60.35	0.256	-0.905	5.539	37.19
23	74	0.290	-0.146	6.340	60.35	0.367	0.158	5.434	26.53
24	74	0.390	-0.305	5.879	60.35	0.447	0.156	4.729	35.33
	Mean	0.314	-0.289	9.256	-	0.529	0.017	8.259	23.74

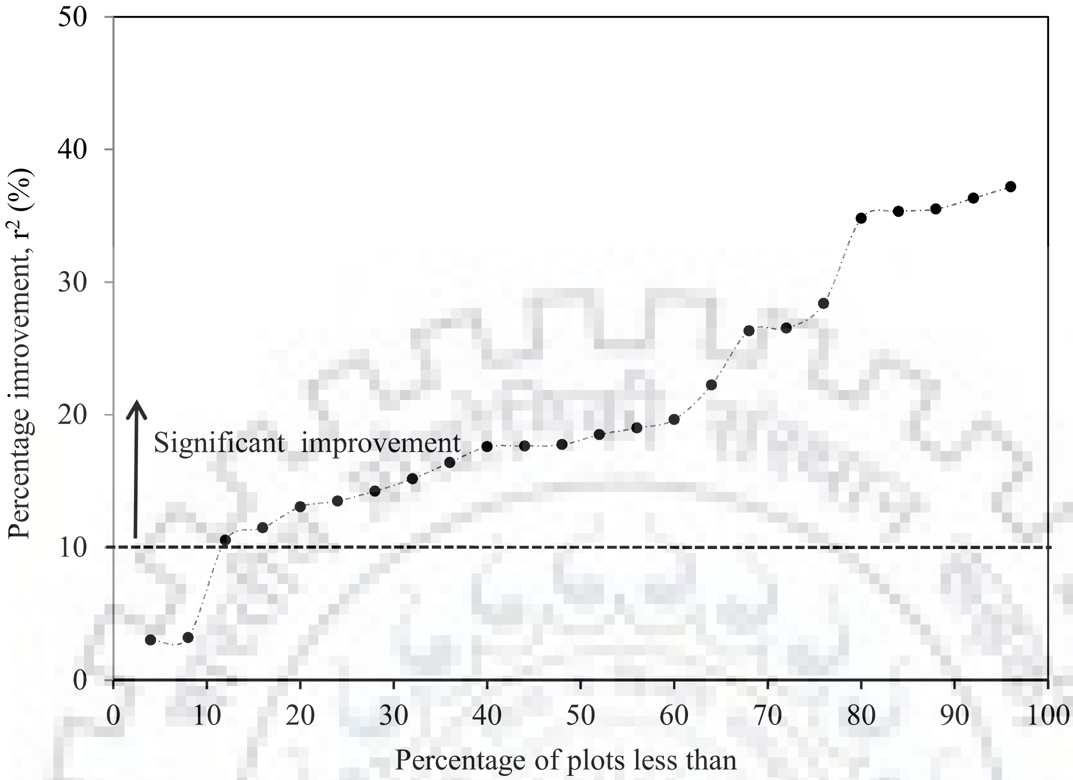

Figure 4.41 The cumulative frequency distribution of improvement in NSE using r^2 criteria

4.4 Effect of AWC on CN (or S)

Table 4.12 compares the performance of four soil moisture indices with three different regression models for improved runoff estimation. As seen, the exponential regression of CN with θ_{o1} (i.e. $CN=69.905exp^{0.0077\theta o}$) performed the best of all in both calibration and validation. However, the existing index based on 5-day antecedent rainfall (P_5) exhibited a poor performance in comparison to one day antecedent moisture (θ_{o1}), consistent with the results reported elsewhere (Brocca et al. 2008, 2009; Beck et al. 2009; Pfister et al. 2003). To check the accuracy of developed relationships of CN with θ_{o1} (i.e. $CN=69.905exp^{0.0077\theta o1}$) and P_5 (i.e. $CN=79.82exp^{0.0011P5}$) in estimation of runoff, runoff was estimated by using both the relationships, for the data of randomly selected 17 plots (plot selected from Table 4.1). As seen from Table 4.13, the $CN=69.905exp^{0.0077\theta o1}$ was found to produce better runoff estimates as compare to $CN=79.82exp^{0.0011P5}$. The use of $CN=69.905exp^{0.0077\theta o1}$ relationship found to improve mean R^2 and E from 0.738 and 0.342 to 0.801 and 0.715, respectively as compared to $CN=79.82exp^{0.0011P5}$. Similarly, the mean RMSE was also improved from 4.738 mm to 3.650 mm upon employment of moisture-CN relationship.

Table 4.12 Performance of various relations between CN and AWC indices

	1-day antecedent soil moisture (θ_{o1})				3-day average antecedent soil moisture (θ_{o3})				5-day average antecedent soil moisture (θ_{o5})				5-day antecedent rainfall (P_5)			
	Re (%)	R^2	E	Bias (e)	Re (%)	R^2	E	Bias (e)	Re (%)	R^2	E	Bias (e)	Re (%)	R^2	E	Bias (e)
Linear regression model (Equation 3.17)																
Calibration	8.58	0.737	0.610	0.51	14.68	0.722	0.493	0.87	14.34	0.704	0.460	0.85	9.51	0.708	0.511	0.56
Validation	16.15	0.835	0.726	0.96	21.31	0.830	0.676	1.26	23.13	0.829	0.649	1.37	17.90	0.816	0.699	1.06
Exponential regression model (Equation 3.18)																
	$CN=69.905exp^{0.0077\theta o1}$				$CN=73.284exp^{0.0058\theta o3}$				$CN=74.617exp^{0.0050\theta o5}$				$CN=79.82exp^{0.0011P5}$			
Calibration	6.71	0.736	0.620	0.39	11.93	0.730	0.512	0.71	12.02	0.709	0.476	0.71	6.06	0.709	0.532	0.36
Validation	13.91	0.837	0.737	0.83	18.43	0.829	0.693	1.09	19.00	0.829	0.674	1.13	14.23	0.817	0.716	0.84
Logarithmic regression model (Equation 3.19)																
Calibration	12.48	0.730	0.560	0.74	15.74	0.718	0.473	0.93	15.28	0.703	0.451	0.90	14.01	0.708	0.441	0.83
Validation	21.21	0.830	0.686	1.26	23.43	0.830	0.652	1.39	23.26	0.829	0.640	1.38	25.94	0.816	0.632	1.54

Table 4.13 Performance statistic for runoff estimation using CN relationship with θ_{o1} and P_5

Plot No.	$CN=69.905exp^{0.0077\theta o1}$			$CN=79.82exp^{0.0011P5}$		
	R^2	E	RMSE (mm)	R^2	E	RMSE (mm)
1	0.812	0.796	5.373	0.710	0.699	6.517
3	0.807	0.702	6.739	0.694	0.677	7.016
7	0.964	0.952	2.693	0.914	0.896	3.968
8	0.945	0.935	3.071	0.971	0.969	2.111
9	0.933	0.920	3.447	0.923	0.904	3.775
10	0.921	0.898	3.010	0.898	0.827	3.921
11	0.864	0.744	4.470	0.864	0.711	4.748
14	0.642	0.508	5.013	0.631	0.449	5.306
15	0.813	0.760	2.932	0.668	0.385	4.691
16	0.914	0.912	1.838	0.872	0.714	3.313
17	0.804	0.587	2.576	0.834	-0.765	5.324
18	0.962	0.861	3.194	0.973	0.969	1.498
20	0.584	0.466	3.364	0.393	-0.925	6.390
21	0.605	0.602	4.429	0.428	0.193	6.308
22	0.545	0.145	3.740	0.427	-1.403	6.268
23	0.779	0.758	2.637	0.619	0.085	5.124
24	0.724	0.612	3.516	0.732	0.428	4.271
Mean	0.801	0.715	3.650	0.738	0.342	4.738

4.5 EVALUATION OF AMC BASED CN–CONVERSION FORMULAE

The five existing (MC1-MC5) and three (MC6-MC8) developed CN–Conversion formulae are shown in Table 3.2. Here, it is to note that P-Q data from locally monitored (i.e. Roorkee experimental site) and published literature have been used in calibration and validation of these existing and developed formulae. Out of 63 (1-27 and 36-71 of Table 3.1), P–Q data from 39 plots/watersheds were used in development of MC1-MC8. The remaining 24 plot/watershed datasets were used in validation. The plots nos. 28-35 were excluded from this analysis due to unavailability of sufficient number of P-Q events and P_5 values.

4.5.1 Comparison using NEH-4 CN Tables

Considering the NEH–4 CN-values for AMC-1 and AMC-3 as target values, the comparative performance evaluation of the proposed formulae with the existing one is accomplished in two steps. First, the representative CN_2 values for AMC–2 condition for the plot/watershed 40–63 used in validation were derived from NEH–4 tables using HSG, land use, and land condition, as shown in Table 4.14. Secondly, the derived CN_2 values were converted into CN_1 or CN_3 using the existing as well as proposed formulae (MC1 to MC7) (Table 4.14). Here, it is notable that MC8 was excluded from the analysis, for the reason it employs λ=0.03 whereas MC1-MC7 and NEH–4 CNs employ λ =0.20.

Considering the above NEH–4 CNs as target, the performance of the existing (MC1 to MC5) and proposed (MC6, MC7) formulae is evaluated as shown in Figures 42–55. As seen, the existing formulae outperform the proposed ones based on E and RMSE criteria. In Figures 47–48, the 1:1 plots show that the CN_1 estimated by MC6 and MC7 clearly over-estimate CN_1 values as compared to the CN_1 estimated by other methods (Figures 42–46). Similarly, Figures 54–55 shows that CN_3 estimated by M6 and MC7 are under-estimated as compared to CN_3 estimated by other methods (Figures 49–53). The proposed relations, however, performed equally well as did the other existing ones, as seen from R^2 values. Based on E- and RMSE-dependent performance, the models can be ranked as follows:

MC1 > MC2 > MC5 > MC4 > MC3 > MC6 > MC7 (for CN_2 to CN_1)

MC1 > MC2 > MC4 > MC3 > MC5 > MC6 > MC7 (for CN_2 to CN_3)

Here, MC1–MC5 formulae have outperformed because these were developed from the same CN-dataset used here as targeted values, i.e. the same NEH–4 AMC defining tabular CN values. Therefore, the degree of agreement between computed and targeted CNs for MC1–MC5 shall be high compared to MC6 or MC7. Moreover, the CNs given in NEH–4 AMC defining tables are the generalized values derived from the annual maximum P–Q datasets monitored at USA watersheds; and a mathematical linear relationship between these CNs will always show a higher R^2 as it was obtained in the development of Equations 2.15 & 2.16. Further, the Hawkins et al. (1985) (i.e. MC1) and Mishra et al. (2008b) (i.e. MC2) had also used the data smoothening technique that further improves the agreement fit between the mathematical linear relationships of generalized values. In contrast, the fitting R^2-values as shown in Table 3.2 for MC6, MC7 and MC8 widely vary from 0.640 to 0.715 for CN_3, and 0.472 to 0.760 for CN_1. The reason for having these slightly lower fitting R^2 might be least square fit of Equation 3.20 using by the un smoothen CNs series derived directly from the observed P–Q of heterogeneous characteristics watersheds.

Table 4.14 Curve number (CN_2) conversion to CN_1 and CN_3 using various criterion

Plot No.	CN_2	NEH-4 table		MC1		MC2		MC3		MC4		MC5		MC6		MC7	
		CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3
40	72	53	86	52.99	85.76	53.05	85.67	51.92	85.54	52.42	86.43	53.41	86.93	57.23	83.58	58.29	82.89
41	72	53	86	52.99	85.76	53.05	85.67	51.92	85.54	52.42	86.43	53.41	86.93	57.23	83.58	58.29	82.89
42	72	53	86	52.99	85.76	53.05	85.67	51.92	85.54	52.42	86.43	53.41	86.93	57.23	83.58	58.29	82.89
43	72	53	86	52.99	85.76	53.05	85.67	51.92	85.54	52.42	86.43	53.41	86.93	57.23	83.58	58.29	82.89
44	72	53	86	52.99	85.76	53.05	85.67	51.92	85.54	52.42	86.43	53.41	86.93	57.23	83.58	58.29	82.89
45	72	53	86	52.99	85.76	53.05	85.67	51.92	85.54	52.42	86.43	53.41	86.93	57.23	83.58	58.29	82.89
46	62	42	79	41.70	79.26	41.76	79.14	40.66	78.96	41.14	80.17	42.57	80.07	45.92	76.36	46.99	75.45
47	62	42	79	41.70	79.26	41.76	79.14	40.66	78.96	41.14	80.17	42.57	80.07	45.92	76.36	46.99	75.45
48	62	42	79	41.70	79.26	41.76	79.14	40.66	78.96	41.14	80.17	42.57	80.07	45.92	76.36	46.99	75.45
49	74	55	88	55.51	86.95	55.57	86.87	54.45	86.75	54.94	87.58	55.70	88.15	59.69	84.93	60.73	84.28
50	74	55	88	55.51	86.95	55.57	86.87	54.45	86.75	54.94	87.58	55.70	88.15	59.69	84.93	60.73	84.28
51	74	55	88	55.51	86.95	55.57	86.87	54.45	86.75	54.94	87.58	55.70	88.15	59.69	84.93	60.73	84.28
52	71	52	86	51.77	85.15	51.83	85.06	50.70	84.92	51.19	85.85	52.28	86.30	56.02	82.90	57.09	82.18
53	51	31	70	31.33	70.91	31.39	70.76	30.42	70.54	30.84	72.06	31.23	70.92	35.13	67.33	36.12	66.23
54	55	35	74	34.89	74.11	34.94	73.97	33.92	73.76	34.37	75.18	35.31	74.45	38.87	70.76	39.90	69.72
55	65	45	82	44.88	81.31	44.94	81.20	43.82	81.03	44.31	82.15	45.75	82.26	49.14	78.62	50.22	77.77

Table 4.14 (continued)

Plot No.	CN_2	NEH-4 table		MC1		MC2		MC3		MC4		MC5		MC6		MC7	
		CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3	CN_1	CN_3
56	76	58	89	58.13	88.12	58.19	88.04	57.08	87.93	57.57	88.70	58.05	89.32	62.23	86.24	63.25	85.64
57	70	51	85	50.57	84.53	50.63	84.44	49.50	84.29	49.99	85.25	51.17	85.66	54.84	82.20	55.90	81.47
58	67	47	83	47.09	82.62	47.15	82.52	46.03	82.36	46.52	83.42	47.89	83.66	51.37	80.08	52.45	79.28
59	66	46	82	45.98	81.97	46.04	81.87	44.91	81.70	45.41	82.79	46.82	82.97	50.25	79.35	51.33	78.53
60	75	57	88	56.81	87.54	56.87	87.46	55.75	87.34	56.24	88.14	56.86	88.74	60.95	85.59	61.98	84.97
61	71	52	86	51.77	85.15	51.83	85.06	50.70	84.92	51.19	85.85	52.28	86.30	56.02	82.90	57.09	82.18
62	77	59	89	59.48	88.69	59.54	88.62	58.44	88.51	58.92	89.24	59.25	89.89	63.53	86.89	64.53	86.32
63	73	54	87	54.24	86.36	54.30	86.28	53.17	86.15	53.67	87.01	54.55	87.55	58.45	84.26	59.50	83.59

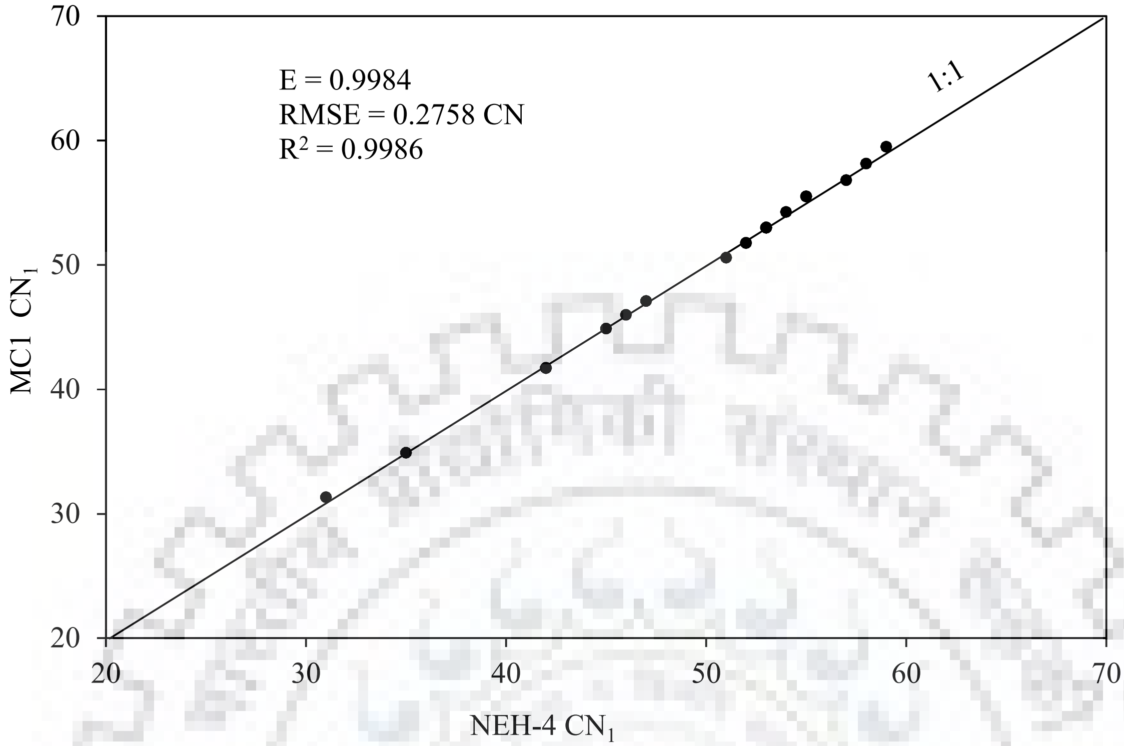

Figure 4.42 Performance of AMC based CN_1 conversion employing MC1. The plots include 1-to-1 lines and goodness-of-fit statistics.

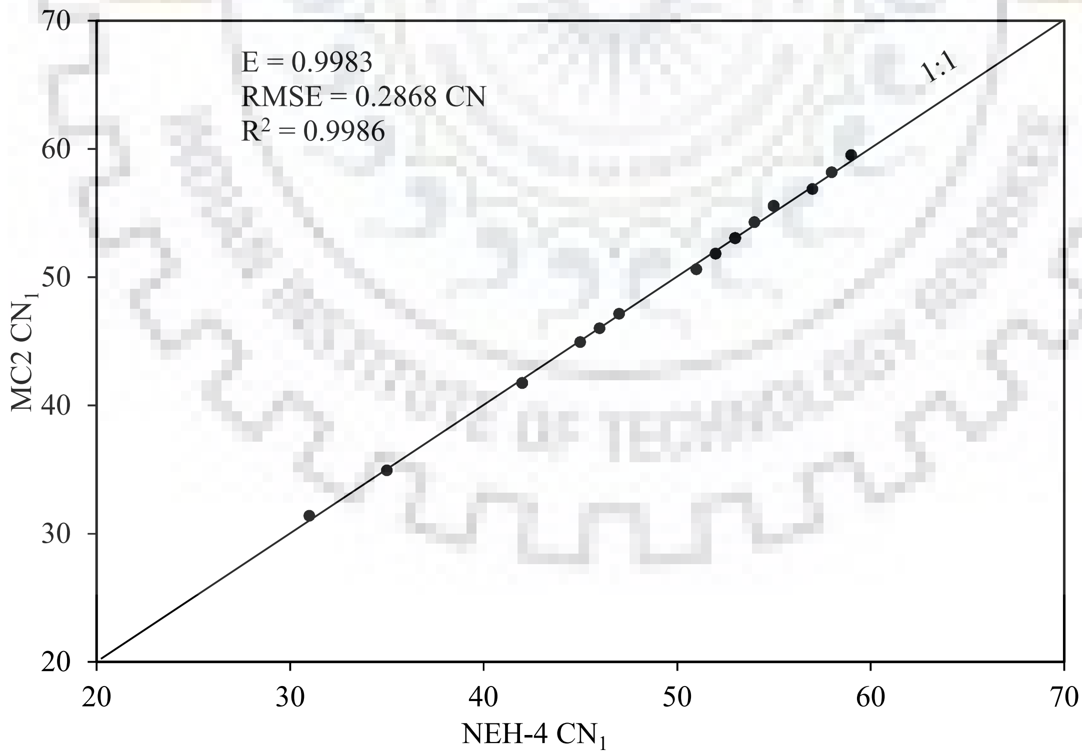

Figure 4.43 Performance of AMC based CN_1 conversion employing MC2. The plots include 1-to-1 lines and goodness-of-fit statistics.

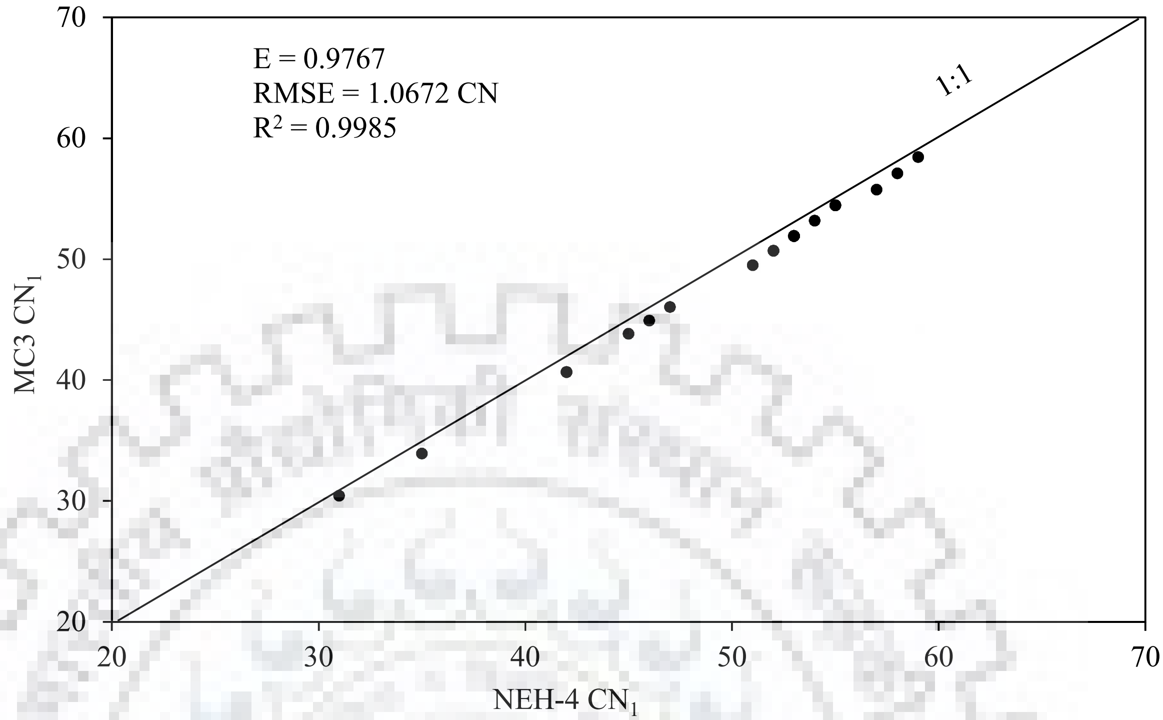

Figure 4.44 Performance of AMC based CN_1 conversion employing MC3. The plots include 1-to-1 lines and goodness-of-fit statistics.

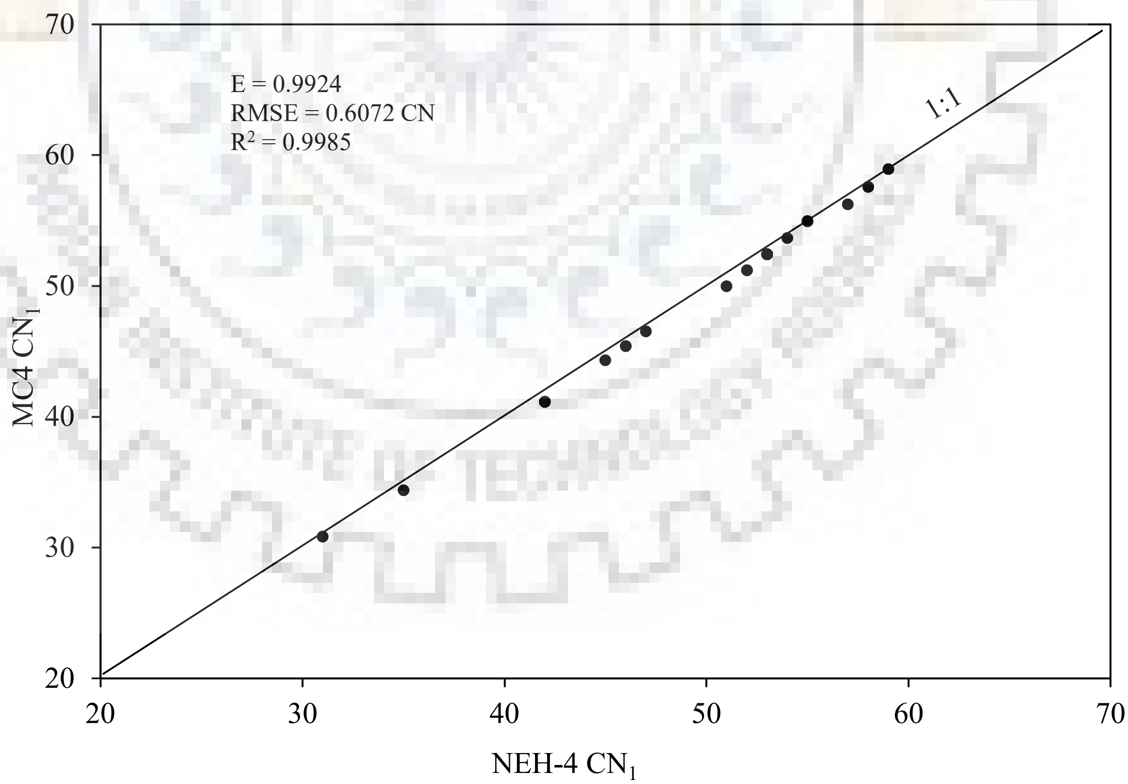

Figure 4.45 Performance of AMC based CN_1 conversion employing MC4. The plots include 1-to-1 lines and goodness-of-fit statistics.

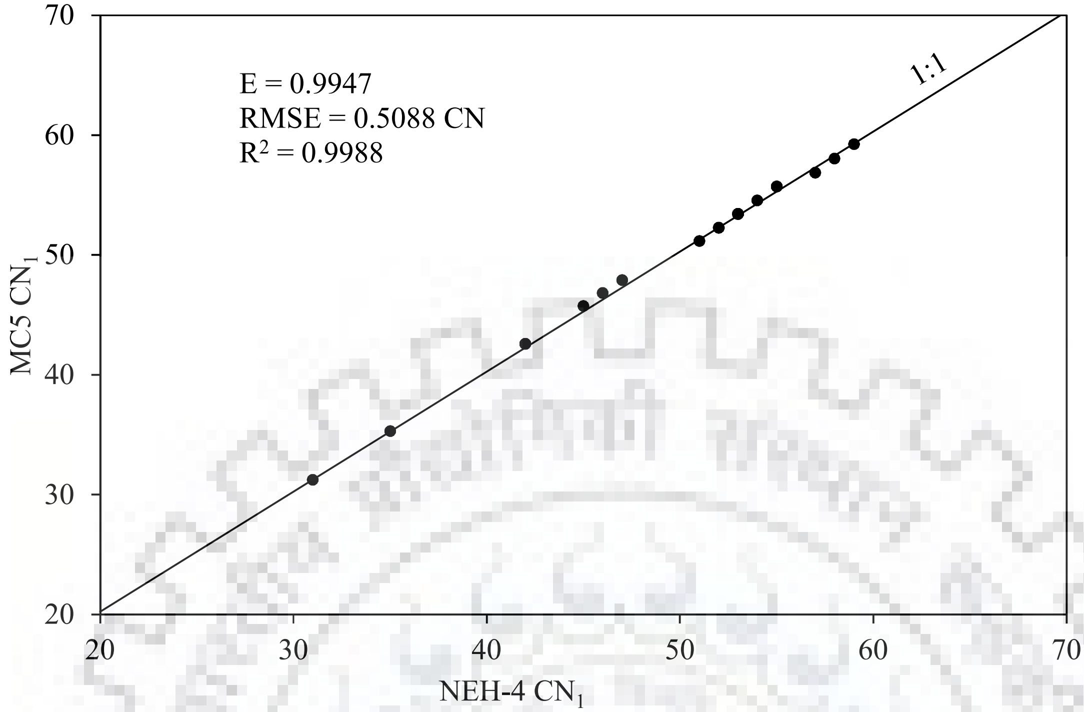

Figure 4.46 Performance of AMC based CN_1 conversion employing MC5. The plots include 1-to-1 lines and goodness-of-fit statistics.

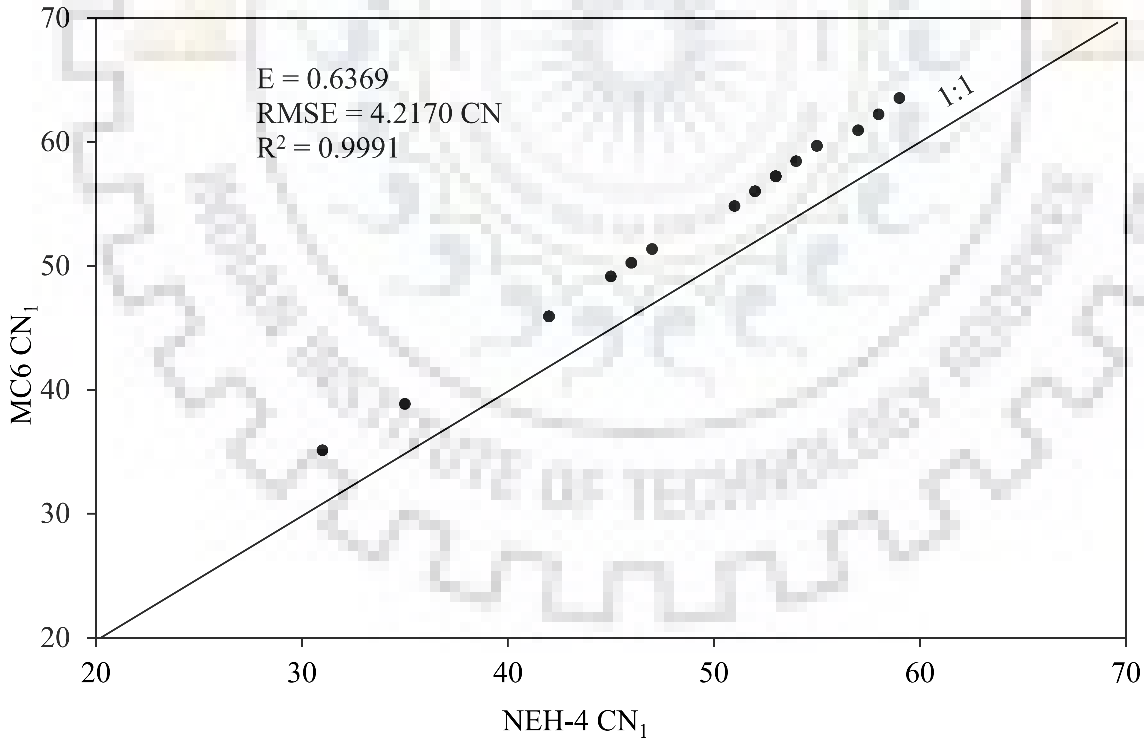

Figure 4.47 Performance of AMC based CN_1 conversion employing MC6. The plots include 1-to-1 lines and goodness-of-fit statistics.

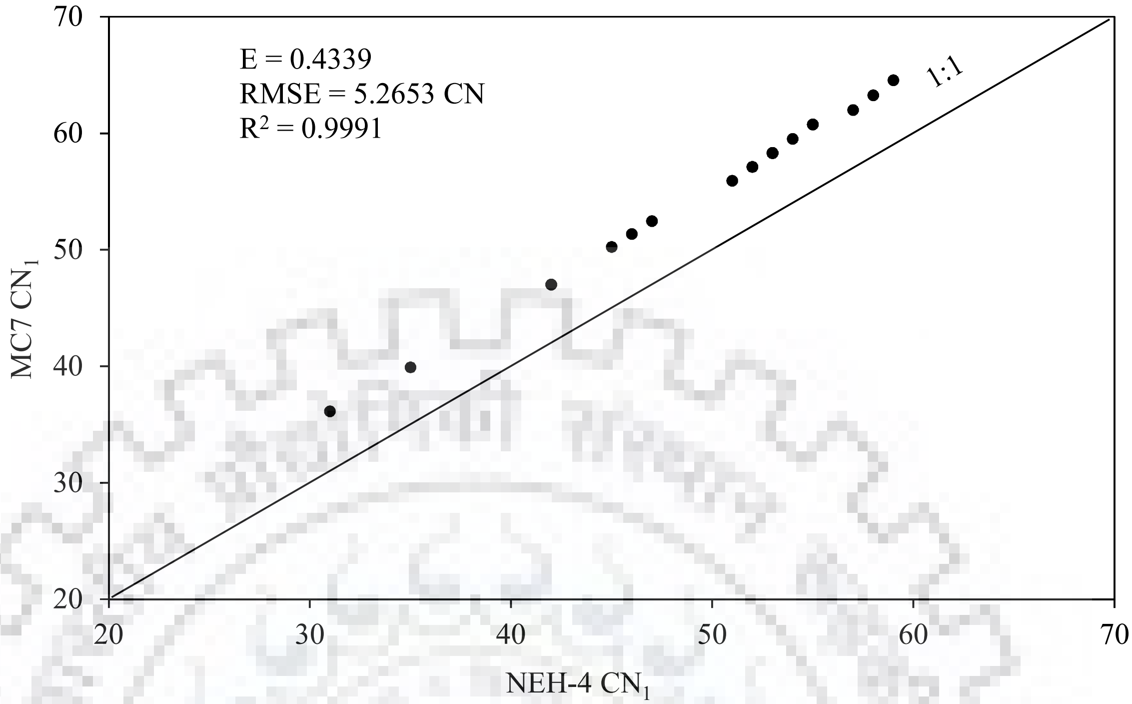

Figure 4.48 Performance of AMC based CN_1 conversion employing MC7. The plots include 1-to-1 lines and goodness-of-fit statistics.

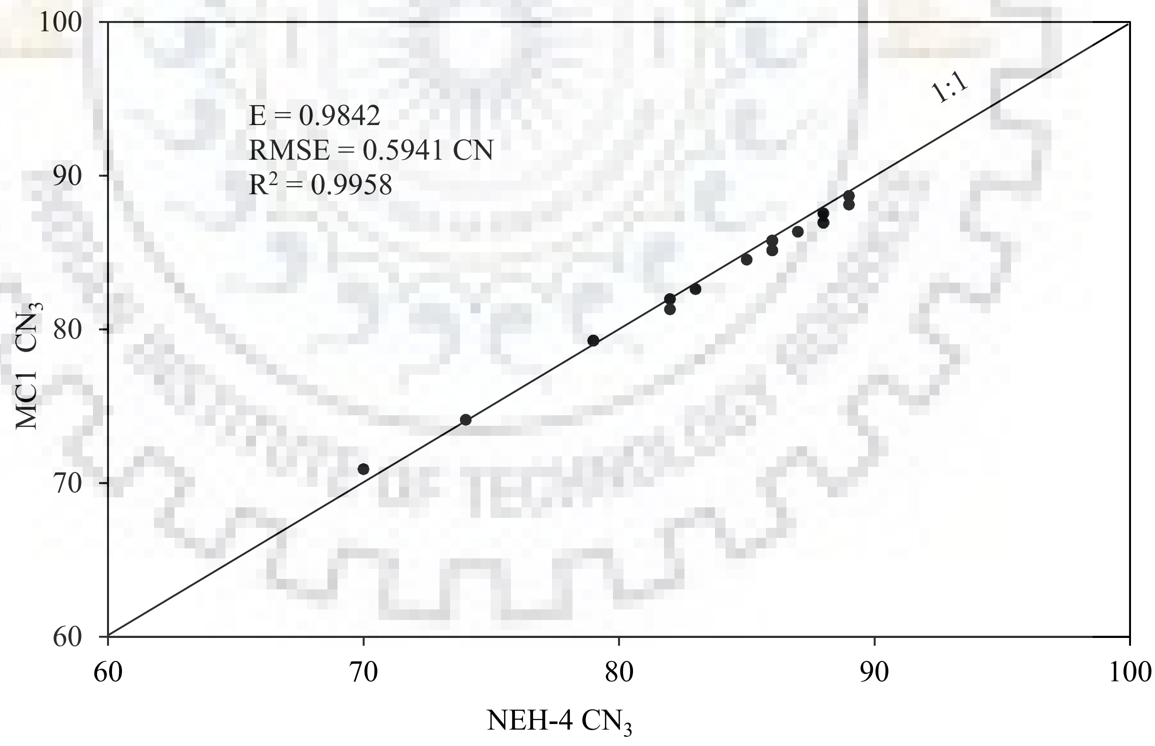

Figure 4.49 Performance of AMC based CN_3 conversion employing MC1. The plots include 1-to-1 lines and goodness-of-fit statistics.

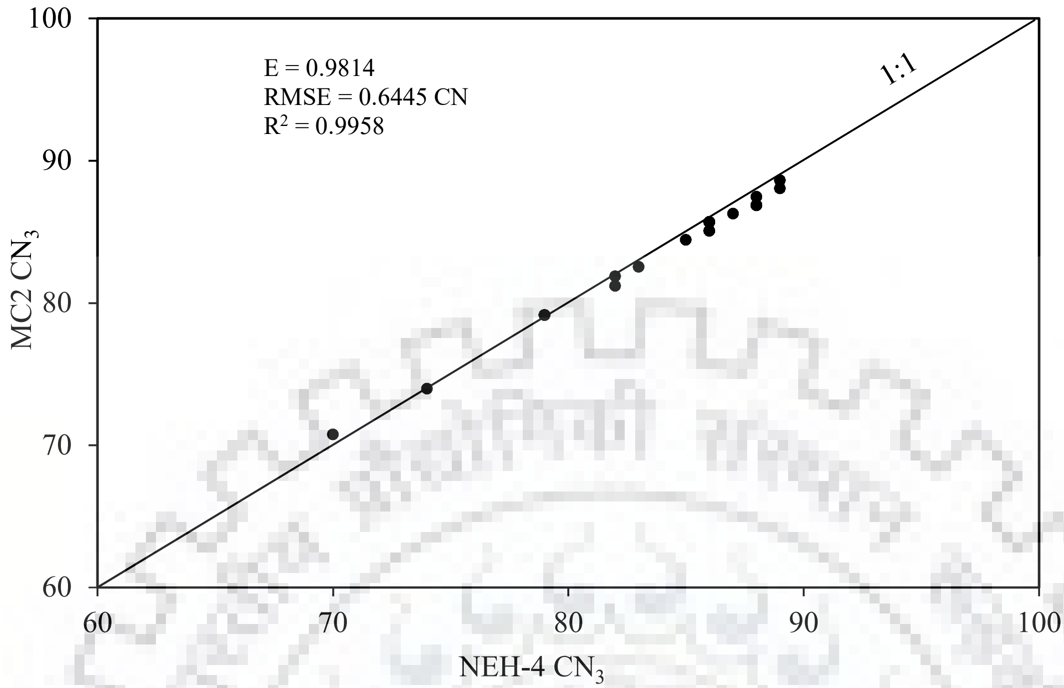

Figure 4.50 Performance of AMC based CN_3 conversion employing MC2. The plots include 1-to-1 lines and goodness-of-fit statistics.

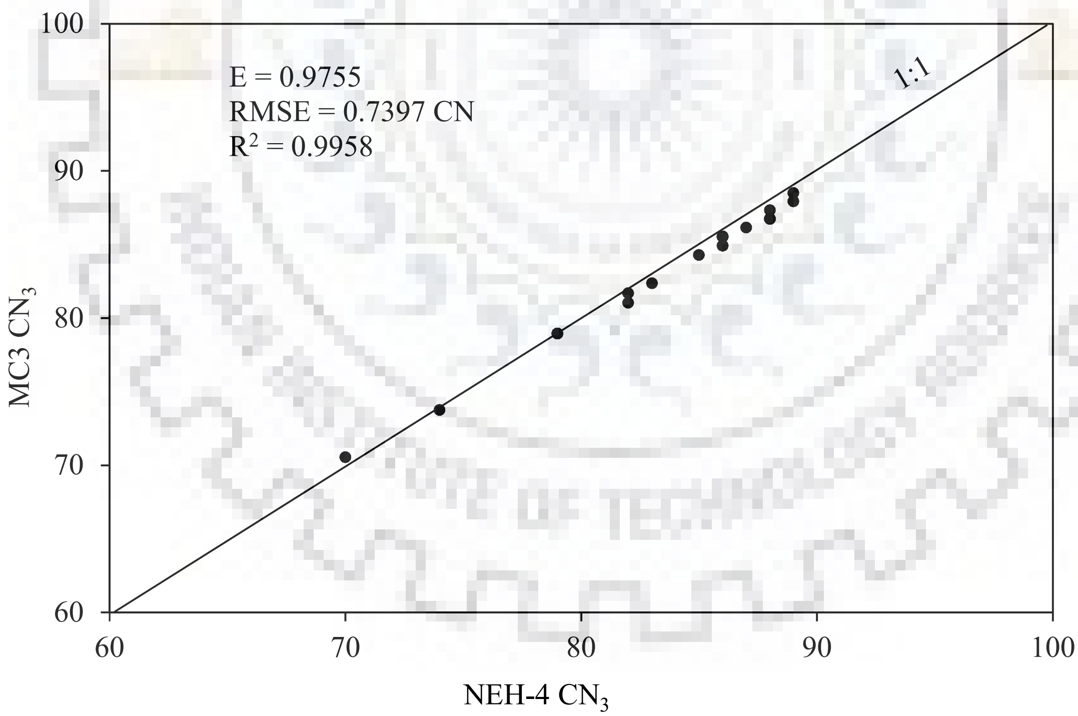

Figure 4.51 Performance of AMC based CN_3 conversion employing MC3. The plots include 1-to-1 lines and goodness-of-fit statistics.

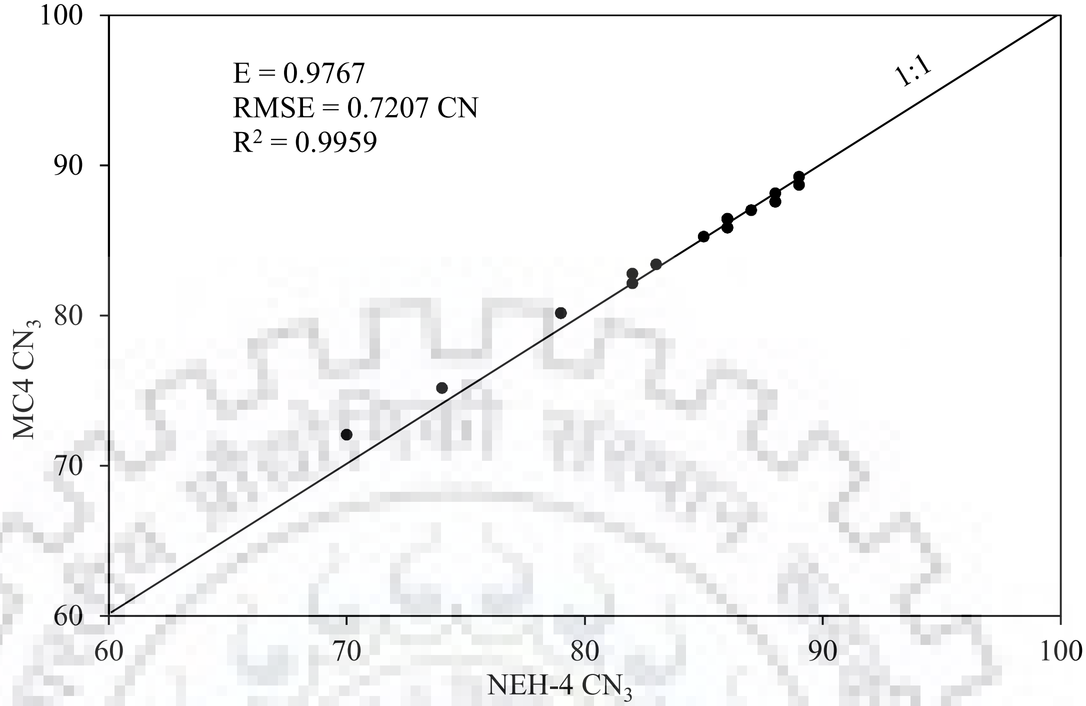

Figure 4.52 Performance of AMC based CN_3 conversion employing MC4. The plots include 1-to-1 lines and goodness-of-fit statistics.

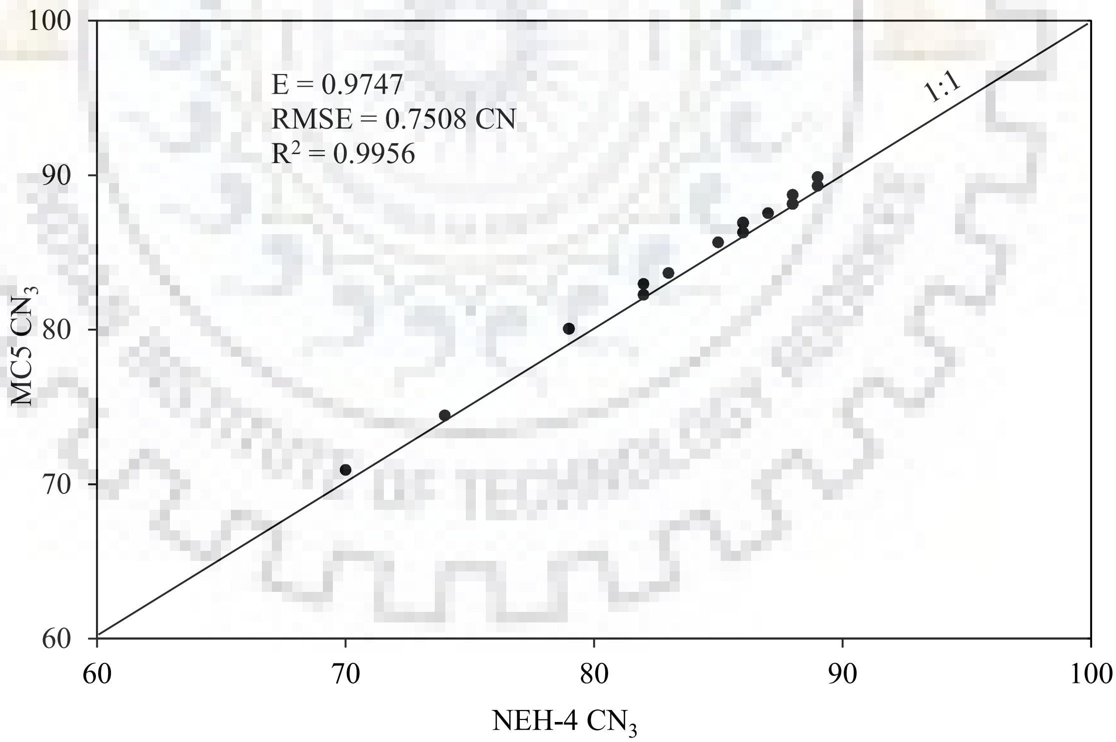

Figure 4.53 Performance of AMC based CN_3 conversion employing MC5. The plots include 1-to-1 lines and goodness-of-fit statistics.

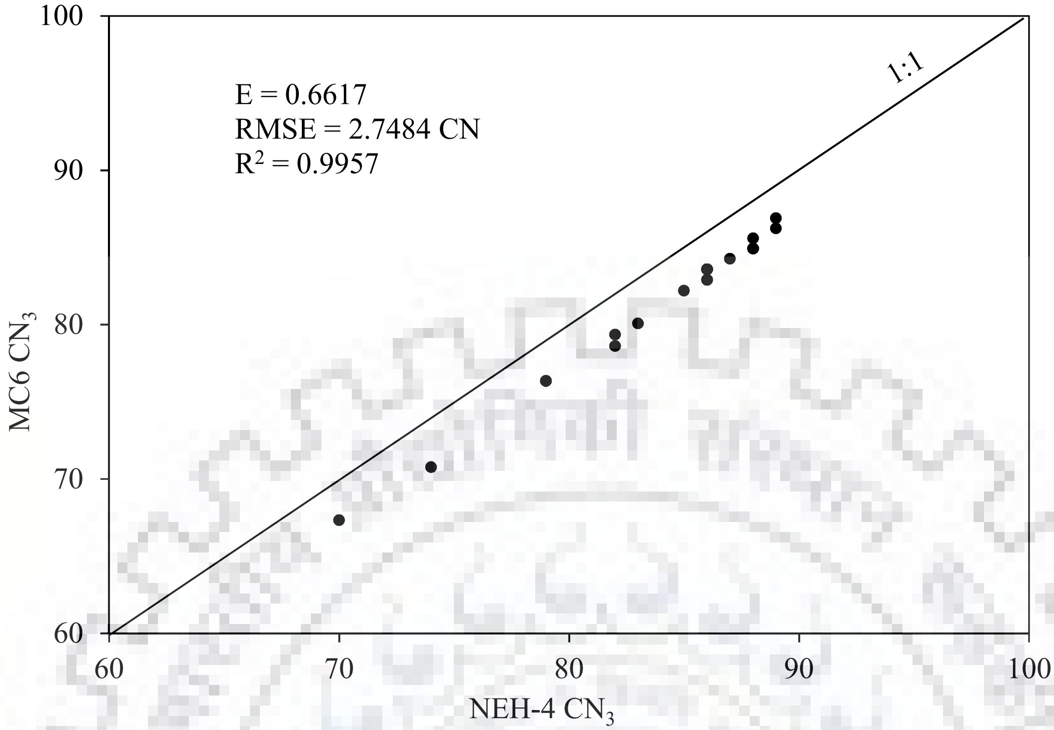

Figure 4.54 Performance of AMC based CN_3 conversion employing MC6. The plots include 1-to-1 lines and goodness-of-fit statistics.

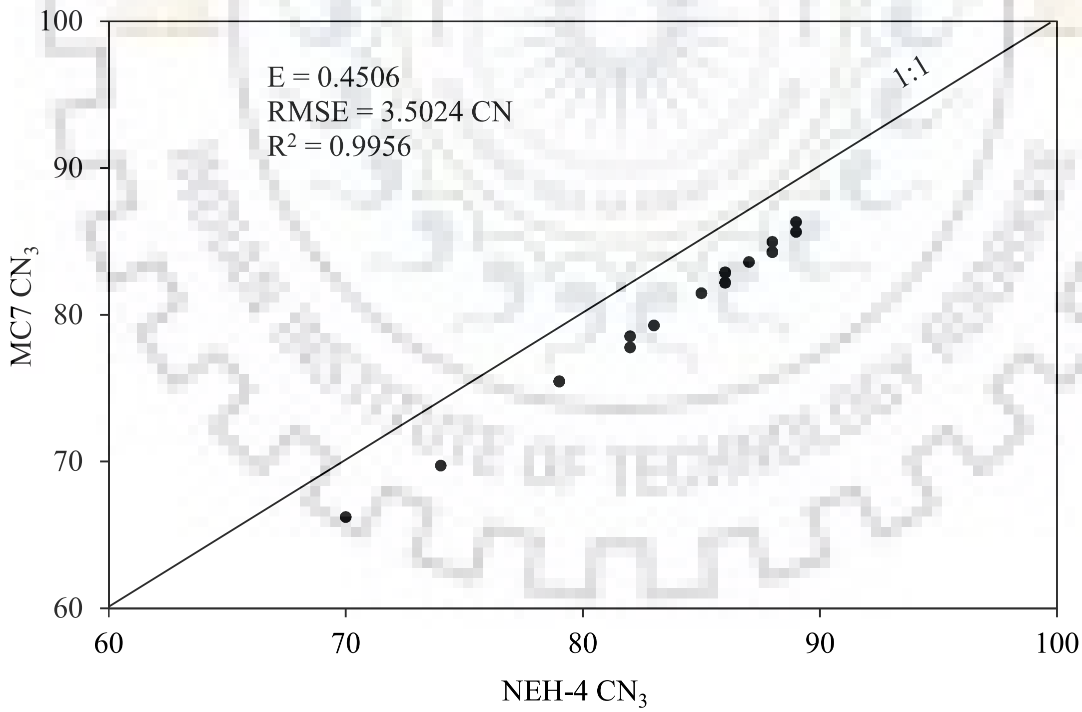

Figure 4.55 Performance of AMC based CN_3 conversion employing MC7. The plots include 1-to-1 lines and goodness-of-fit statistics.

4.5.2 Performance evaluation of AMC conversion formulae using field data

As shown in section 4.5.1, MC1–MC5 excelled because they were applied to the same AMC-conversion NEH-4 dataset from which they were originally developed whereas the proposed ones did not, and therefore, performed relatively much poorly. To make the evaluation more realistic, there is a need of testing these formulae on the real field data employing P–Q datasets observed from watersheds of heterogeneous characteristics and climatic conditions. Despite the use of different datasets, CN_1 and CN_3 values derived for MC6 or MC7 were well correlated with the original AMC Table based CNs, justifying the pragmatic applicability of the proposed formulae. Since the generated surface runoff heavily depends on AMC (Mishra et al. 2008b), the derived CN_2 for watersheds 40–63 be corrected for the desired AMC level (i.e. CN_1 or CN_3) before using it further in runoff estimation. To this end, three AMC's were calculated using P_5 as per the criteria given in section 3.6.6.

The derived CN_2 were converted into CN_1 or CN_3 using the existing (MC1–MC5) as well as proposed (MC6–MC8) formulae, and runoff was estimated employing the standard NEH–4 procedure (SCS, 1972, 1985). In this procedure, the AMC corrected CNs were first converted into S using Equation 3.9, and then Equation 3.5 was utilized for runoff estimation.

The MC8 uses the λ value as 0.03 in place of traditionally recommend value of $\lambda = 0.2$. Here it is worth to note that, in the model MC8, the choice of using λ=0.03, which is the mean value, resulting from the optimized λ yielded from the entire 63 plots/watersheds P–Q data sets. The λ for the entire 63 plots/watersheds were optimized employing the Equation 3.14. The results of optimized λ values from 63 watersheds natural P–Q datasets are given in Appendix C. As seen from this appendix, λ values vary from 0 to 0.3310 with 0.0312 and 0.0002 as mean and median values, respectively. The figure C2 given in Appendix C shows the frequency histogram of optimized λ values (estimated from entire 63 plots datasets), where the frequency of occurrence of zero is 30. 61 out of 63 λ-values were below the standard value of 0.20, consistent with the results of studies carried out elsewhere (Fu et al. 2011; Shi et al. 2009; Yuan et al. 2014; Zhou and Lei 2011). The examination of appendices B1 & B2 reasonably justified the use of mean value $\lambda = 0.030$ in the present study. Notably, for MC8, a transformation of CN_2 from $\lambda = 0.2$ to $\lambda = 0.03$ is mandatory before using it further in runoff estimation. To this end, the empirical Equation 4.3 for converting CNs from $\lambda = 0.2$ ($CN_{0.2}$) to $\lambda = 0.03$ ($CN_{0.03}$) was used. The converted $CN_{0.03}$ were then corrected for the desired AMC, and Equation 3.5 with $\lambda = 0.03$ was utilized for runoff estimation. Similarly, for formulae MC1–MC7, the runoff was estimated using Equation 3.5 with standard $\lambda = 0.20$.

The results for runoff estimation for the watersheds 40–63 are given in appendix Tables D1 to D4 (appendix D) along with the resulting R^2, E, d and RMSE. Moreover, the cumulative frequency distribution of all the four statistics R^2, E, d and RMSE used for quantifying the performance are also shown in Figures 4.56–4.59 As seen, MC8, MC7 and MC6 found to show relatively high R^2, E and d, and low RMSE compared to those due to existing formulae.

Table 4.15 compares all 8 formulae based on the mean values of RMSE, E, d and R^2 derived from the analysis of 24 watershed P–Q datasets. In general, the methods can be ranked as follows:

MC8 > MC7 > MC6 > MC2 > MC1 > MC3 > MC5 > MC4 (based on RMSE and R^2)

MC8 > MC7 > MC6 > MC2 > MC1 > MC5 > MC4 > MC3 (based on d and E)

As seen from this table, compared to the best existing method MC2, the MC8 improved the mean R^2 and d from 0.329 to 0.501 and 0.630 to 0.758, respectively. Similarly, the E and RMSE were also improved from -1.049 to 0.120 and 12.001 mm to 9.303 mm, respectively.

Further to evaluating the overall performance, the MC1–MC8 methods were ranked based on the mean statistics viz. d, RMSE, R^2 and E. To this end, a rank of 1–8 was assigned to show the RMSE from lowest to highest, and d, R^2 and E from highest to lowest. After assigning of ranks, corresponding marks of 8 to 1 are given to each index. For example, a method having the minimum RMSE, and maximum d, R^2 and E will be ranked 1. The method corresponding to rank 1 will be achieved to score 8 marks. Similarly, the method corresponding to rank 2 will be achieved to score 7 marks and so on. The overall performance of method was judged based on the total marks gained by method using all four statistics. The first rank will be given to the method scoring highest marks whereas last rank (i.e. eight) will be given to method scoring lowest marks. Table 4.16 shows the ranks and marks achieved by all methods for their respective performance indices. As seen from this table, MC8 performed best followed by MC7. Among existing formulae, MC2 found to perform best followed by MC1. Notably the performance of MC4 was least good. These results of existing formulae performance are consistent with Mishra et al (2008b) work.

Based on overall score the methods performance can be described as follows:

MC8 > MC7 > MC6 > MC2 > MC1 > MC3 > MC5 > MC4

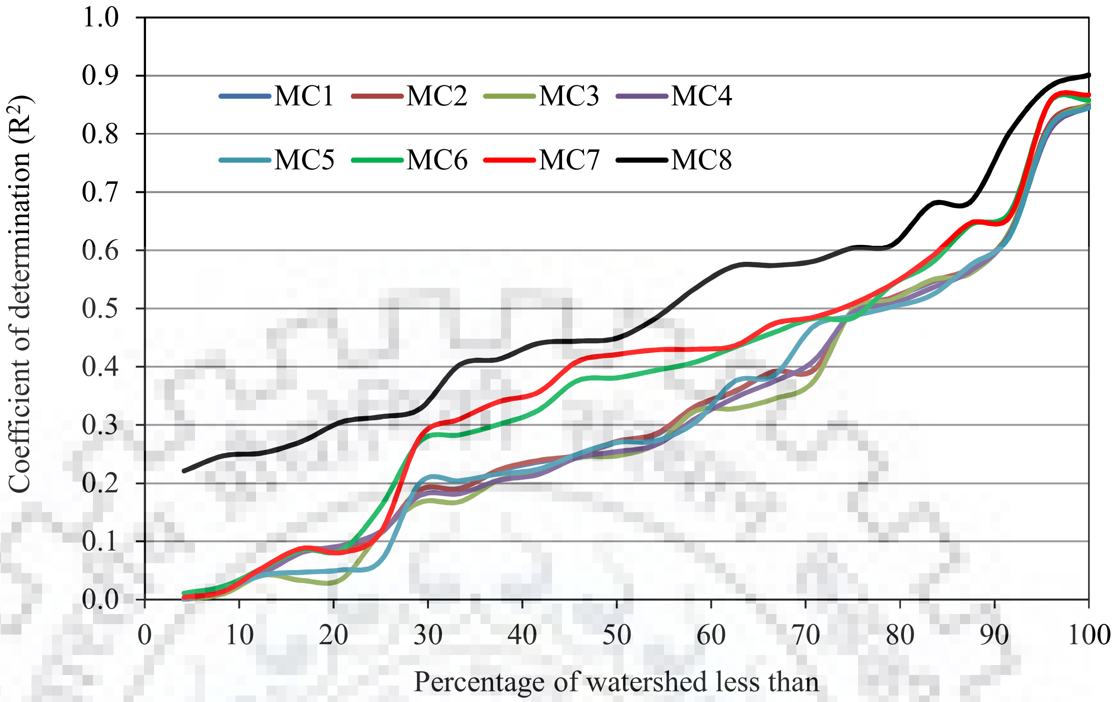

Figure 4.56 The cumulative frequency distribution of improvement in R^2

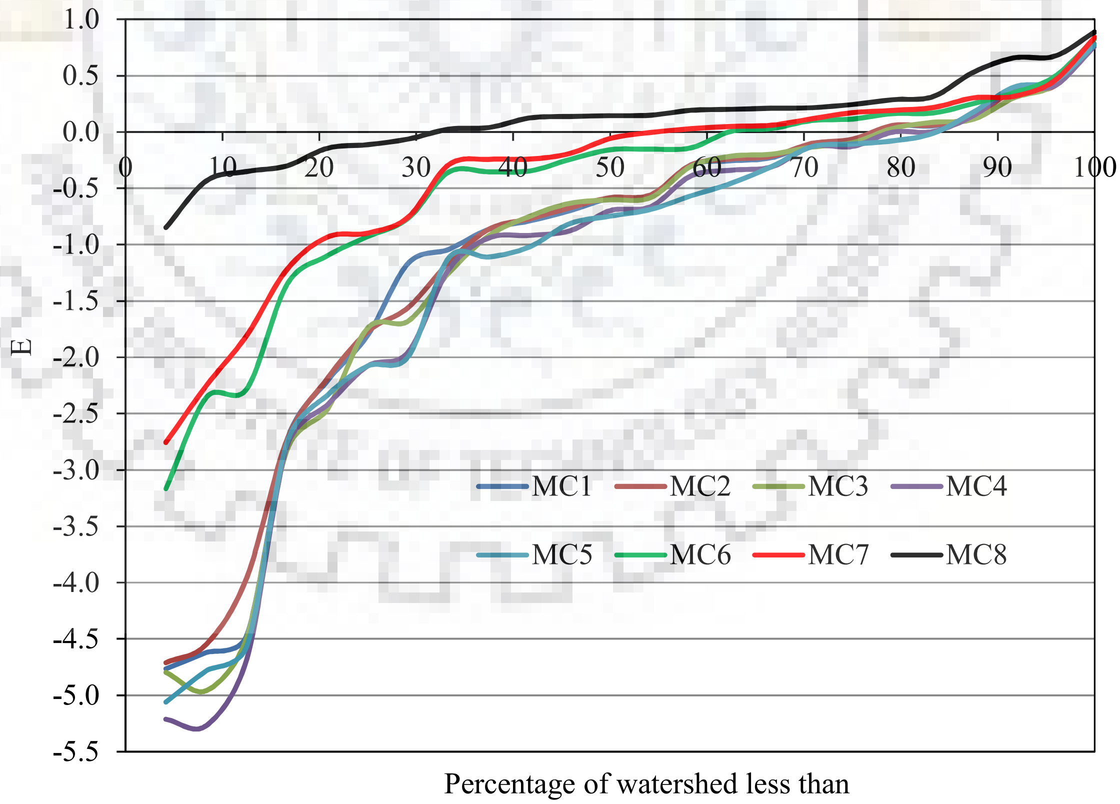

Figure 4.57 The cumulative frequency distribution of improvement in E

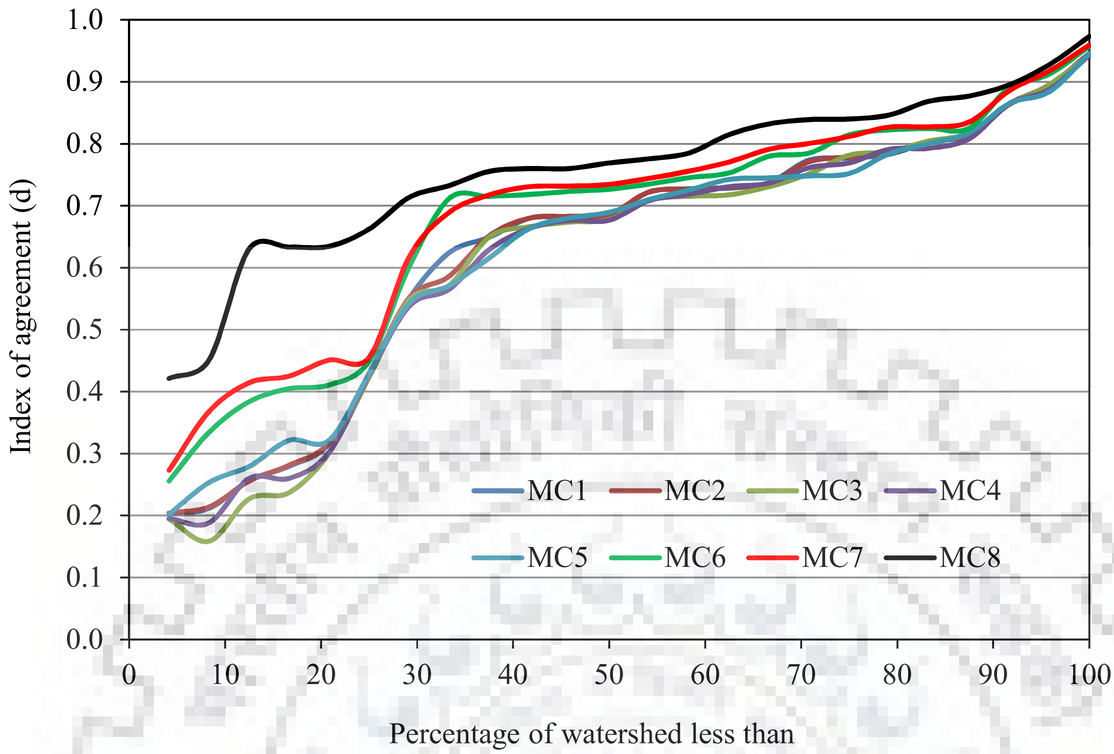

Figure 4.58 The cumulative frequency distribution of improvement in d

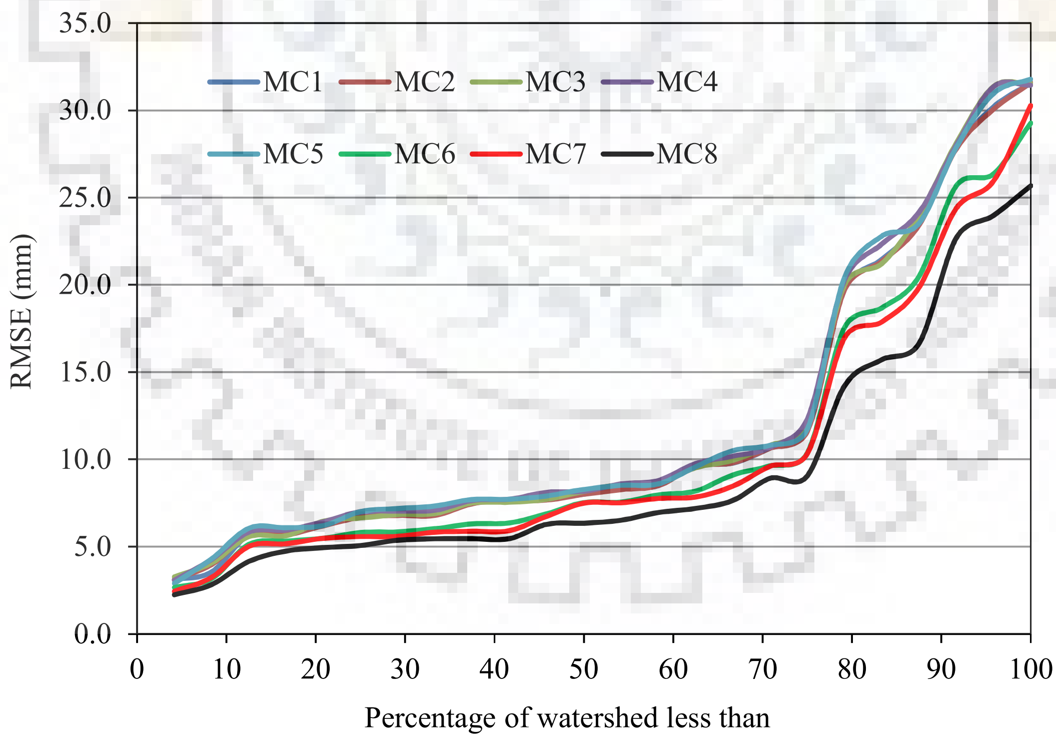

Figure 4.59 The cumulative frequency distribution of improvement in RMSE

Table 4.15 Mean and Standard deviation (SD) values of performance statistic for runoff estimation using field data

Model ID	R^2		RMSE (mm)		d		E	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
MC1	0.329	0.237	12.017	8.602	0.630	0.225	-1.062	1.598
MC2	0.329	0.238	12.001	8.569	0.630	0.225	-1.049	1.544
MC3	0.325	0.234	12.166	8.721	0.618	0.235	-1.122	1.649
MC4	0.322	0.237	12.344	8.713	0.620	0.228	-1.222	1.733
MC5	0.324	0.242	12.325	8.691	0.629	0.216	-1.205	1.651
MC6	0.373	0.251	10.724	7.769	0.678	0.197	-0.466	0.972
MC7	0.385	0.252	10.468	7.720	0.689	0.189	-0.371	0.881
MC8	0.501	0.198	9.303	6.787	0.758	0.135	0.120	0.373

From Tables 4.15–4.16 and Figures 4.56–4.59, it can be inferred that MC8 performed the best of all, and MC7 and MC6 were better than all other existing formulae. Notably, MC2 followed by MC1 performed the best of all existing formulae. The results also indicate that CN methodology has an improved runoff simulation capability, if λ =0.03 and AMC corrected CNs are used in MC8. Here, it is noted that the RMSE variation (9.303–12.017 mm) might appear to be insignificant, it is however significant in volumetric terms, when the depth is multiplied by a large value of catchment area.

The K-W test was used for multiple comparison of runoff estimated by MC1-MC8, and the results are shown in Table 4.17. As seen, the runoff due to existing formulae (i.e. MC1–MC5) is not significantly different at 0.05 significance level for all 24 watersheds. Similar results were also obtained when all eight (i.e. MC1–MC8) formulae were compared together. As seen from the Table 4.17 with different grouping patterns, the runoff estimated by the MC1–MC8 is not significantly different for 22 out of 24 watersheds. The runoff due to MC8 was significantly different in only 2 watersheds (i.e. 53, 54) when compared with the existing formulae (i.e. MC1–MC5). However, the runoff due to MC8 was insignificantly different in all 24 watersheds when compared with MC6 or MC7. Further, the runoff estimated by MC8 was significantly ($p < 0.05$) different from the observed runoff in 3 (i.e. 47, 48, 56) out of 24 watersheds. Similarly, the runoff estimated by existing formulae was significantly ($p < 0.05$) different from the observed runoff in 3 (i.e. 53, 56, 62) out of 24 watersheds.

Table 4.16 Performance evaluation of AMC-conversion models based on ranks (scores)

	Performance indices (mean values) and their ranks (scores)									
Model ID	R^2	Rank (Score)	RMSE	Rank (Score)	d	Rank (Score)	E	Rank (Score)	Total Score	Overall Rank
MC1	0.329	5 (4)	12.017	5 (4)	0.630	4 (5)	-1.062	5 (4)	17	5
MC2	0.329	4 (5)	12.001	4 (5)	0.630	5 (4)	-1.049	4 (5)	19	4
MC3	0.325	6 (3)	12.166	6 (3)	0.618	8 (1)	-1.122	6 (3)	10	6
MC4	0.322	8 (1)	12.344	8 (1)	0.620	7 (2)	-1.222	8 (1)	05	8
MC5	0.324	7 (2)	12.325	7 (2)	0.629	6 (3)	-1.205	7 (2)	09	7
MC6	0.373	3 (6)	10.724	3 (6)	0.678	3 (6)	-0.466	3 (6)	24	3
MC7	0.385	2 (7)	10.468	2 (7)	0.689	2 (7)	-0.371	2 (7)	28	2
MC8	0.501	1 (8)	9.303	1 (8)	0.758	1 (8)	0.120	1 (8)	32	1

Table 4.17 Multiple comparisons using Least Significant Difference (LSD) grouping of runoff

Watershed		Least Significant Difference (LSD) Grouping								
		Observed	MC1	MC2	MC3	MC4	MC5	MC6	MC7	MC8
40		A	A	A	A	A	A	A	A	A
	Mean	8.19	6.83	6.80	6.83	7.09	7.20	6.06	5.88	6.32
	n	13	13	13	13	13	13	13	13	13
41		A	A	A	A	A	A	A	A	A
	Mean	11.47	6.83	6.80	6.83	7.09	7.20	6.06	5.88	6.32
	n	13	13	13	13	13	13	13	13	13
42		A	A	A	A	A	A	A	A	A
	Mean	9.63	6.83	6.80	6.83	7.09	7.20	6.06	5.88	6.32
	n	13	13	13	13	13	13	13	13	13
43		A	A	A	A	A	A	A	A	A
	Mean	8.86	6.39	6.36	6.44	6.63	6.68	5.57	5.38	5.69
	n	11	11	11	11	11	11	11	11	11
44		A	A	A	A	A	A	A	A	A
	Mean	7.44	6.39	6.36	6.44	6.63	6.68	5.57	5.38	5.69
	n	11	11	11	11	11	11	11	11	11
45		A	A	A	A	A	A	A	A	A
	Mean	11.25	6.39	6.36	6.44	6.63	6.68	5.57	5.38	5.69
	n	11	11	11	11	11	11	11	11	11
46		A	A	A	A	A	A	A	A	A
	Mean	5.09	5.88	5.84	6.13	6.21	5.79	4.41	4.08	3.13
	n	11	11	11	11	11	11	11	11	11
47		A	A, B	A, B	A, B	A, B	A, B	A, B	A, B	B
	Mean	7.76	5.88	5.84	6.13	6.21	5.79	4.41	4.08	3.13
	n	11	11	11	11	11	11	11	11	11
48		A	A, C	A, C	A, C	A, C	A, C	B, C	B, C	B, C
	Mean	9.49	5.88	5.84	6.13	6.21	5.79	4.41	4.08	3.13
	n	11	11	11	11	11	11	11	11	11
49		A	A	A	A	A	A	A	A	A
	Mean	6.90	7.39	7.36	7.35	7.62	7.82	6.75	6.60	7.11
	n	13	13	13	13	13	13	13	13	13

Table 4.17 (continued)

Watershed		Least Significant Difference (LSD) Grouping								
		Observed	MC1	MC2	MC3	MC4	MC5	MC6	MC7	MC8
50		A	A	A	A	A	A	A	A	A
	Mean	6.69	6.83	6.80	6.84	7.05	7.18	6.14	5.98	6.39
	n	11	11	11	11	11	11	11	11	11
51		A	A	A	A	A	A	A	A	A
	Mean	7.43	7.39	7.36	7.35	7.62	7.82	6.75	6.60	7.11
	n	13	13	13	13	13	13	13	13	13
52		A	A	A	A	A	A	A	A	A
	Mean	1.65	2.77	3.17	3.27	3.40	3.39	2.07	1.91	2.55
	n	31	31	31	31	31	31	31	31	31
53		A	B, C	B, C	B, C	B, C	B, C	A, C	A, C	A
	Mean	2.79	8.85	8.79	9.31	9.34	8.91	6.52	6.01	3.03
	n	24	24	24	24	24	24	24	24	24
54		A, C	A, C	A, C	B, C	B, C	A, C	A, C	A, C	A
	Mean	4.34	6.88	6.83	7.16	7.29	6.80	5.16	4.80	3.25
	n	23	23	23	23	23	23	23	23	23
55		A	A	A	A	A	A	A	A	A
	Mean	36.62	37.87	37.78	37.10	38.51	39.29	37.23	36.97	33.25
	n	13	13	13	13	13	13	13	13	13
56		A	B	B	B	B	B	B	B	B
	Mean	29.43	6.52	6.53	6.23	6.45	6.66	7.58	7.89	8.17
	n	30	30	30	30	30	30	30	30	30
57		A	A	A	A	A	A	A	A	A
	Mean	35.29	40.32	40.24	40.01	40.93	41.42	38.76	38.28	35.71
	n	8	8	8	8	8	8	8	8	8
58		A	A	A	A	A	A	A	A	A
	Mean	57.78	50.46	50.39	49.73	50.97	51.83	50.13	49.96	50.80
	n	12	12	12	12	12	12	12	12	12

Table 4.17 (continued)

Watershed		Least Significant Difference (LSD) Grouping								
		Observed	MC1	MC2	MC3	MC4	MC5	MC6	MC7	MC8
59		A	A	A	A	A	A	A	A	A
	Mean	37.26	38.18	38.24	37.10	37.60	39.05	41.51	42.80	31.30
	n	48	48	48	48	48	48	48	48	48
60		A	A	A	A	A	A	A	A	A
	Mean	15.12	13.75	13.59	13.26	13.58	13.93	14.51	14.76	16.07
	n	17	17	17	17	17	17	17	17	17
61		A	A	A	A	A	A	A	A	A
	Mean	2.88	2.39	2.37	2.41	2.57	2.61	1.78	1.62	2.04
	n	15	15	15	15	15	15	15	15	15
62		A	B, C	B, C	B, C	B, C	B, C	A, C	A, C	A, C
	Mean	7.52	12.61	12.56	12.48	13.04	13.56	11.33	10.95	11.59
	n	42	42	42	42	42	42	42	42	42
63		A	A, C	A, C	A, C	A, C	B, C	A, C	A, C	A, C
	Mean	4.83	8.56	8.51	8.44	8.92	9.24	7.48	7.17	7.77
	n	40	40	40	40	40	40	40	40	40

Note: The mean runoff (mm) with no letter (alphabet A, B, C) in common is significantly different at the 0.05 significance level (based on the K–W test); n= number of P-Q events.

As shown above, the analysis of K–W test revealed that both the existing and proposed formulae behave statistically similar as estimated runoff in 22 out of 24 watersheds is not significantly different. However, Tables 4.15–4.16 and Figures 4.56–4.59 clearly show that the proposed formulae improved the results in all 24 watersheds. To analyze the improvement due to application of the proposed formulae over the existing ones, r^2–statistic (Equation 3.29) was employed for assessment of relative percentage improvement in runoff estimation efficiency. To this end, MC8 was compared with the best existing MC2 and the second best proposed MC7, and the results are shown in Figure 4.60. As seen, MC8 significantly (r^2 >10%) improved the runoff prediction efficiency (E) in all 24 watersheds when it compared with MC2. On the other hand, MC8 improved E in 23 out of 24 watersheds when compared with MC7. This improvement was, however, significant (r^2 > 10%) in 20 watersheds. Compared to MC7, MC8 could not perform well in watershed no. 52. It might be due to employment of Equation 4.3 purely developed from experimental plot-data of humid sub–tropical climate with agricultural land uses. Therefore, this equation may not be valid for Tropical savanna climate with Natural savannah land use of Brazil. Further research is needed for developing and testing the regional λ-based equation for broader applicability.

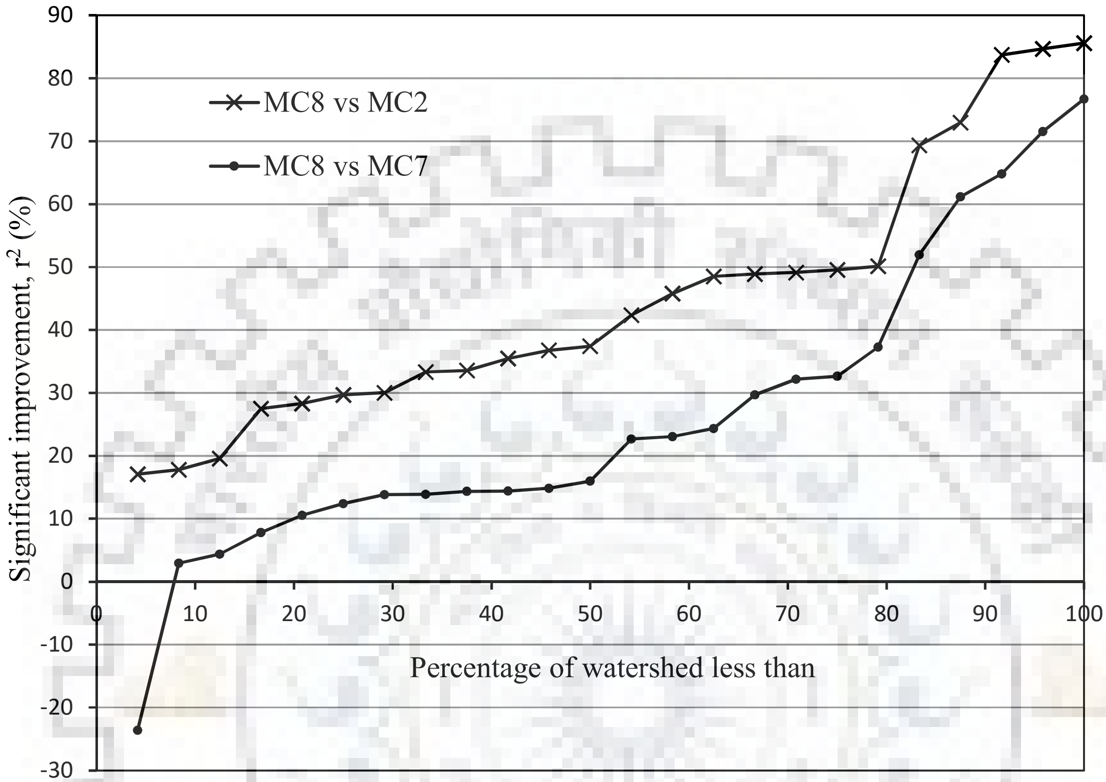

Figure 4.60 The cumulative frequency distribution of improvement using the r^2criterion

CHAPTER 5

SUMMARY AND CONCLUSIONS

5.1 SUMMARY

The present research has been carried out with an objective to investigate the SCS-CN methodology on experimental plot and catchment scales, particularly for the Indian climatic condition. The Soil Conservation Service curve number (SCS-CN) presently known as Natural Resources Conservation Service curve number (NRCS–CN) is widely used for predicting surface runoff from small agricultural watersheds, primarily because of its simplicity and the requirement of only two parameters for runoff prediction, which are the initial abstraction ratio (λ) and the potential maximum retention (S) expressed in terms of curve number (CN). In practice, for ungauged watersheds, CNs are derived from the well–known National Engineering Handbook chapter–4 (NEH–4) tables using watershed characteristics. The empirical evidences however show that the use of NEH–4 tables CN values normally over-design the hydrological systems, and therefore, use of CN values based on observed rainfall (P)–runoff (Q) data is recommended. Thus, there is need of such regional studies for analyzing the accuracy of various parameters like CN determination methods, initial abstraction coefficient, relative accuracy of existing AMC formulae, and relationship between CN (or S) and AWC etc. in runoff prediction using locally measured P–Q data. The accuracy of curve number method for Indian watersheds is rarely been examined due to lack of observed P–Q data from agricultural watershed.

In this study, locally monitored (i.e. Roorkee experimental site falls in River Solani watershed) and published literature rainfall (P) and runoff (Q) data have been used. The experimental work was conducted during August 2012 – April 2015 (or three crop growing years in study area) in which P–Q data was monitored for a total 35 experimental plots of various slopes, land use, and hydrologic soil group (HSG) (i.e. Infiltration capacity). For local data collection, the plots of size 22 m length and 5 m width having four land uses: sugarcane, maize, black gram and fallow land and three slopes (5%, 3% and 1%) were developed. The surface runoff generated during rain storms was collected in separate chambers (1m × 1m × 1m) constructed at the downstream end of each plot and the variation in depth of water stored with respect to time was monitored regularly, but manually. Precipitation was recorded with the help of Tipping Bucket rain gauge and a non-recording rain gauge installed within the experimental site. Infiltration tests were conducted for each plot using the double ring infiltrometer (45/30) for identification of the hydrologic soil group (HSG). In addition to locally monitored, the P–Q data of 36 watersheds/plots having at least 10 natural events per watershed and cover the various climatic regions around the globe were collected from published literature.

1. Initially, rainfall−runoff behaviour pattern was analysed in study plots. Regression analysis were performed to investigate relationships of runoff (Q)–depth and runoff coefficient (Rc) with P-depth and previous day soil moisture (θ) (%) for each plot separately. The summarized results of rainfall−runoff behaviour, rainfall threshold (I), and effect of soil type, land use and slope on runoff and Curve number are as follows:

a) The non−linear variation of Rc with P is similar to the variation of Q with P, but the correlation between Rc and P is much lower than that between Q and P. The P–Q relationship was statistically significant ($p<0.05$) for all the tested runoff plots. θ did not correlate well with Q as well as Rc in study plots. Theoretically, higher θ means higher Q (or Rc), but this was not observed in the dataset. However, in the present study, Q is largely controlled by P, consistent with the findings of other researchers, rather than θ.

b) The rainfall threshold (I) for runoff generation was determined for each plot including all daily observed P–Q data and results show that highest I was observed for the plots having HSGs A. In contrast, the lowest I was observed for the plots having HSGs C whereas I for HSG B was in between HSGs A and C. The concept of I is also supported by response of runoff to rainfall, i.e. runoff coefficient which followed the similar pattern as does I.

c) The non-parametric Kruskal–Wallis test revealed that land uses did not show any significant difference in Rc except sugarcane which produced significantly ($p < 0.05$) higher Rc than blackgram and fallow land uses. The HSG C had significantly higher Rc than did B and A, but the last ones did not differ from each other. Notably, slope did not show any effect on Rc as all three groups of slopes were insignificantly different from each other. An inverse relationship between CN and *f*c for all 27 study plots was detected with significant correlation ($R^2 = 0.461$, $p<0.01$). Compared to land use and slope, *f*c is the main explanatory variable for runoff (or CN) production in the study plots. The results from this analysis support the applicability of NEH-4 tables where CNs decline with *f*c (or HSG).

2. The relative accuracy of different CNs determination methods was analyzed to find the best method for study region. In order to check the suitability of Handbook table CNs for study

region, comparison of observed P-Q data-based Curve number with Handbook table CNs are made for which results given as follows:

a) P-Q data-based curve number estimation analysis show that, in general, the CNs estimated by Geometric-mean method are usually larger (17 of 36 plots) followed by S-probability (15 of 36 plots). The K−W test analysis revealed that there was no single method which has produced significantly higher (or lower) CNs than other. Geometric-mean produced significantly ($p < 0.05$) higher CNs than M2 and M4, but it was statistically insignificant with others. The S-probability method proves to be best among all methods followed by geometric mean method. Based on overall score the methods performance can be described as follows: S-probability > geometric mean > storm event mean > rank order median > rank order mean > least square fit > storm event median > log normal frequency.

b) The observed P–Q data CNs were considerably different from the conventional NEH-4 table values. P–Q derived CNs are higher than those from NEH-4 tables. However, these are closer for higher CN values, consistent with the general notion that the existing SCS-CN method performs better for high P-Q (or CN) events. The group of CN_{HT} lower than 75 shows a higher PBIAS (=-12.84%) than the group of CN_{HT} higher than 75 (=1.03%).

3. In order to find the suitable initial abstraction coefficient (λ) value for study region, λ–values were derived for both natural and ordered P-Q data sets of 27 plots employing least square fit method. The summarized results are as follows:

a) The optimized λ–values derived for both natural (ranging from 0 to 0.208) and ordered (ranging from 0 to 0.659) P–Q datasets are seen to vary widely from plot to plot with 0 as the most frequent value. The cumulative frequency distribution of λ-values for both datasets shows that λ values are larger for ordered data, the distribution is skewed, and most λ-values (out of 27, 26 for natural and 21 for ordered P–Q datasets) are less than the standard λ=0.2 value. The mean and median λ-values are 0.030 & 0 for natural, and 0.108 & 0 for ordered data, quite different from standard λ = 0.20, but consistent with the results of other studies carried out elsewhere

b) In contrast to the existing notion, I_a when plotted against S exhibited no correlation for both natural and ordered datasets, consistent with the findings of Jiang (2001).

c) Runoff estimation improves as λ decreases; for 26 out of 27 plots by changing λ-value from 0.2 to 0.03. A relationship between $CN_{0.20}$ (λ = 0.20) and $CN_{0.03}$ (λ = 0.03), useful for CN conversion for field application is developed.

4. The existence of a relationship between CN (or S) and AWC was explored to improve the runoff prediction using regression models between CN derived from P-Q dataset and corresponding observed antecedent soil moisture indices such as θ_{o1}, θ_{o3}, θ_{o5}, and P_5. The exponential regression of CN with θ_{o1} performed the best of all in both calibration and validation. However, the existing index based on 5-day antecedent rainfall (P_5) exhibited a poor performance in comparison to one day antecedent moisture (θ_{o1}), consistent with the results reported elsewhere.

5. The performance of five existing viz., Hawkins et al. (1985), Mishra et al. (2008b), Chow et al. (1988), Sobhani (1975), and Arnold et al. (1990) and three proposed (MC6, MC7 and MC8) antecedent moisture condition (AMC)-based runoff curve number (CN) conversion formulae was evaluated utilizing the data of a large number of naturally observed rainfall (P)–runoff (Q) for an experimental agricultural plots and available published data around the globe. For developing the MC6 and MC7 formulae, CNs were derived for P–Q datasets from 39 watersheds/plots using standard initial abstraction ratio (λ) values as 0.20. On the other hand, MC8 was developed incorporating the λ effect as 0.03. The summarized results from these analyses are as follows:

a) The existing formulae outperformed the proposed formulae when tested numerically using the available National Engineering Handbook chapter–4 (NEH–4) tabular AMC-dependent CNs as target values. It might be because the existing formulae were derived from the same datasets used as targeted values (i.e. NEH–4 AMC defining tables).

b) The three proposed formulae perform best followed by Mishra et al. (2008) and Hawkins et al. (1985) in their application to field data. Among existing formulae, Chow et al. (1988) and Sobhani (1975) formulae are the poorest when tested for field data.

c) A comparison of the results derived from the eight different methods concluded that the M8 formula that incorporates the effect of λ into standard SCS–CN method showed a superior performance in runoff simulation than the others.

5.2 CONCLUSIONS

The following major conclusions can be drawn from the study:

1. Compared to land use and slope, soil type is the main explanatory variable for runoff (or CN) production in the study plots. CN is inversely related to infiltration capacity, which supports the applicability of NEH-4 tables CNs declining with infiltration capacity (or HSG).

2. The performance of the storm event mean, least square fit, log normal frequency, NEH-4 median, and Rank order methods was found to be almost identical except for the S-probability and geometric mean methods, which exhibited the closest agreement with observed runoff.
3. CNs estimated from the handbook tables do not compare well with those derived from experimentation. Runoff estimates using tabulated curve numbers are unreliable to estimate runoff for 22 of the 24 agricultural plots investigated. Therefore, P-Q data based CNs are suggested as a preference over tabulated ones for use in the study area.
4. λ is of the order of 0.03, rather than the traditional 0.20. Mean and median λ-values are respectively 0.030 & 0 for natural and 0.108 & 0 for ordered P–Q data. λ was greater than 0.2 for only 1 natural plot-data and 6 ordered plot-data. Runoff estimation improves as λ decreases; for 26 out of 27 plots by changing λ-value from 0.2 to 0.03. Contrary to traditionally assumed Ia–S linear relationship, the present study exhibits no correlation between Ia and S.
5. CNs do not correlate well with the cumulative precipitation of previous five days. CN showed greater dependence on the physically measured 1-day antecedent soil moisture (θo) rather than the other soil moisture indices considered in this study.
6. The performance of the existing AMC-conversion formulae, viz., Sobhani (1975), Hawkins et al. (1985), Chow et al. (1988), Arnold et al. (1990) and Mishra et al. (2008b) was found to be almost identical. The proposed formula MC8 that incorporates the effect of λ=0.03 into standard SCS–CN method performed better than the others existing and proposed formulae in runoff simulation.

5.3 RESEARCH CONTRIBUTIONS

The following research contributions can be drawn from the study:

1. CN has a physical significance as it is correlated with the soil's physical retention and transmission characteristics.
2. Soil type plays a more dominating role in runoff generation than slope and land use.
3. CN correlates well with physically measured soil water content.
4. S-probability method among other 8 CN determination methods is the best in runoff estimation.
5. NEH-4 CNs be used in field with caution and CNs should be derived for each watershed using observed data to the extent possible.

6. CN is inversely related with infiltration capacity (*f*c), supporting CNs declining with *f*c (or HSG).
7. λ=0.03 is more appropriate than the existing λ=0.2.
8. A new formula incorporating λ in AMC formulae is proposed and recommended for field use.
9. The empirical equation was developed for converting $CN_{0.20}$ into $CN_{0.03}$ which can be very useful in field application.

5.4 LIMITATIONS OF THE STUDY

There are few limitations in the study which can be overcome in the near future listed as:

1. The results of this study are limited to the experimental boundaries such as plot size, slopes, soils, agricultural land uses, and climatic conditions.
2. Replication of such a study for a wider range of physical and climatic settings is imperative for indicating its broader applicability.
3. An automation of measurement of data may further help refine the results of the present study which based on manual data collection. The automation of data measurement may help in investigating the development runoff hydrograph with the help of SCS method.

5.5 SCOPE FOR FURTHER STUDY

This research provided useful insight into the runoff estimation by SCS-CN method in the Solani watershed region. The present study opens scope for further research in the area of modelling runoff, and some of the recommendations for future works are listed below:

1. Rainfall intensity and duration are excluded in SCS-CN method which affect I_a and λ.
2. CN model can be further extended for the development of runoff hydrograph using λ as 0.03.
3. The effect of land use and land cover (i.e. seasonal effect) on CN can be investigated.
4. Additional parameters such as soil wetness index, climate variability like evapotranspiration and groundwater variables (infiltration rate, water table, hydraulic conductivity, field capacity etc.) can be incorporated in in SCS-CN methodology.
5. Testing the SCS-CN methodology using the data of plots having slopes greater than 5%.
6. Use of improved RS & GIS can be made in for improving the simulation capability of the SCS method.

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The following research papers have been published from the present thesis work.

A. Journal Paper:

1. **Lal, M.**, Mishra, S. K. and Kumar, M. (2019). Reverification of antecedent moisture condition dependent runoff curve number formulae using experimental data of Indian watersheds. Catena 173:48–58. (SCI Impact Factor = 3.256)

2. **Lal, M.**, Mishra, S. K., Pandey, A., Pandey, R. P., Meena, P. K., Chaudhary, A., Jha, R. K., Shreevastava, A. K. and Kumar, Y. (2017). Evaluation of the Soil Conservation Service curve number methodology using data from agricultural plots. Hydrogeology Journal, 25(1):151-167. (SCI Impact Factor = 2.071)

3. **Lal, M.**, Mishra, S. K. and Pandey, A. (2015). Physical verification of the effect of land features and antecedent moisture on runoff curve number. Catena 133:318–327. (SCI Impact Factor = 3.256)

B. Paper published in Springer Book Series:

1. **Lal, M.**, Mishra, S. K., Pandey, A. and Kumar, Y. (2017). Runoff curve number for 36 small agricultural plots at two different climatic conditions in India. Development of Water Resources in India. Water science and Technology Library, Springer Publication Volume 84. Chapter DOI: 10.1007/978-3-319-55125-8_22

C. Paper presented at Conference:

1. **Lal, M.**, Mishra, S. K. and Pandey, A. (2015) Curve number derivation for experimental plots of different slopes, hydrologic soil groups and land uses. Paper presented at 20th International Conference on Hydraulics, Water Resources and River Engineering, 17-19 December, 2015 at IIT Roorkee, India.
2. **Lal, M.**, Mishra, S. K., Pandey, A., Kumar, Y. (2016). Runoff curve number for 36 small agricultural plots at two different climatic conditions in India. Paper presented at

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APPENDIX A

Table A1 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 1, 2 and 3

Event No.	Date	Rainfall(P) mm	Runoff (Q) mm			Previous day soil moisture (%)		
			Plot 1	Plot 2	Plot 3	Plot 1	Plot 2	Plot 3
1	16-Jun-13	73.00	44.77	49.84	43.76	22.70	24.27	30.87
2	28-Jun-13	32.00	11.61	11.47	15.18	26.57	23.87	29.33
3	20-Jul-13	88.50	28.14	29.42	31.51	17.70	21.77	25.33
4	29-Jul-13	46.50	18.93	20.02	20.70	22.50	21.70	23.33
5	05-Aug-13	16.80	0.37	0.04	0.38	25.73	20.93	26.57
6	13-Aug-13	17.00	1.95	4.37	2.16	21.30	23.50	24.07
7	22-Aug-13	42.00	3.90	1.85	7.85	17.43	18.47	19.80
8	28-Aug-13	16.00	0.08	0.15	0.15	20.73	22.07	22.70
9	30-Aug-13	27.40	3.74	2.19	12.28	23.97	24.47	24.17
10	11-Oct-13	18.40	0.68	0.50	0.70	11.80	8.40	5.40
11	18-Jan-14	53.9	5.72	3.57	4.78	19.50	21.20	22.60
12	23-Jan-14	35.2	5.42	4.94	4.52	21.50	26.20	26.50
13	14-Feb-14	24.8	0.64	0.45	0.02	19.10	20.50	22.50
14	15-Feb-14	39	14.32	8.20	18.02	27.30	30.90	30.40
15	12-03-2014	22	1.849	1.728	0.228	19.3	23.7	30.1

Table A2 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 4, 5 and 6

Event No.	Date	Rainfall (mm)	Runoff (Q) mm			Previous day soil moisture (%)		
			Plot 4	Plot 5	Plot 6	Plot 4	Plot 5	Plot 6
1	16-Jun-13	73.00	38.20	39.59	30.61	27.3	22.3	19.7
2	28-Jun-13	32.00	3.43	5.05	0.49	18.77	25.40	21.37
3	20-Jul-13	88.50	20.14	16.73	17.32	17.60	19.53	16.23
4	29-Jul-13	46.50	6.65	11.02	1.97	19.73	19.83	19.73
5	05-Aug-13	16.80	0.37	0.09	0.48	21.10	22.23	22.20
6	13-Aug-13	17.00	2.39	2.47	0.35	22.60	23.33	24.93
7	22-Aug-13	42.00	N.A.	N.A.	N.A.	18.60	18.53	18.43
8	28-Aug-13	16.00	0.23	0.04	0.08	20.37	19.63	21.30
9	30-Aug-13	27.40	1.33	9.56	1.53	24.10	23.73	23.27
10	11-Oct-13	18.40	0.23	0.12	0.20	8.3	7.7	5.7

Table A3 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 7, 8 and 9

Event No.	Date	Rainfall (mm)	Runoff (Q) mm			Previous day soil moisture (%)		
			Plot 7	Plot 8	Plot 9	Plot 7	Plot 8	Plot 9
1	16-Jun-13	73.00	30.29	27.53	45.56	20.67	28.30	26.80
2	28-Jun-13	32.00	11.43	8.31	15.84	28.47	24.07	22.13
3	20-Jul-13	88.50	43.37	44.51	43.87	17.10	13.73	22.97
4	29-Jul-13	46.50	20.34	10.97	13.24	22.53	24.10	26.57
5	05-Aug-13	16.80	0.18	0.06	0.10	20.47	26.13	27.40
6	13-Aug-13	17.00	0.68	1.12	0.92	22.17	24.07	25.87
7	22-Aug-13	42.00	5.35	4.58	9.72	17.70	18.77	19.33
8	28-Aug-13	16.00	0.02	0.20	0.24	22.67	23.33	24.67
9	30-Aug-13	27.40	10.01	5.65	8.60	23.73	23.90	26.67
10	11-Oct-13	18.40	0.30	0.11	0.18	10.30	11.20	11.60

Table A4 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 10, 11 and 12

Event No.	Date	Rainfall (mm)	Runoff (Q) mm			Previous day soil moisture (%)		
			Plot 10	Plot 11	Plot 12	Plot 10	Plot 11	Plot 12
1	16-Jun-13	73.00	48.95	37.09	39.17	25.40	25.25	26.05
2	28-Jun-13	32.00	13.67	13.20	15.35	20.67	23.17	21.37
3	20-Jul-13	88.50	33.46	31.19	29.23	14.33	14.90	19.73
4	29-Jul-13	46.50	10.56	7.74	12.84	20.27	22.97	22.07
5	05-Aug-13	16.80	0.10	0.26	0.19	18.30	23.13	26.03
6	13-Aug-13	17.00	0.83	0.28	1.77	24.10	23.70	25.00
7	22-Aug-13	42.00	4.44	1.81	0.53	15.77	20.20	18.80
8	28-Aug-13	16.00	0.24	0.38	0.31	21.50	23.07	24.73
9	30-Aug-13	27.40	3.56	2.10	0.87	23.37	24.77	26.43
10	11-Oct-13	18.40	0.30	0.20	0.28	8.90	12.50	12.70

Table A5 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 13, 14 and 15

Event No.	Date	Rainfall (mm)	Runoff (Q) mm			Previous day soil moisture (%)		
			Plot 13	Plot 14	Plot 15	Plot 13	Plot 14	Plot 15
1	01-Jul-14	71.50	19.66	21.19	16.61	12.30	16.10	13.45
2	02-Jul-14	29.40	8.95	14.90	8.33	28.70	31.53	31.88
3	14-Jul-14	20.20	1.80	1.72	2.05	10.83	10.57	12.70
4	15-Jul-14	24.20	6.44	6.08	4.18	29.07	31.67	29.83
5	16-Jul-14	38.80	7.48	19.18	17.41	24.90	23.93	28.90
6	18-Jul-14	54.20	10.96	20.87	17.55	20.60	21.17	22.00
7	29-Jul-14	24.20	3.35	5.26	5.82	16.73	18.93	19.40
8	05-Aug-14	27.00	3.90	12.47	8.14	14.37	14.70	17.37
9	29-Aug-14	29.10	0.57	0.55	0.78	15.70	17.20	16.77
10	06-Sep-14	68.60	17.88	16.18	19.41	19.00	20.77	21.10
11	08-Sep-14	28.20	6.50	6.69	7.77	28.83	29.07	29.03
12	02-Mar-15	62.40	9.83	9.80	8.26	20.00	19.30	20.53
13	04-Apr-15	45.40	9.12	14.22	8.85	21.73	25.33	23.77

Table A6 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 16, 17 and 18

Event No.	Date	Rainfall (mm)	Runoff (Q) mm			Previous day soil moisture (%)		
			Plot 16	Plot 17	Plot 18	Plot 16	Plot 17	Plot 18
1	01-Jul-14	71.50	12.20	16.04	18.79	9.00	14.00	14.00
2	02-Jul-14	29.40	11.25	9.63	18.40	26.40	31.33	29.70
3	14-Jul-14	20.20	1.16	0.80	0.30	9.70	10.20	9.73
4	15-Jul-14	24.20	2.99	1.90	1.82	26.55	22.97	26.50
5	16-Jul-14	38.80	12.51	4.86	10.94	19.90	21.77	23.60
6	18-Jul-14	54.20	18.17	13.16	27.03	20.67	17.17	21.33
7	29-Jul-14	24.20	0.91	2.06	0.84	15.53	15.67	19.57
8	05-Aug-14	27.00	2.09	4.76	3.74	16.43	14.27	24.37
9	29-Aug-14	29.10	0.24	0.05	0.78	16.73	16.57	15.80
10	06-Sep-14	68.60	26.94	21.38	30.88	21.83	20.20	23.27
11	08-Sep-14	28.20	9.03	7.19	10.19	29.80	29.83	28.83

Table A7 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 19, 20 and 21

Event No.	Date	Rainfall (mm)	Runoff (Q) mm			Previous day soil moisture (%)		
			Plot 19	Plot 20	Plot 21	Plot 19	Plot 20	Plot 21
1	01-Jul-14	71.5	6.20	15.96	18.64	9.30	15.10	12.45
2	02-Jul-14	29.4	8.86	12.13	16.67	25.47	32.13	28.13
3	14-Jul-14	20.2	1.28	1.19	0.36	10.43	10.90	14.77
4	15-Jul-14	24.2	2.88	3.03	1.68	26.23	24.73	27.80
5	16-Jul-14	38.8	10.33	15.16	21.50	17.40	23.43	24.07
6	18-Jul-14	54.2	8.24	9.39	12.64	18.33	17.20	19.06
7	29-Jul-14	24.2	1.08	2.08	1.65	18.47	15.57	22.67
8	05-Aug-14	27	2.41	5.79	4.09	15.27	14.17	13.37
9	29-Aug-14	29.1	0.43	0.69	0.57	15.10	17.63	15.43
10	06-Sep-14	68.6	9.01	13.18	17.54	19.07	19.00	22.37
11	08-Sep-14	28.2	5.22	6.74	9.00	29.73	26.83	28.57

Table A8 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 22, 23 and 24

Event No.	Date	Rainfall (mm)	Runoff (Q) mm			Previous day soil moisture (%)		
			Plot 22	Plot 23	Plot 24	Plot 22	Plot 23	Plot 24
1	01-Jul-14	71.5	14.99	15.37	13.86	11.75	14.00	15.70
2	02-Jul-14	29.4	7.87	11.27	4.89	33.67	34.27	28.00
3	14-Jul-14	20.2	2.67	1.17	1.11	10.27	10.93	8.70
4	15-Jul-14	24.2	3.82	2.17	4.68	26.13	23.43	21.23
5	16-Jul-14	38.8	13.24	15.75	15.47	23.53	23.70	17.23
6	18-Jul-14	54.2	10.26	13.58	16.87	18.83	17.37	18.47
7	29-Jul-14	24.2	3.08	3.06	4.08	17.47	15.53	19.70
8	05-Aug-14	27	7.61	5.23	6.65	13.50	13.23	14.70
9	29-Aug-14	29.1	0.34	0.58	1.04	10.07	10.27	9.43
10	06-Sep-14	68.6	6.60	0.15	2.38	18.60	17.60	14.10
11	08-Sep-14	28.2	4.57	5.25	5.69	29.70	29.13	29.33
12	02-Mar-15	62.40	7.63	N.A.	9.03	20.13	N.A.	19.47
13	04-Apr-15	45.40	7.03	N.A.	10.83	22.8	N.A.	21.73

Table A9 Observed rainfall, runoff and previous day soil moisture data for experimental plot nos. 25, 26 and 27

Event No.	Date	Rainfall (mm)	Previous day soil moisture (%)			Runoff (mm)		
			Plot 25	Plot 26	Plot 27	Plot 25	Plot 26	Plot 27
1	13-Sep-12	22.2	32.7	30.7	30.1	14.73	6.69	5.35
2	14-Sep-12	30.2	32.5	27.4	27.6	14.74	11.49	9.18
3	17-Sep-12	42.1	34.5	32	31	24.38	22.30	21.17
4	18-Sep-12	29.1	34.8	32.1	31.84	23.05	18.18	16.45
5	18-Jan-13	56.2	28.4	27.6	26.8	19.46	18.75	15.05
6	05-Feb-13	48.2	29.8	27.9	26.6	20.14	13.82	9.87
7	06-Feb-13	22.4	29.3	29.1	26.9	8.25	4.84	3.51
8	16-Feb-13	43.2	28.6	25.6	24.4	25.32	17.68	16.35
9	17-Feb-13	53.8	32.4	29.8	27.6	30.85	25.83	23.09
10	23-Feb-13	10.2	31.15	31.43	30.93	2.85	0.68	0.35

Table A10 Observed rainfall and runoff data for experimental plot nos. 28, 29 and 30

Event No.	Date	Rainfall (mm)	Runoff (Q) mm		
			Plot 28	Plot 29	Plot 30
1	13-Sep-12	22.20	15.46	8.73	3.64
2	14-Sep-12	30.20	19.00	18.79	15.88
3	17-Sep-12	42.10	25.56	22.30	16.16
4	18-Sep-12	29.10	20.65	18.18	8.75

Table A11 Observed rainfall and runoff data for experimental plot nos. 31 and 32

Event No.	Date	Rainfall (mm)	Runoff (Q) mm	
			Plot 31	Plot 32
1	18-01-2014	53.90	3.04	2.75
2	23-01-2014	35.20	12.34	5.06
3	14-02-2014	24.80	0.79	0.02
4	15-02-2014	39.00	11.44	14.58
5	12-03-2014	22.00	1.14	0.32

Table A12 Observed rainfall and runoff data for experimental plot nos. 33, 34 and 35

Event No.	Date	Rainfall (mm)	Runoff (Q) mm		
			Plot 33	Plot 34	Plot 35
1	18-01-2014	53.90	1.54	0.02	0.27
2	23-01-2014	35.20	5.63	1.45	8.10
3	14-02-2014	24.80	0.49	0.27	0.06
4	15-02-2014	39.00	4.56	4.80	9.80
5	12-03-2014	22.00	3.152	1.652	1.334

APPENDIX B

Table B1 Infiltration test data for experimental plot no. 1

Plot 1 (Date of test: 04/02/2014)					
Time	Time Interval (min.)	Cumulative Time (min.)	Volume of Water Added ml (cm^3)	Infiltration Depth (mm)	Infiltration Capacity (mm/hr.)
12:25 PM	0	Start = 0			
12:26 PM	1	1	250	3.54	212.21
12:27 PM	1	2	110	1.56	93.37
12:28 PM	1	3	100	1.41	84.88
12:30 PM	2	5	135	1.91	57.30
12:32 PM	2	7	115	1.63	48.81
12:34 PM	2	9	110	1.56	46.69
12:40 PM	6	15	310	4.39	43.86
12:45 PM	5	20	225	3.18	38.20
12:50 PM	5	25	220	3.11	37.35
1::00 PM	10	35	400	5.66	33.95
1:10 PM	10	45	380	5.38	32.26
1:25 PM	15	60	540	7.64	30.56
1:40 PM	15	75	500	7.07	28.29
2:00 PM	20	95	650	9.20	27.59
2:20 PM	20	115	550	7.78	23.34
2:40 PM	20	135	550	7.78	23.34
3:05 PM	25	160	650	9.20	22.07
3:30 PM	25	185	450	6.37	15.28
4:00 PM	30	215	500	7.07	14.15
4:30 PM	30	245	400	5.66	11.32
5:00 PM	30	275	345	4.88	9.76
5:30 PM	30	305	260	3.68	7.36
6:00 PM	30	335	260	3.68	7.36

Table B2 Infiltration test data for experimental plot no. 2

Plot 2 (Date of test: 04/02/2014)					
Time (Hr: Min)	Time interval (min)	Cumulative time (min)	Volume of water added (ml)	Infiltration depth (mm)	Infiltration Capacity (mm/hr)
12:32	Start	0	0	0	0
12:33	1	1	250	3.54	212.21
12:34	1	2	190	2.69	161.28
12:37	3	5	35	0.50	9.90
12:40	3	8	50	0.71	14.15
12:45	5	13	125	1.77	21.22
12:50	5	18	130	1.84	22.07
12:55	5	23	140	1.98	11.88
1:05	10	33	115	1.63	9.76
1:15	10	43	180	2.55	15.28
1:25	10	53	170	2.41	9.62
1:40	15	68	225	3.18	12.73
1:55	15	83	210	2.97	11.88
2:10	15	98	155	2.19	6.58
2:30	20	118	190	2.69	8.06
2:50	20	138	220	3.11	9.34
3:10	20	158	170	2.41	4.81
3:40	30	188	275	3.89	7.78
4:10	30	218	310	4.39	8.77
4:40	30	248	310	4.39	8.77

Table B3 Infiltration test data for experimental plot no. 3

Plot 3 (Date of test: 03/02/2014)					
Time	Time Interval (min.)	Cumulative Time (min.)	Volume of Water Added ml (cm^3)	Infiltration Depth (mm)	Infiltration Capacity (mm/hr.)
12:14 PM	0	Start = 0			
12:15 PM	1	1	90	1.27	76.39
12:16 PM	1	2	80	1.13	67.91
12:18 PM	2	4	95	1.34	40.32
12:20 PM	2	6	50	0.71	21.22
12:22 PM	2	8	60	0.85	25.46
12:27 PM	5	13	50	0.71	8.49
12:32 PM	5	18	130	1.84	22.07
12:37 PM	5	23	140	1.98	23.77
12:42 PM	5	28	125	1.77	21.22
12:52 PM	10	38	135	1.91	11.46
1:02 PM	10	48	275	3.89	23.34
1:12 PM	10	58	180	2.55	15.28
1:27 PM	15	73	220	3.11	12.45
1:42 PM	15	88	320	4.53	18.11
1:57 PM	15	103	290	4.10	16.41
2:17 PM	20	123	290	4.10	12.31
2:37 PM	20	143	400	5.66	16.98
2:57 PM	20	163	400	5.66	16.98
3:27 PM	30	193	340	4.81	9.62
3:57 PM	30	223	250	3.54	7.07
4:27 PM	30	253	250	3.54	7.07
4:57 PM	30	283	240	3.40	6.79
5:27 PM	30	313	230	3.25	6.51
5:57 PM	30	343	230	3.25	6.51

Table B4 Infiltration test data for experimental plot no. 4

Plot 4 (Date of test: 05/09/2013)					
Watch time	Time Elapsed (t) min.	Cumulative time (min)	Reading on Scale (cm)	Real Dropdown, d (cm)	Rate of infiltration (cm/hr)
11:00	0	0	5.6	0	0
11:01	1	1	5.8	0.2	12
11:02	1	2	5.9	0.1	6
11:05	3	5	6	0.1	2
11:10	5	10	6.2	0.2	2.4
11:15	5	15	6.4	0.2	2.4
11:20	5	20	6.5	0.1	1.2
11:25	5	25	6.7	0.2	2.4
11:30	5	30	6.8	0.1	1.2
11:35	5	35	7	0.2	2.4
11:40	5	40	7.2	0.2	2.4
11:45	5	45	7.4	0.2	2.4
11:50	5	50	7.6	0.2	2.4
11:55	5	55	7.8	0.2	2.4
12:00	5	60	8	0.2	2.4
12:10	10	70	8.2	0.2	1.2
12:20	10	80	8.5	0.3	1.8
12:30	10	90	8.7	0.2	1.2
12:40	10	100	9	0.3	1.8
12:50	10	110	9.2	0.2	1.2
13:00	10	120	9.6	0.4	2.4
13:10	10	130	9.8	0.2	1.2
13:20	10	140	10	0.2	1.2
13:35	15	155	10.2	0.2	0.8
13:50	15	170	10.5	0.3	1.2
14:05	15	185	10.8	0.3	1.2
14:20	15	200	11.1	0.3	1.2
14:35	15	215	11.4	0.3	1.2
14:50	15	230	11.7	0.3	1.2
15:05	15	245	12	0.3	1.2
15:20	15	260	12.3	0.3	1.2
15:40	20	280	12.8	0.5	1.5
16:00	20	300	13.2	0.4	1.2
16:20	20	320	13.5	0.3	0.9
16:40	20	340	13.9	0.4	1.21

Table B5 Infiltration test data for experimental plot no. 5

Plot 5 (Date of test: 07/09/2013)					
Watch time	Time Elapsed (t) min.	Cumulative time (min)	Reading on Scale (cm)	Real Dropdown (cm)	Rate of infiltration (cm/hr)
10:06	0	0	19.2	0	0
10:07	1	1	19	0.2	12
10:08	1	2	18.8	0.2	12
10:13	5	7	18.7	0.1	1.2
10:18	5	12	18.5	0.2	2.4
10:23	5	17	18.4	0.1	1.2
10:33	5	22	18.3	0.1	1.2
10:43	10	32	18.2	0.1	0.6
10:53	10	42	18.1	0.1	0.6
11:03	10	52	17.9	0.2	1.2
11:13	10	62	17.7	0.2	1.2
11:23	10	72	17.6	0.1	0.6
11:38	15	87	17.4	0.2	0.8
11:53	15	102	17.3	0.1	0.4
12:08	15	117	17.2	0.1	0.4
12:23	15	132	17	0.2	0.8
12:38	15	147	16.9	0.1	0.4
12:58	20	167	16.8	0.1	0.3
13:18	20	187	16.6	0.2	0.6
13:38	20	207	16.4	0.2	0.6
13:58	20	227	16.3	0.1	0.3
14:28	30	257	16	0.3	0.6
14:58	30	287	15.7	0.3	0.6
15:28	30	317	15.4	0.3	0.6
15:58	30	347	15.1	0.3	0.615

Table B6 Infiltration test data for experimental plot no. 6

Plot 6 Date of test: 07/09/2013					
Watch time	Time Elapsed (t) min.	Cumulative time (min)	Reading on Scale (cm)	Real Dropdown (cm)	Rate of infiltration (cm/hr)
10:22	0	0	9.4	0	0
10:23	1	1	9.5	0.1	6
10:24	1	2	9.6	0.1	6
10:25	1	3	9.7	0.1	6
10:26	1	4	9.8	0.1	6
10:27	1	5	9.9	0.1	6
10:32	5	10	10.0	0.1	1.2
10:37	5	15	10.1	0.1	1.2
10:42	5	20	10.3	0.2	2.4
10:47	5	25	10.5	0.2	2.4
10:52	5	30	10.6	0.1	1.2
10:57	5	35	10.7	0.1	1.2
11:02	5	40	10.8	0.1	1.2
11:07	5	45	10.9	0.1	1.2
11:17	10	55	11.3	0.4	2.4
11:27	10	65	11.5	0.2	1.2
11:37	10	75	11.7	0.2	1.2
11:47	10	85	11.9	0.2	1.2
11:57	10	95	12.2	0.3	1.8
12:07	10	105	12.4	0.2	1.2
12:22	15	120	12.7	0.3	1.2
12:37	15	135	12.9	0.2	0.8
12:52	15	150	13.1	0.2	0.8
13:07	15	165	13.3	0.2	0.8
13:22	15	180	13.5	0.2	0.8
13:42	20	200	13.8	0.3	0.9
14:02	20	220	14.0	0.2	0.6
14:32	30	250	14.5	0.5	1.22
15:02	30	280	15.0	0.5	1.22
15:32	30	310	15.5	0.5	1.21
16:02	30	340	16.0	0.5	1.21

Table B7 Infiltration test data for experimental plot no. 7

Plot 7 (Date of test: 01/02/2014)					
Time (Hr:Min)	Time interval (min)	Cumulative time (min)	Volume of water added (ml)	Infiltration depth (mm)	Infiltration Capacity (mm/hr)
12:15	start	0	0	0	0
12:16	1	1	150	2.12	127.33
12:17	1	2	100	1.41	84.88
12:18	1	3	50	0.71	42.44
12:20	2	5	50	0.71	21.22
12:22	2	7	50	0.71	21.22
12:24	2	9	55	0.78	9.34
12:29	5	14	25	0.35	4.24
12:34	5	19	35	0.50	2.97
12:44	10	29	100	1.41	8.49
12:54	10	39	55	0.78	4.67
1:04	10	49	125	1.77	10.61
1:14	10	59	120	1.70	5.09
1:34	20	79	60	0.85	2.55
1:54	20	99	65	0.92	2.76
2:14	20	119	100	1.41	4.24
2:34	20	139	100	1.41	2.83
3:04	30	169	135	1.91	3.82
3:34	30	199	140	1.98	3.96
4:04	30	229	150	2.12	4.24
4:34	30	259	150	2.12	4.24

Table B8 Infiltration test data for experimental plot no. 8

Plot 8 (Date of test: 01/02/2014)					
Time (Hr:Min)	Time interval (min)	Cumulative time (min)	Volume of water added (ml)	Infiltration depth (mm)	Infiltration Capacity (mm/hr)
12:33	Start	0	0	0	0
12:34	1	1	80	1.13	67.91
12:36	2	3	35	0.50	14.85
12:48	12	15	120	1.70	8.49
12:53	5	20	70	0.99	11.88
12:58	5	25	35	0.50	5.94
1:08	10	35	305	4.31	25.89
1:18	10	45	50	0.71	4.24
1:28	10	55	60	0.85	5.09
1:38	10	65	165	2.33	9.34
1:53	15	80	90	1.27	3.82
2:13	20	100	190	2.69	8.06
2:33	20	120	95	1.34	4.03
2:53	20	140	230	3.25	6.51
3:23	30	170	205	2.90	5.80
3:53	30	200	195	2.76	5.52
4:23	30	230	195	2.76	5.52

Table B9 Infiltration test data for experimental plot no. 9

Plot 12 (Date of test: 31/12/2014)					
Time (Hr:Min)	Time interval (min)	Cumulative time (min)	Volume of water added (ml)	Infiltration depth (mm)	Infiltration Capacity (mm/hr)
12:37	start	0	0	0	0
12:39	2	2	255	3.61	108.23
12:41	2	4	85	1.20	36.08
12:43	2	6	55	0.78	23.34
12:48	5	11	195	2.76	33.10
12:53	5	16	25	0.35	4.24
1:03	5	21	150	2.12	12.73
1:13	10	31	140	1.98	11.88
1:23	10	41	145	2.05	12.31
1:33	10	51	60	0.85	5.09
1:43	10	61	130	1.84	7.36
1:58	15	76	155	2.19	8.77
2:13	15	91	170	2.41	9.62
2:28	15	106	65	0.92	2.76
2:48	20	126	225	3.18	9.55
3:08	20	146	185	2.62	7.85
3:28	20	166	160	2.26	4.53
3:58	30	196	200	2.83	5.66
4:28	30	226	200	2.83	5.66

APPENDIX C

Table C1 Optimized λ values yielded from 63 watershed natural P-Q datasets

Watershed/Plot No.	λ
1	0.0204
2	0.0000
3	0.0631
4	0.0314
5	0.2079
6	0.0999
7	0.1141
8	0.0879
9	0.0328
10	0.0003
11	0.0000
12	0.0002
13	0.0000
14	0.0001
15	0.0000
16	0.0000
17	0.0000
18	0.0000
19	0.0000
20	0.0000
21	0.0000
22	0.0000
23	0.0000
24	0.0000
25	0.0375
26	0.0334
27	0.1244
28	0.0002
29	0.0000
30	0.0319
31	0.0020
32	0.0000
33	0.0000
34	0.0000
35	0.0002
36	0.0003
37	0.0310
38	0.3310
39	0.0005
40	0.0000

Table C1 (continued)

Watershed/Plot No.	λ
41	0.0000
42	0.0000
43	0.0000
44	0.0002
45	0.1301
46	0.0000
47	0.0116
48	0.0003
49	0.0004
50	0.0000
51	0.0000
52	0.0002
53	0.0000
54	0.0000
55	0.0000
56	0.0819
57	0.0885
58	0.0000
59	0.0000
60	0.1862
61	0.0000
62	0.1706
63	0.0449
Maximum	0.3310
Minimum	0.0000
Mean	0.0312
Median	0.0002
Standard deviation	0.0630
Skewness	2.7213
Kurtosis	8.4921

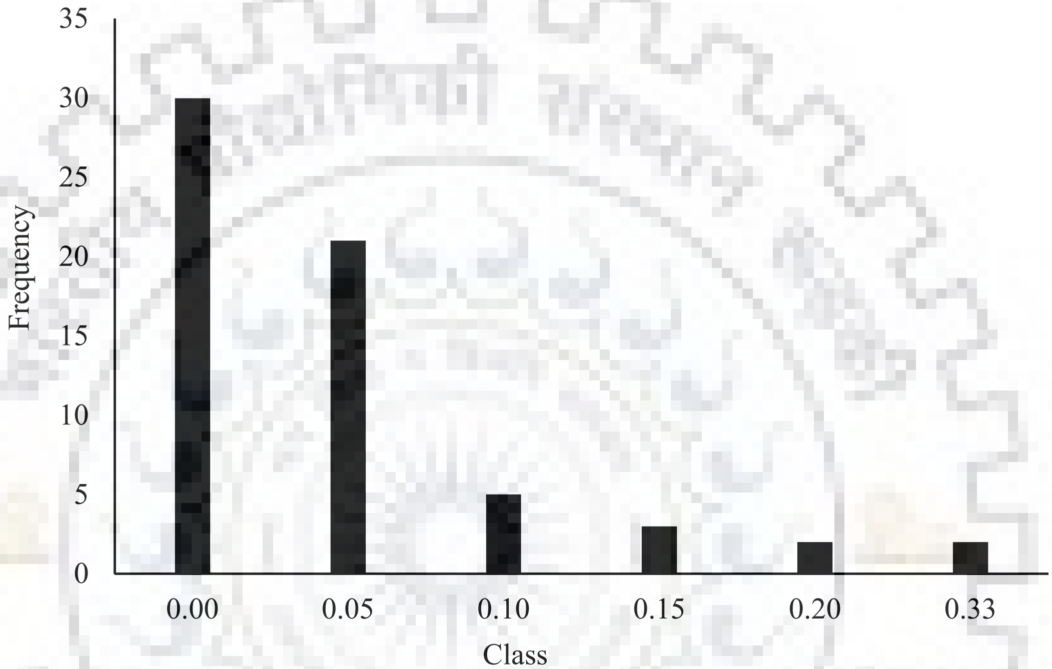

Figure C1 Frequency distribution of optimized λ values yielded from 63 watershed/plots natural P-Q data set

APPENDIX D

Table D1 Comparison of methods using RMSE (mm) criterion

Plot No.	MC1	MC2	MC3	MC4	MC5	MC6	MC7	MC8
40	6.821	6.789	6.841	7.085	7.188	5.850	5.593	5.370
41	7.678	7.674	7.714	7.722	7.716	7.529	7.519	6.957
42	7.481	7.461	7.507	7.649	7.705	6.882	6.741	6.284
43	8.505	8.495	8.621	8.600	8.519	7.969	7.847	7.192
44	6.818	6.796	6.895	7.004	7.008	6.029	5.831	5.458
45	9.791	9.797	9.946	9.760	9.576	9.626	9.611	8.920
46	6.218	6.197	6.457	6.420	6.088	5.323	5.172	4.152
47	8.010	8.000	8.171	8.114	7.906	7.557	7.497	6.519
48	10.648	10.645	10.808	10.687	10.504	10.363	10.334	9.064
49	6.720	6.681	6.643	7.040	7.330	5.814	5.579	5.456
50	5.671	5.652	5.576	5.837	6.057	5.485	5.479	5.069
51	5.703	5.673	5.629	5.954	6.207	5.129	5.018	4.746
52	3.549	3.972	4.065	4.268	4.297	2.667	2.448	2.532
53	11.691	11.613	11.994	12.315	11.739	9.109	8.470	6.348
54	8.324	8.271	8.572	8.792	8.283	6.361	5.882	4.945
55	30.199	30.055	31.520	31.351	30.963	25.671	24.378	22.683
56	27.814	27.793	28.120	28.000	27.878	26.354	25.944	25.669
57	21.450	21.340	21.210	22.334	22.791	18.676	17.871	15.713
58	23.505	23.432	24.008	24.155	23.520	20.490	19.851	16.644
59	31.556	31.569	31.363	31.440	31.779	29.267	30.271	23.973
60	19.758	19.721	19.994	20.279	20.436	17.558	16.964	14.216
61	3.120	3.128	3.273	3.082	2.902	3.164	3.239	2.244
62	9.679	9.616	9.518	10.184	10.810	8.185	7.763	7.648
63	7.698	7.641	7.548	8.179	8.597	6.309	5.920	5.463

Table D2 Comparison of methods using R^2 criterion

Plot No.	MC1	MC2	MC3	MC4	MC5	MC6	MC7	MC8
40	0.236	0.239	0.219	0.215	0.224	0.376	0.421	0.449
41	0.392	0.394	0.375	0.375	0.385	0.484	0.508	0.574
42	0.221	0.223	0.205	0.205	0.216	0.325	0.356	0.413
43	0.188	0.189	0.165	0.179	0.201	0.283	0.310	0.403
44	0.270	0.272	0.247	0.254	0.273	0.394	0.430	0.484
45	0.357	0.358	0.328	0.347	0.375	0.459	0.485	0.581
46	0.085	0.086	0.135	0.081	0.042	0.023	0.015	0.305
47	0.088	0.087	0.133	0.093	0.051	0.011	0.004	0.328
48	0.114	0.114	0.168	0.117	0.067	0.025	0.014	0.314
49	0.330	0.332	0.324	0.311	0.305	0.408	0.429	0.444
50	0.496	0.496	0.498	0.493	0.487	0.483	0.474	0.535
51	0.518	0.519	0.515	0.508	0.503	0.541	0.542	0.573
52	0.191	0.190	0.167	0.182	0.204	0.301	0.340	0.440
53	0.015	0.015	0.010	0.017	0.017	0.025	0.028	0.252
54	0.000	0.000	0.000	0.000	0.001	0.024	0.041	0.247
55	0.248	0.248	0.244	0.244	0.250	0.272	0.279	0.272
56	0.050	0.051	0.042	0.045	0.047	0.096	0.111	0.221
57	0.850	0.850	0.851	0.847	0.845	0.854	0.855	0.881
58	0.815	0.817	0.811	0.805	0.811	0.858	0.867	0.916
59	0.569	0.570	0.561	0.565	0.575	0.666	0.659	0.684
60	0.283	0.285	0.267	0.266	0.270	0.381	0.409	0.609
61	0.395	0.392	0.345	0.410	0.469	0.434	0.436	0.804
62	0.545	0.547	0.549	0.535	0.523	0.578	0.589	0.604
63	0.633	0.633	0.634	0.629	0.626	0.644	0.647	0.679

Table D3 Comparison of methods using d criterion

Plot No.	MC1	MC2	MC3	MC4	MC5	MC6	MC7	MC8
40	0.681	0.683	0.674	0.663	0.663	0.753	0.770	0.785
41	0.737	0.737	0.731	0.736	0.742	0.745	0.744	0.776
42	0.685	0.686	0.678	0.677	0.680	0.723	0.731	0.760
43	0.680	0.680	0.666	0.676	0.689	0.711	0.717	0.760
44	0.728	0.729	0.718	0.718	0.725	0.780	0.791	0.815
45	0.727	0.727	0.715	0.731	0.745	0.735	0.734	0.769
46	0.256	0.256	0.237	0.260	0.279	0.334	0.368	0.713
47	0.212	0.214	0.159	0.188	0.253	0.384	0.414	0.662
48	0.280	0.281	0.227	0.260	0.322	0.405	0.425	0.630
49	0.649	0.651	0.649	0.629	0.616	0.715	0.731	0.732
50	0.814	0.814	0.817	0.808	0.800	0.814	0.812	0.832
51	0.803	0.804	0.804	0.793	0.784	0.825	0.827	0.840
52	0.624	0.586	0.571	0.565	0.571	0.726	0.756	0.755
53	0.203	0.204	0.194	0.195	0.202	0.256	0.273	0.421
54	0.316	0.318	0.301	0.302	0.321	0.411	0.451	0.634
55	0.549	0.551	0.548	0.538	0.542	0.601	0.617	0.633
56	0.428	0.429	0.423	0.426	0.429	0.450	0.455	0.451
57	0.894	0.894	0.895	0.887	0.884	0.912	0.917	0.928
58	0.945	0.945	0.943	0.942	0.945	0.957	0.959	0.973
59	0.864	0.864	0.863	0.864	0.865	0.890	0.885	0.895
60	0.722	0.722	0.709	0.708	0.710	0.785	0.800	0.877
61	0.774	0.771	0.752	0.791	0.818	0.718	0.689	0.869
62	0.783	0.785	0.787	0.769	0.752	0.825	0.827	0.839
63	0.777	0.779	0.782	0.761	0.748	0.822	0.835	0.846

Table D4 Comparison of methods using E criterion

Plot No.	MC1	MC2	MC3	MC4	MC5	MC6	MC7	MC8
40	-0.574	-0.559	-0.583	-0.698	-0.748	-0.157	-0.058	0.025
41	-0.294	-0.293	-0.306	-0.309	-0.307	-0.244	-0.241	-0.063
42	-0.591	-0.582	-0.602	-0.663	-0.688	-0.346	-0.292	-0.113
43	-0.104	-0.101	-0.134	-0.129	-0.107	0.031	0.060	0.211
44	-0.070	-0.063	-0.094	-0.129	-0.131	0.163	0.217	0.314
45	0.141	0.139	0.113	0.146	0.178	0.169	0.172	0.286
46	-2.209	-2.187	-2.461	-2.421	-2.077	-1.352	-1.220	0.138
47	-1.166	-1.160	-1.254	-1.222	-1.110	-0.927	-0.897	-0.435
48	-0.864	-0.863	-0.920	-0.878	-0.814	-0.766	-0.756	-0.351
49	-1.804	-1.771	-1.740	-2.077	-2.336	-1.098	-0.933	-0.848
50	0.054	0.061	0.086	-0.002	-0.079	0.115	0.117	0.245
51	-0.228	-0.215	-0.197	-0.339	-0.455	0.006	0.049	0.149
52	-1.042	-1.558	-1.678	-1.953	-1.993	-0.153	0.029	-0.201
53	-4.469	-3.957	-4.487	-4.683	-4.782	-0.353	-0.191	0.192
54	-4.620	-4.548	-4.959	-5.269	-4.564	-2.282	-1.806	0.201
55	-4.765	-4.710	-4.797	-5.213	-5.060	-3.166	-2.757	0.124
56	-2.738	-2.733	-2.821	-2.789	-2.756	-2.356	-2.253	-0.144
57	-0.790	-0.772	-0.750	-0.940	-1.021	-0.357	-0.242	0.040
58	0.775	0.776	0.765	0.762	0.775	0.829	0.839	0.887
59	0.407	0.407	0.414	0.412	0.399	0.490	0.455	0.658
60	0.055	0.058	0.032	0.004	-0.011	0.253	0.303	0.531
61	0.366	0.363	0.303	0.382	0.452	0.348	0.317	0.672
62	-0.256	-0.240	-0.215	-0.391	-0.567	0.102	0.192	0.216
63	-0.699	-0.674	-0.633	-0.918	-1.119	-0.141	-0.004	0.145