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# LONG TERM HYDROLOGIC SIMULATION USING SCS-CN METHOD



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## PREFACE

Long-term hydrologic simulation studies are important for providing the necessary input to the water resources planning and watershed management practices. The Soil Conservation Service Curve Number (SCS-CN) method is the most widely used event-based method of runoff computation world over. Using the SCS-CN method, some attempts have been made to develop hydrologic models by varying the model's only parameter potential maximum retention. These models have ranged widely in performance. The present study attempts to develop a hydrologic model varying the potential maximum retention or the curve number of the SCS-CN method with the known antecedent moisture condition (AMC), an important factor affecting the curve number besides the soil type, land use, and hydrologic conditions of the watershed. For the given physiological characteristics of a watershed, AMC forms an important factor which largely depends on antecedent meteorologic conditions.

The model presented in this report has been applied to three large catchments falling in sub-humid and arid regions of India and its performance is evaluated. The results are compared with the available linear perturbation model. The report also presents a sensitivity analysis of the model parameters for better understanding of the model's functional behaviour.

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## ABSTRACT

Hydrologic simulation studies provide a useful and important input to water resources planning and watershed management practices. The Soil Conservation Service (SCS, 1956) Curve Number (SCS-CN) method is a widely used event based rainfall-runoff method. In this report, the SCS-CN method is used for simulating daily rainfall-runoff data of three catchments, viz., Ramganga (area=3134 sq. km) and Hemavati catchments (area=600 sq. km) falling in sub-humid regions and Sabarmati catchment (area = 5240 sq. km) falling in the arid region of India. In the model formulation, the daily variation of parameter potential maximum retention is governed by known antecedent moisture condition. Simulation of Ramganga data is performed using data in its primitive form as well as the data perturbed about seasonal means, identified as Case A and Case B, respectively. The usage of perturbed data in Case B parallels the concept of linear perturbation model (LPM) (Nash and Barsi, 1983). The simulation results of Case B exhibit better performance than those of Case A as well as the results of the LPM, in validation period of 6 years. The Case A results exhibit efficiency of 50.073% in calibration and 67.299% in validation in Ramganga application, 72.444% in calibration and 75.567% in validation in Hemavati application, and 47.693% in calibration and 59.694% in validation in Sabarmati application. Thus, the simulation model has exhibited better performance on the catchments falling in the sub-humid region than that falling in the arid region. A sensitivity analysis of the model is also performed on the Hemavati data used in validation. The parameters CN,  $d_1$ ,  $d_2$ ,  $d_3$ ,  $d_4$  are found to be more sensitive than  $\lambda$ , NLAG, and  $b$ , and, therefore, require careful estimation for field applications.

## 1.0 INTRODUCTION

The existing Soil Conservation Service Curve Number (SCS-CN) method (SCS, 1956) is primarily based on two equations: The universal water balance equation

$$P = I_a + F + Q \quad (1)$$

and the two hypotheses:

$$\frac{Q}{P - I_a} = \frac{F}{S} \quad (2)$$

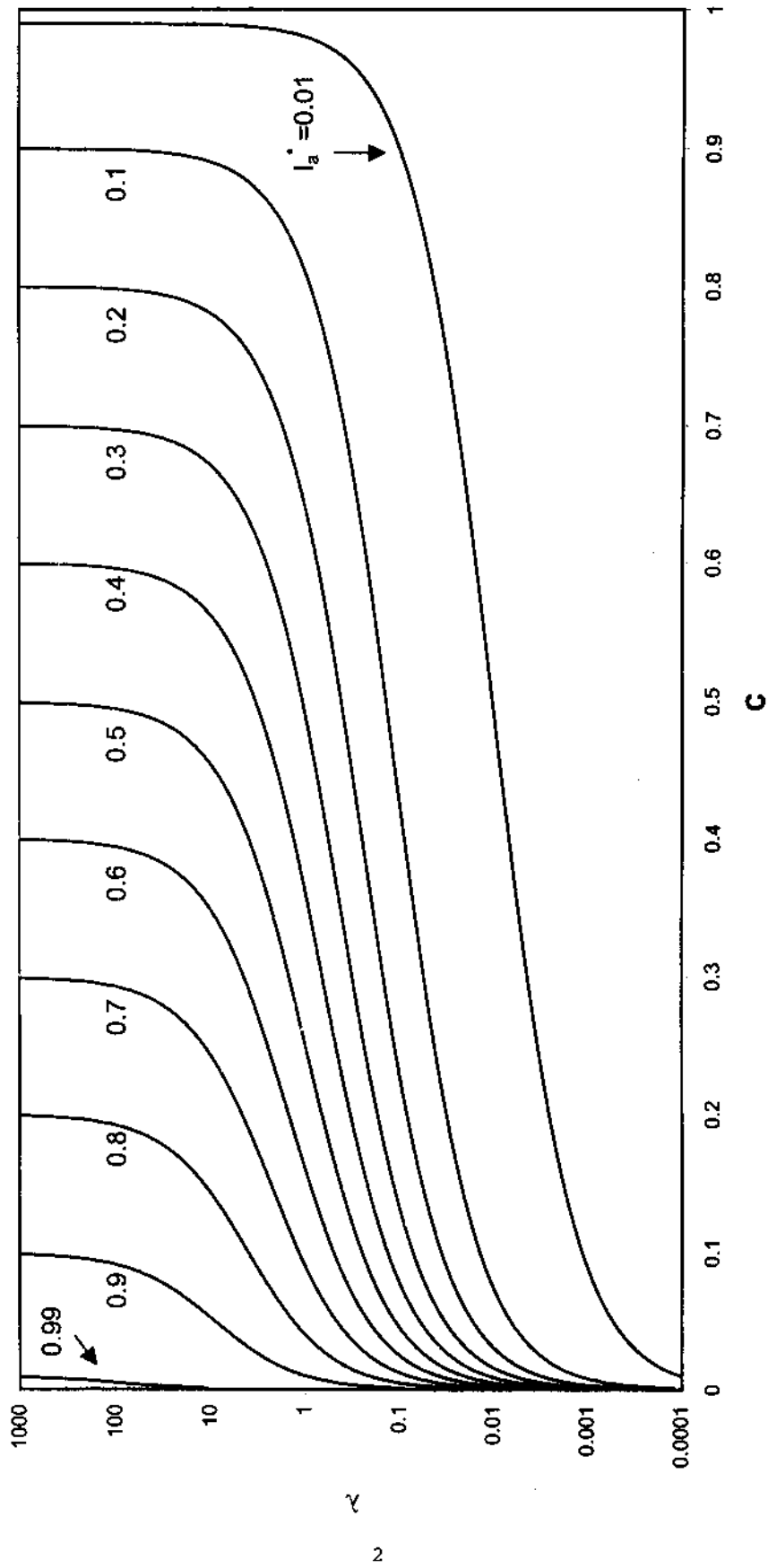
and

$$I_a = \lambda S \quad (3)$$

where,  $P$ =total precipitation;  $I_a$ =initial abstraction;  $F$ =cumulative infiltration;  $Q$ =direct runoff;  $S$ =potential maximum retention or infiltration;  $\lambda$  is the initial abstraction coefficient.  $\lambda$  is taken equal to 0.2 in practical applications. Mishra (1998) defined  $S$  as the maximum amount of space available in the soil profile under given antecedent moisture amount. The hypothesis given by Eq. 2 is a proportionality concept (Mishra and Singh, 1999c). Ponce and Hawkins (1996) provided a good overview of the SCS-CN method. The popular form of the SCS-CN method can be derived by combining Eqs. 1 and 2 as

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

Here,  $P > I_a$  and  $Q=0$  otherwise. Mishra and Singh (1999a, 1999b) explained the functional behaviour of the SCS-CN method using  $I_a$  as a key descriptor and derived  $C-I_a^*-\lambda$  spectrum, as shown in Fig. 1, where  $C$  is the runoff factor ( $=Q/P$ ) and  $I_a^*$  is the non-dimensional initial abstraction ( $=I_a/P$ ).



**Fig. 1. Variation of initial abstraction coefficient ( $\lambda$ ) with runoff coefficient ( $C$ ) and non-dimensional initial abstraction ( $\lambda_a^*$ )**



The relation between S and CN is expressed as

$$S = \frac{1000}{CN} - 10 \quad (5)$$

This relation (Eq. 5) is empirical one, supposedly based on field experience and scaling. It is not, however, entirely clear as to the extent to which S could assume a value that is practically meaningful. A brief revisit of this equation is therefore in order.

Eq. 5 can be recast as

$$\frac{S}{10} = \frac{100}{CN} - 1 \quad (6)$$

Eq. 5 or Eq. 6 shows that CN varies from 1 to 100, resulting in the range of S (0,90) inches. If CN is taken equal to 0, S will approach infinity. Further interpretation of Eq. 6 follows (Mishra and Singh, 1999c).

Using daily experimental data, the absolute maximum retention of 10 inches, within the confines of available experimental data, was examined. The minimum possible S could be 0, is of common knowledge. Therefore, S was varied to a larger scale through CN taking non-linear scaling (Eq. 6). An examination of Eq. 6 reveals that the stated range of S (0,10) inches is completely exhausted in CN range of (50,100). Therefore, CN values less than 50 should fall in the extrapolated range of experimental data. If this holds true, the application of  $CN < 50$  is unwarranted. The experimentally derived data (Hawkins, 1979) which did not, in general, lend CN values less than 50 also support the above argument. While assessing CN for its practical applications, Ponce (1989) recommended CN-variation in the aforementioned range. Incorporating the absolute maximum retention ( $S_{abs}$ ), a new parameter, in Eq. 6, the general form of the equation can be written as

$$\frac{S}{S_{abs}} = \frac{100}{CN} - 1 \quad (7)$$

Here,  $S$  varies between 0 and  $S_{abs}$  inches (or any other unit). The importance of such a manipulation can be found in Williams and LaSuer (1976), Rallison and Miller (1982) and Ponce (1989).

It seems that the originator's predilection for introducing non-linearity in Eqs. 4 and 7 was perhaps due to maintaining the non-linear nature of the rainfall-runoff relation expressed by the following equation (Rallison and Miller, 1982):

$$Q = P[1 - (10)^{-bP}] \quad (8)$$

where,  $b$  is an index which depends on antecedent moisture condition, cover practice, time of the year, storm duration, and soil type. Thus, ' $b$ ' is a reasonable variation of CN with the difference that CN is a non-dimensional quantity, and ' $b$ ' a dimensional one.

### 1.1 Long-Term Hydrologic Simulation

Several models are available for hydrologic simulation varying in degree of complexity of inputs, number of parameters to be determined, time interval used, and output. Some models like Stanford Watershed Model, USDAHL (Holtan and Lope, 1971) and its versions, System Hydrologique Europien (SHE), HEC-1, etc. have many parameters, usually use a short time interval, and output hydrographs as well as water yield. These models are designed for detailed hydrologic studies. Furthermore, the Stanford Watershed Model and SHE models are not applicable to ungauged watersheds because these need to be calibrated with measured runoff data for each watershed. The USDAHL model can be used for on ungauged watersheds, but prediction accuracy is not high considering input detail.

The curve number method is an infiltration loss model. Therefore, its applicability is restricted to modelling storm losses (Ponce and Hawkins, 1996). The method has, however, been used in long-term hydrologic simulation and several models have been developed in the past two decades. The models of Williams and LaSuer (1976), Huber et al. (1976), Knisel (1980), Soni and Mishra (1985) applied with varying degree of success (Woodward and Gburek, 1992) are notable among others. The models of Williams and Lasuer (1976) and Hawkins are described

below for emphasising the importance of the SCS-CN-based long-term hydrologic models.

### **Williams-Lasuer Model**

This model is based on the SCS-CN equations (Eqs. 4 and 5). This model has one parameter, uses a 1-day time interval, has simple inputs, and only outputs runoff volume. The input requirements are: (1) an estimate of the curve number (for AMC-II condition) for the watershed; (2) measured monthly runoff; (3) daily rainfall; and (4) average monthly lake evaporation. The model computes a soil moisture index deletion parameter that forces agreement between measured and predicted average annual runoff. Other optimisation schemes, like optimising on monthly or annual runoff, were not used because these do not predict consistently the proper average annual runoff and thus, do not provide a good estimate of average curve number. This model has the advantage that when it is used on nearby ungauged watersheds, the curve number corresponding to AMC-II condition is adjusted for the ungauged watershed in proportion to the ratio of the AMC-II curve number to the average predicted curve number for the calibrated watershed.

This model, however, utilises a value of 20 for the  $S_{abs}$ , assigned arbitrarily; assumes a decay pattern for the soil moisture as a function of lake evaporation; and simulates the runoff on monthly and annual bases though the runoff is computed daily, treating the rainfall of a day as a storm. Since lake evaporation was taken on monthly basis, the daily average of evaporation was used in the model calibration and validation. It is worth noting that the model efficiencies for a greater time interval are usually higher than those derived using a shorter time interval.

### **Hawkins Model**

Hawkins (1978) developed a model that accounted the site moisture on a continuous basis. The accounting of soil moisture is based on the variation of AMC conditions with time and the AMC-based curve numbers are derived using Eq. 5.  $S$  in Eq. 5 varies with the evapotranspiration. This model, however, assumes a total storage of  $(1.2 S)$  that varies with time according to the evaporation and infiltration. It does not prescribe any boundary for the  $1.2 S$  to deplete. Hawkins, however, suggested  $S_{abs} = 20$  in accordance to the perception of Williams and LaSuer.

Soni and Mishra (1985) applied the Hawkins model to the 1-year daily data of Hemawati watershed located in the sub-humid region of India with the Nash and Sutcliffe efficiency equal to about 85%. They used a root zone depth of 1.2 m for the computation of S varying with the evapo-transpiration. In an attempt to apply this model to a large set of daily data, the first author found the model to be performing unsatisfactorily, with much low efficiencies. Therefore, it was found necessary to develop an alternate to the above models, applicable to different climatic and geologic settings.

In the present study, an event-based SCS-CN method of runoff computation is developed. The parameter S is varied according to the antecedent moisture conditions of a day. This is a simple one-parameter model and requires only daily rainfall, daily runoff, and an estimate of the curve number (AMC-II) as input. The model is used for simulating daily flows at the outlets of Ramganga, Hemavati, and Sabarmati catchments, the first two falling in the sub-humid region and the last in the arid-region of India and the model performance is evaluated.

## 2.0 LONG-TERM HYDROLOGIC MODEL

Replacing Q by RO (runoff) in Eq. 4 for avoiding confusion, Eq. 4 can be re-written with time (in day) as sub-script as

$$RO_t = \frac{P_e^2}{P_e + S_t} \quad (9)$$

Where,  $(P_e)_t = P_t - (I_a)_t$ ;  $(I_a)_t = \lambda S_t$ , and  $\lambda=0.2$ . Eq. 5 can be re-written in metric units as

$$S_t = \frac{25400}{CN_t} - 254 \quad (10)$$

where  $S_t$  is in mm and  $CN_t$  can be computed for varying antecedent moisture conditions (AMC) (Table 1) as ( Hawkins et al., 1985)

$$CN_t = \frac{CN_o}{2.3 - 0.013 CN_o}; \text{ or} \quad (11)$$

$$CN_t = \frac{CN_o}{0.43 - 0.0057 CN_o} \quad (12)$$

which are valid for AMC I or AMC III. The initial value of CN ( $=CN_o$ ) corresponds to AMC II. Thus, the variation of  $CN_t$  is primarily governed by AMC.

The computed RO represents the direct runoff amount corresponding to  $P_e$  and its transformation to direct runoff produced at the outlet of the basin is represented by linear regression as

$$q_t = d_1 RO_t + d_2 RO_{t-1} + d_3 RO_{t-2} + \dots \quad (13)$$

where  $d_1, d_2, d_3, \dots$  are the non-dimensional regression coefficients.

**TABLE 1. ANTECEDENT SOIL MOISTURE CONDITIONS (AMC)****(Source: Ponce 1989)**

AMC	5-day antecedent rainfall (cm)	
	Dormant season	Growing season
I	Less than 1.3	Less than 3.6
II	1.3 to 2.8	3.6 to 5.3
III	More than 2.8	More than 5.3

The base flow ( $q_b$ ) is assumed to be a fraction,  $b_f$ , of  $F$  as below:

$$q_{b(t+NLAG)} = b_f F_t \quad (14)$$

The total daily flow,  $Q_t$ , is the sum of  $q_t$  and  $q_b$ . The parameters of the model are determined using non-linear Marquardt algorithm utilising the objective function of minimising the errors between the computed and observed data or maximising model efficiency, described below.

### 2.1 Model Efficiency

The model efficiency is computed using

$$\text{Efficiency} = [1 - RV/IV] \quad (15a)$$

Where

$$RV = \sum_{i=1}^n (Q_i - \hat{Q}_i)^2 \quad (15b)$$

and

$$IV = \sum_{i=1}^n (Q_i - \bar{Q})^2 \quad (15c)$$

Here, RV is the remaining variance; IV is the initial variance;  $Q_i$  is the observed runoff for  $i$ th day;  $\hat{Q}_i$  is the computed runoff for  $i$ th day;  $n$  is the total number of observations; and  $\bar{Q}$  is the overall mean daily runoff. Efficiency is used for evaluating the model performance in calibration and validation periods.

## 2.2 Parameter Estimation

Model parameters,  $CN_0$ ,  $b_f$ ,  $d_1$ ,  $d_2$ ,  $d_3$ , etc. and NLAG (all parameters except NLAG (day) are dimensionless) are determined using Marquardt algorithm of constrained least squares. The algorithm has the advantage of offering unique set of parameters irrespective of initially supplied values of the parameters given the range of parameters' variation. However, for the purpose of using the algorithm one needs to supply their initial values along with their range of variation. The initial value of CN can be computed using the physical characteristics of the basin as normally done with its range (1,100). The initial guess on  $d_1$ ,  $d_2$ ,  $d_3$  can be had from derived/available unit hydrograph of one day duration. Evidently, each of these parameters can range (0,1). Initial guesses on  $b_f$  can be had from the above unit hydrograph, and on NLAG, from the observed rainfall-runoff records of calibration period as follows. A continuous dry spell with no or little runoff is selected and the difference in time of the first rise in runoff and rainfall is taken as the first guess on NLAG whose range is, however, determined by trial and error.

### 3.0 STUDY AREAS

#### 3.1 Ramganga Catchment

The Upper Ramganga Catchment lies in the foothills of Himalayas in the northern part of Uttar Pradesh, India. River Ramganga is a major tributary of River Ganga with origin at Diwali Khel. It emerges out of the hills at Kalagarh (District Almora) where, for harnessing the waters of Ramganga catchment, a major multi-purpose dam, also known as Ramganga dam, is situated. The river traverses approximately 158 km before it meets the reservoir and then continues its journey in the downstream plains for 370 km before joining River Ganga at Farrukhabad (Uttar Pradesh). During its travel up to Ramganga dam, the river is joined by main tributaries: (i) Ganges; (ii) Bino; (iii) Khatraun; (iv) Nair; (v) Badangad; (vi) Mandal; (vii) Helgad; and (viii) Sona Nadi. Its catchment (area= 3134 sq. km) (Fig. 2) lies between elevation 262 and 2926 m above mean sea level, and is considerably below the perpetual snow line of the Himalayas. About 50% of the drainage basin is covered with forest and 30% is under cultivation on terraced fields.

The Ramganga valley experiences approximately an annual precipitation of 1550 mm. The raingauge network consists of Ranikhet, Chaukhatia, Naula, Marchulla, Lansdowne and Kalagarh besides the other existing stations. The present study utilises the continuous rainfall records that were available at the first six stations. The Theissen weights computed for these stations are 0.088, 0.298, 0.190, 0.251, 0.092, 0.081, respectively. Stream flow records of the Ramganga river including river stages, instantaneous as well as monthly, are available at Kalagarh from the year 1958. At this site various high floods were recorded in the years 1963, 1966, 1969, and 1978. It is worth mentioning that after the commencement of the operation of Ramganga dam in Dec. 1974, the available later discharges have been computed using the mass balance approach-- for the computations of inflows to Ramganga dam-- assuming a linear variation in monthly evaporation computed using Rowher's formula. Even though the quality of runoff data is not indubitable, it is used as such without any modification; the gaps during a few short spells were, however, filled up by visual interpretation.



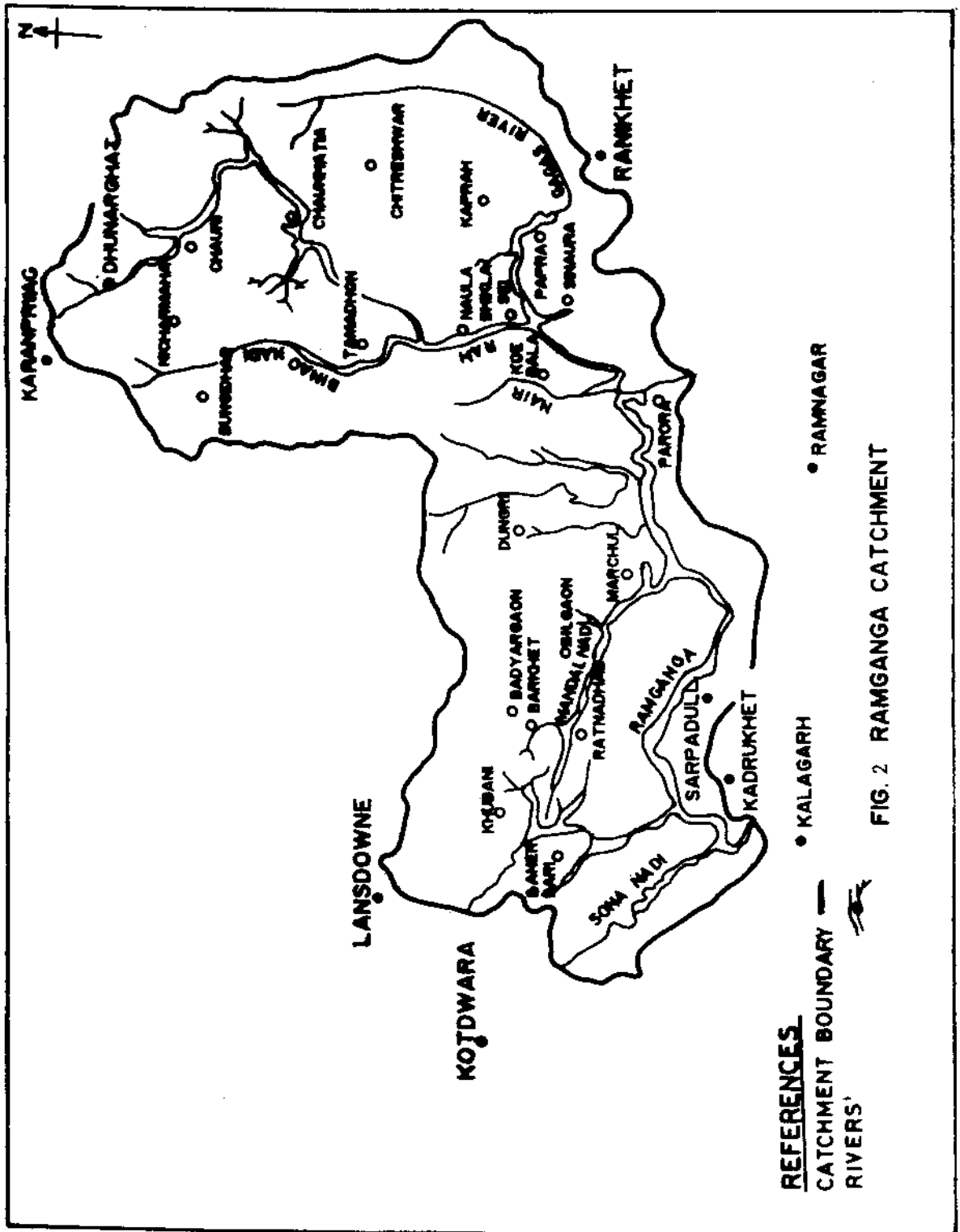


FIG. 2 RAMGANGA CATCHMENT

### **3.2 Hemavati Catchment**

River Hemavati is one of the tributaries of River Cauvery. It rises in Ballairayanadurga in the western ghats in Mundgiri taluk of Chikmanglur district in Karnataka State (Fig. 3). Hemavati river, in its early reaches, passes through a very heavy rainfall region in the vicinity of Kotigehara and Mudigere. The river is joined by Yagachi and Algur. It drains an area of 600 sq. km. up to Sakleshpur, lying between 12°55' and 13°11' north latitude and 75°20' and 75°51' east longitude. The area is a typical monsoon type of climate. It is a hilly catchment with steep to moderate slopes. The agriculture and plantation are the main industries in the basin. The land use can be characterised by forests (12%), coffee plantations (29%), and agricultural lands (59%). The principal soil types are red loamy soil (67%) and red sandy soil (33%). Soils in the forest area and coffee plantations are greyish due to high humus content.

### **3.3 Sabarmati Catchment**

The River Sabarmati is one of the major west flowing rivers of India. It originates in the Aravalli Hills in Rajasthan State and after traversing a distance of about 419 km, the river outfalls into the Gulf of Cambay in the Arabian Sea. Five major tributaries that meet Sabarmati during its course are Sei, Wakal, Harnav, Hathmati, and Watrak. The drainage basin of the river extends over an area of 21, 085 sq. km and lies between longitude 71°55'E and 73°49'E and latitude 22°15'N and 25°54'N. The basin drains a part of Rajasthan State and parts of Sabarkantha, Ahmedabad, Banaskantha, Mesana, Surendra Nagar, and Kaira districts of Gujarat State. The length of the basin is about 300 km. and width is about 105 km. The basin is triangular in shape with the main river as the base and the source of the Watrak river as the apex. Ahmedabad and Gandhinagar are the major cities located near the banks of the river. The catchment area up to Dharoi gauging site is 5240 sq. km. A dam has been built on the site in 1976. Therefore, the flow data series of the monsoon (June-Oct.) for the years 1962 to 1975 has been used in the present study. The index map for the Sabarmati basin up to Ahmedabad is shown in Fig. 4.

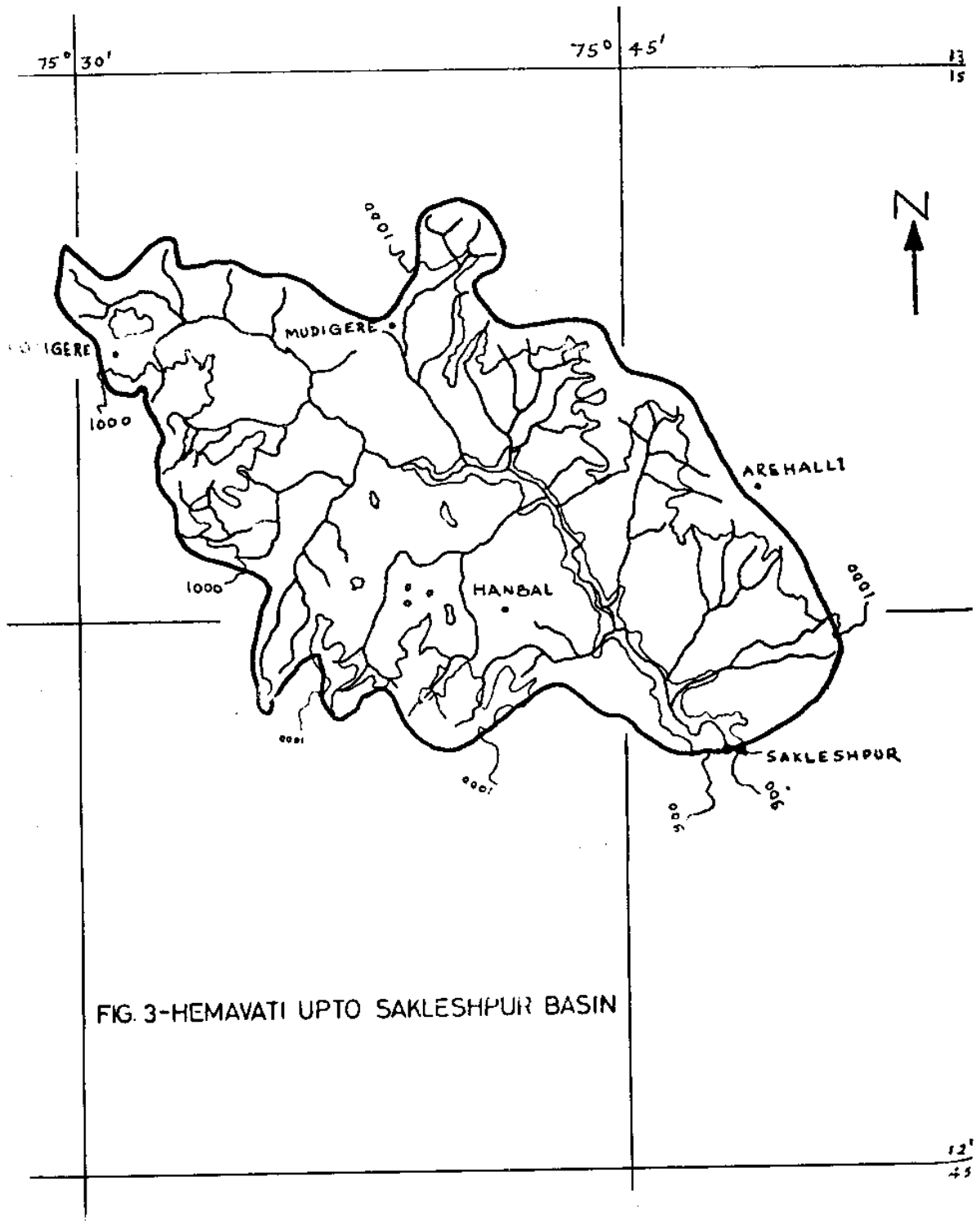
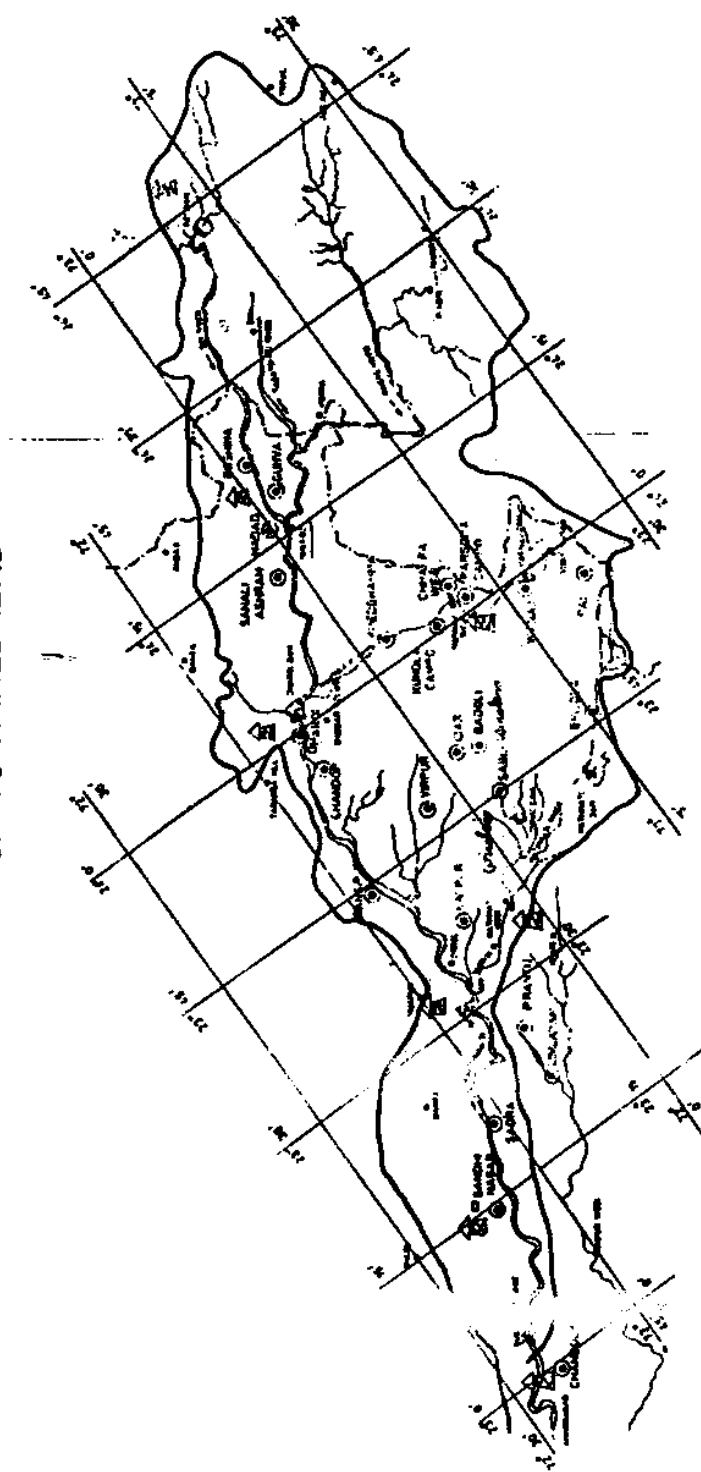


FIG. 3-HEMAVATI UPTO SAKLESHPUR BASIN

FIG.4. INDEX MAP SABARMATI BASIN  
UP TO AHMEDABAD



- LEGEND**
- 1. RIVERS WITH TANGENTIAL DAM & WEIR
  - 2. STATE BOUNDARY
  - 3. DAMS & BARRAGES
  - 4. TANGENTIAL STATIONS (ORDINARY)
  - 5. TANGENTIAL STATIONS (SELF RECORDING)

## 4.0 ANALYSIS

### 4.1 SCS-CN-based Model

The developed SCS-CN model was applied to earlier described three catchments, viz., Ramganga, Hemavati, and Sabarmati. The details of the data used are summarised in Table 2. For the calibration of the parameters of the SCS-CN-based model using Marquardt algorithm, initial estimates of the model parameters  $CN_0$ ,  $b_f$ ,  $d_1$ ,  $d_2$ ,  $d_3$ ,  $d_4$ , and NLAG for Ramganga catchment were determined as follows.

**TABLE 2. DATA USED FOR MODELS' CALIBRATION AND VALAIDATION**

Catchment	Area (sq. km)	Region	Data Length (Years)		AMC (Day)
			Calibration	Validation	
Ramganga	3134	Sub-humid	10	6	5
Hemavati	600	Sub-humid	3	2	5
Sabarmati	5240	Arid	8	7	4

#### 4.1.1 Estimation of initial values of the parameters

Parameter  $CN_0$  was computed using the physical characteristics of the basin with its range (50, 100) (Ponce, 1989; Mishra and Singh, 1999a and 199b). Using the Integrated Land and Water Information System (ILWIS),  $CN_0$  was estimated to be of the order of 70, which is well within the range of CN variation (61-95) computed for various events up to Naula sub-catchment of the Ramganga catchment (Fig. 2) by SWCED (1989).  $\lambda$  was set at 0.2, a standard value of the existing SCS-CN method, and was not optimized. Initial guesses on  $d_1$ ,  $d_2$ ,  $d_3$ ,  $d_4$  (Table 3) represent the fractions of the amount of direct surface runoff resulting from 1-day storm. Apparently these parameters can range (0,1). The  $b_f$ -value assumes that  $(1-b_f)\%$  of infiltrated water does not appear at the outlet of the catchment, implying a loss towards evaporation, evapo-transpiration, and deep percolation. The range of  $b_f$  was determined by trial and error. Parameter NLAG was determined from the observed rainfall-runoff records of

calibration period. A continuous dry spell with no or little runoff was selected for the purpose and from that the difference in time of the first rise in runoff and that in rain rainfall was taken as first guess on NLAG whose range was determined by trial and error. This NLAG indicates that the water infiltrated today appears at the outlet of the catchment after NLAG days. The estimated parameters are shown in Table 5. For simulation using AMC, June-Oct. was treated as dormant season and Nov.-May as growing season.

**TABLE 3. INITIAL ESTIMATES OF THE SCS-CN-BASED HYDROLOGIC SIMULATION MODEL**

Catchment	CN <sub>1</sub>	$\lambda$	b <sub>r</sub>	NLAG (day)	d <sub>1</sub>	d <sub>2</sub>	d <sub>3</sub>	d <sub>4</sub>
Ramganga	70.00	0.2000	0.0900	26	0.0440	0.5507	0.3529	0.0524
Hemavati	70.00	0.2000	0.1000	19	0.0440	0.5507	0.3529	0.0524
Sabarmati	50.00	0.2000	0.1000	20	0.0440	0.5507	-	-

#### 4.2. Linear Perturbation Model

For the application of linear perturbation model (LPM) (described in APPENDIX-I), mean runoff and mean rainfall for each day were computed. The order of the LPM was determined using a trial and error approach. The memory length for PM was selected as 5 and for EM it was 4. The calibrated parameters on the 10-year data set of Ramganga are shown in Table 4 and validation results are shown in Table 5. In these tables and elsewhere if not mentioned, PM stands for perturbation model and EM for error model. From Table 5 it is apparent that the model yields an efficiency of 70.756% with EM (or PM + EM), and 58.763% without EM (or only PM). The linear perturbation models usually exhibit poorer performance in validation than in calibration because the calibrated parameters correspond to the minimum deviation from the observed. The lower efficiencies shown by the model are attributed to the following: 1. The length of the data; experimentation showed that the efficiency increased with the reduction in data length. 2. The dubitable quality of the observed runoff data. As described earlier, the runoff data were computed using mass balance approach, which might include uncertain amount of leakage, evaporation, and the reservoir storage characteristics. Thus, given the quality of data, the LPM performs satisfactorily.

**TABLE 4. CALIBRATED PARAMETERS OF PM AND EM ON RAMGANGA DATA**

Model	Order	Regression coefficients				
PM	5	0.0801	0.0788	0.0306	0.0233	0.0226
EM	4	0.4273	0.0542	0.0960	0.0654	----

**4.3 Calibration of SCS-CN-based Model and Comparison with LPM using Ramganga Data**

As described earlier, the SCS-CN-based simulation model was applied to (i) the given rainfall-runoff data and (ii) the perturbations about mean-rainfall and -runoff similar to the LPM. These applications are identified as Case A and Case B, respectively. Application of the SCS-CN-based model to perturbed data can be supported by assuming that the positive rainfall (if observed rainfall of a day is greater than the mean of that day) passes through the process of absorption and the negative rainfall (if observed rainfall of a day is less than the mean of that day) passes through the process of desorption and hysteresis effects are ignored. The calibrated parameters for all the data sets of three catchments are summarized in Table 5. For the Ramganga data set, the calibration efficiencies of the SCS-CN-based model are 50.073% for Case A and 61.149% for Case B. These efficiencies are, however, lower than those by the LPM showing 63.827% for PM and 74.095% for (PM+EM). However, the efficiency of the SCS-CN-based model for Case B (=61.149%) is comparable with that of the LPM with PM (=63.827%). The sample results for 2 years data of Ramganga are depicted in Figs. 5 and 6.

It is worth mentioning that the EM, as described earlier, updates the output based on previous errors (in computed daily flows) which are not observed ones. Therefore, employment of EM does not support its physical significance whereas the perturbation model can be reasonably supported by the above described two realistic physical processes. Therefore, it is in order to compare the results of the PM of LPM with those of the other model utilising perturbed data. Thus, the overall inference is that the SCS-CN-based model performs reasonably well on Ramganga data set compared to the LPM.

**TABLE 5. MODELS' CALIBRATION AND VALIDATION ON THE DATA OF VARIOUS CATCHMENTS**

Catchment	Model	Calibration										Validation
		CN	$\lambda$	$b_r$	NLAG (day)	$d_1$	$d_2$	$d_3$	$d_4$	Efficiency (%)	Efficiency (%)	
Ramganga	SCS-CN: Case A	94.12	0.2000	0.2214	26	0.1430	0.1314	0.0598	0.0687	50.073	67.299	
	SCS-CN: Case B	85.51	0.2000	0.0449	26	0.2914	0.2161	0.1043	0.1158	61.149	77.724	
Hemavati	LPM: PM	Parameters are given in Table 2										63.827
	PM+EM											74.095
	SCS-CN: Case A											99.57
Sabarmati	SCS-CN: Case A	38.54	0.2000	0.0273	20	0.5119	0.3999	-	-	47.693	59.694	

**Note:** Case A stands for model application to data in primitive form; and

Case B stands for model application to perturbed data about mean.



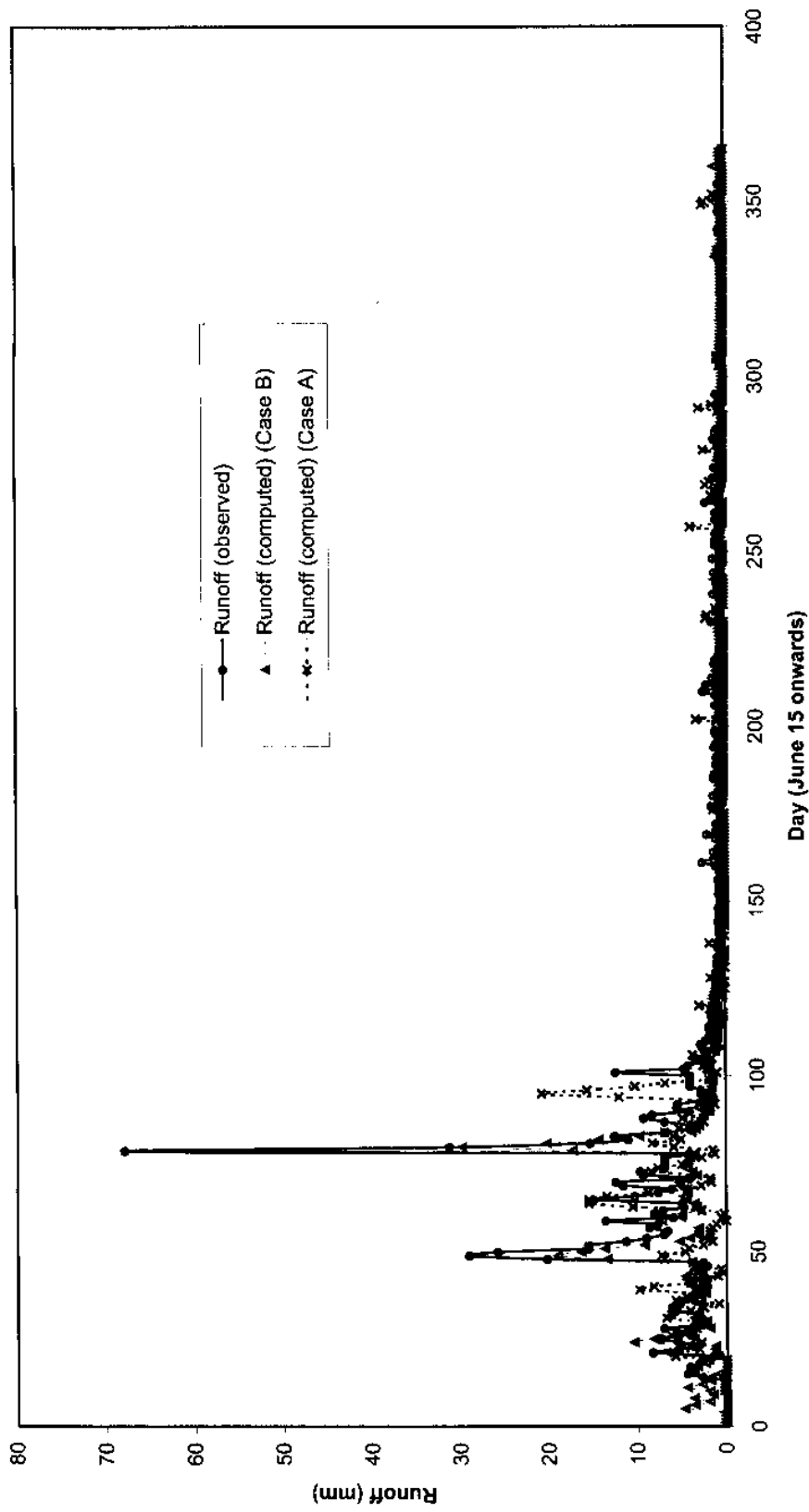


Fig. 5. Ramganga runoff computed for the two cases for the year 1978-79.

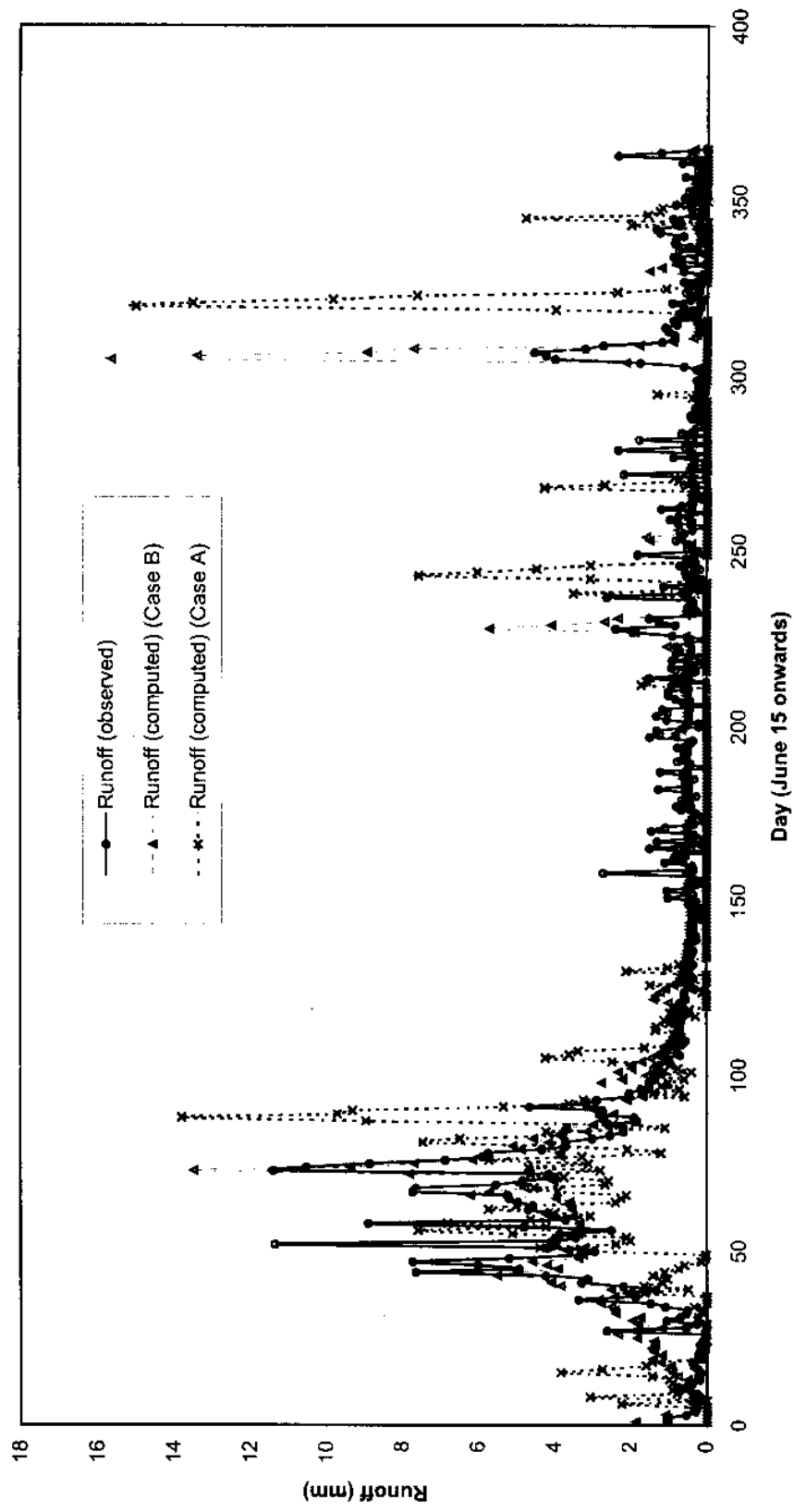


Fig. 6. Ramganga runoff computed for the two cases for the year 1982-83.

#### **4.4 Validation of SCS-CN-based Model and Comparison with LPM using Ramganga Data**

The following discussion is based on the validation of the SCS-CN-based simulation model on 6-year data set of Ramganga catchment, shown in Table 5. The SCS-CN-based simulation model shows efficiencies of 67.299% for Case A and 77.724% for Case B. It performs better than the LPM showing efficiencies of 54.225% with PM and 68.840% with (PM+EM). It implies better performance of the SCS-CN-based simulation model (Case A) than the LPM in validation. The sample results of validation on two years of Ramganga data are depicted in Figs. 7 and 8.

The higher efficiencies shown by the SCS-CN-based model in Case B are apparently attributed to the better fitting of the model to generally lowered (or perturbed) magnitudes of rainfall in which the error of runoff computation will generally be less than that if total rainfall is used. It also infers that seasonal means describe the process for the most part of the modelling process.

#### **4.5 Application of SCS-CN-based Model to Various Catchments**

In an attempt to verify the model's suitability to the various catchments falling in different hydro-meteorologic climatic settings, two catchments from sub-humid region, viz., Ramganga and Hemavati catchments and one from arid region, viz., Sabarmati catchment were selected for the study. The initial estimates of the parameters of the SCS-CN-based simulation model applied to actual data (Case A) are shown in Table 3 along with the length of data used in calibration and validation of the model and final estimates are shown in Table 5. Parameter  $\lambda$  was set at 0.2 in simulations. The CN values of 94.12 for Ramganga, 99.57 for Hemavati, and 38.54 for Sabarmati also characterize the land use conditions of these catchments. The high CN values indicate high runoff producing catchment characteristics and the low CN values indicate low runoff producing catchment characteristics. In calibration, the model yielded an efficiency of 50.073% in Ramganga application, 72.444% in Hemavati application, and 47.693% in Sabarmati application. Thus, the model performed most poorly on Sabarmati data and most efficiently on Hemavati data. The model efficiency in validation on Ramganga data

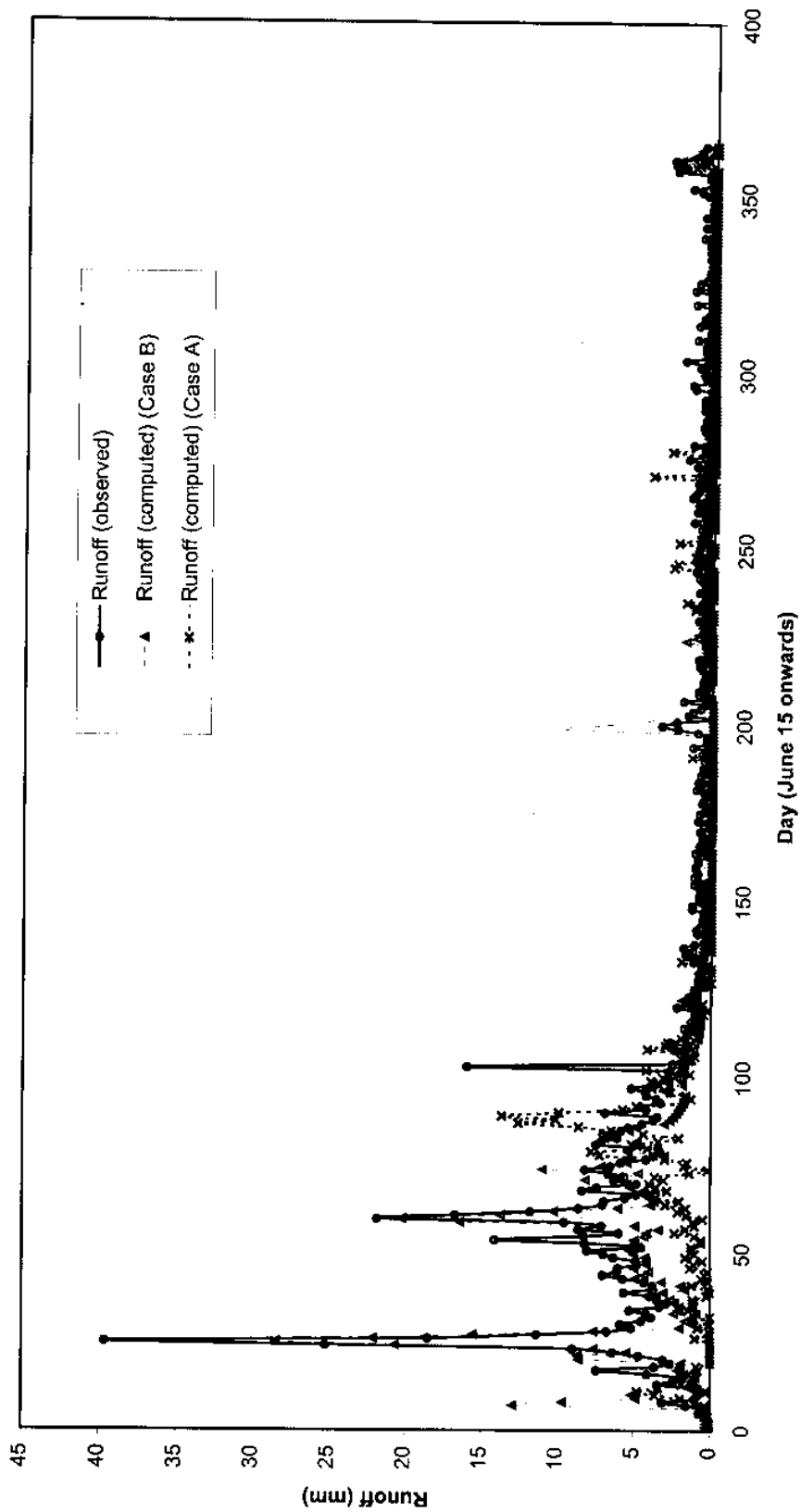


Fig. 7. Ramganga runoff computed for the two cases for the year 1990-91.

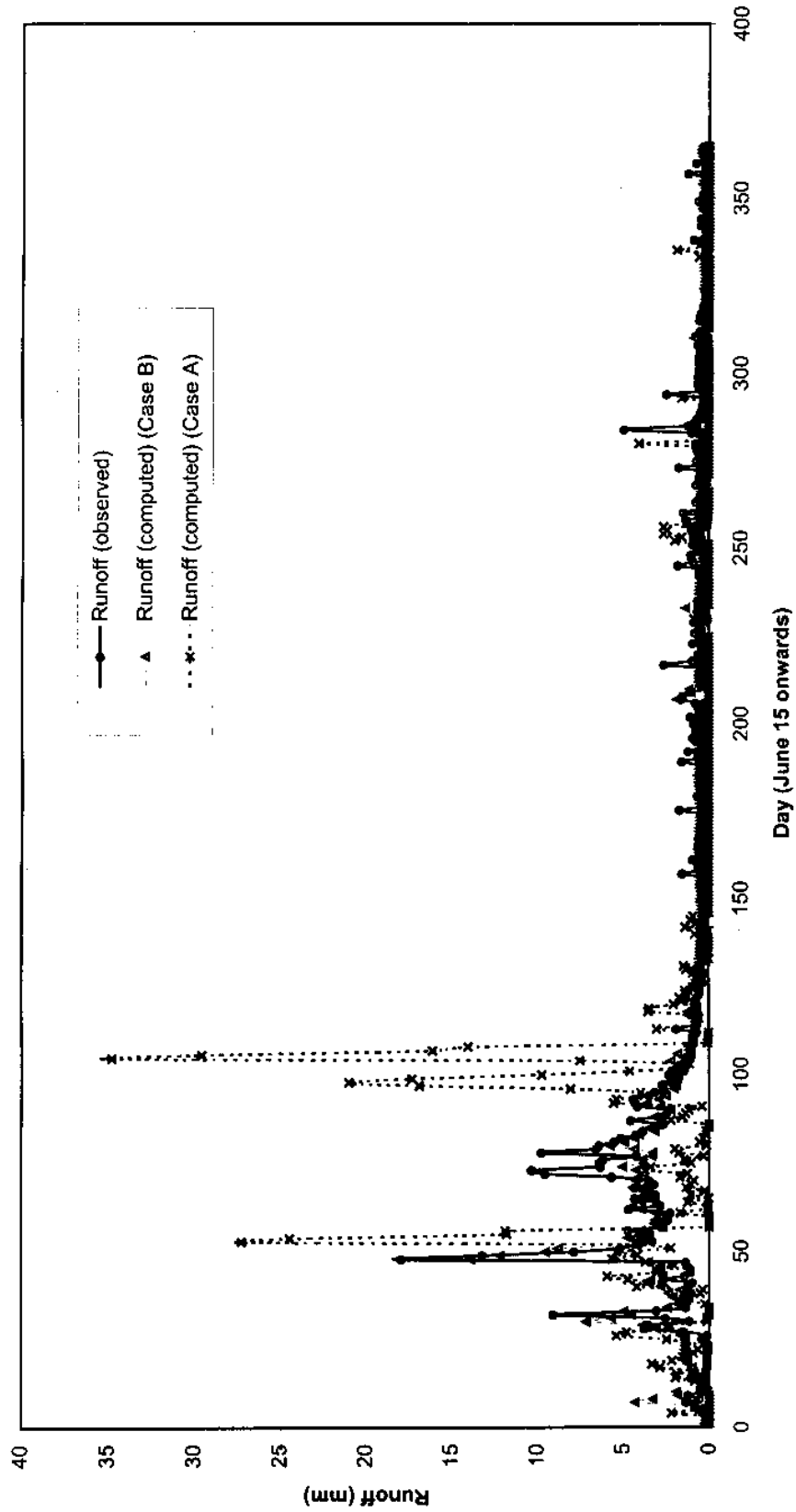


Fig. 8. Ramganga runoff computed for the two cases for the year 1992-93.

is 67.299%, on Hemavati data it is 75.567%, and on Sabarmati data, it is 59.694%. Thus, in all the three applications, the model performed better in validation than in calibration. The sample results of calibration and validation of the model application are shown in Figs. 9 through 21. Within the premise of available data and limited applications, the results infer that the model is more suitable to the watersheds located in sub-humid regions than to the watersheds located in arid regions.

#### **4.6 Sensitivity Analysis of SCS-CN-based Model Parameters using Hemavati Data**

A sensitivity analysis of the model parameters is made using the validation data of Hemavati catchment. The results are shown in Figs. 22. Since validation data are used, it is important to note that the values of the parameters used in validation may not be optimal, as this data set is not used in calibration.

##### **4.6.1 Sensitivity of CN**

From Fig. 22 it is evident that as CN increases from 50 to 100, efficiency increases from 29.050% to 75.353% consistently. Such a large variation in efficiency with CN is largely attributed to the model structure that is primarily dependent on the CN variation for runoff computation. Thus, it is a sensitive parameter and need to be determined carefully and accurately.

##### **4.6.2 Sensitivity of $\lambda$**

Fig. 22 shows that as  $\lambda$  increases, efficiency decreases. However, within the range of  $\lambda$  variation (0,1), the efficiency has been of the order of 75.58% with the range (75.549%, 75.586%). Since  $\lambda$  can vary between 0 and  $\infty$ ,  $\lambda$  was varied up to 100. The increase in  $\lambda$ -value from 1 to 100 decreases the efficiency from 75.58% to 43.152%. Thus, within the usual range of variation (0.1,0.3) (Ponce, 1989),  $\lambda$  is not much sensitive to runoff computations for the Hemavati watershed. It is primarily due to CN assuming a very high value (=99.57) for this watershed. It implies an excessively lower value of the parameter potential maximum retention, S. Thus, the variation of  $\lambda$  in lower range (0,1) has little bearing on the initial abstraction computations and, in turn, the runoff computations.

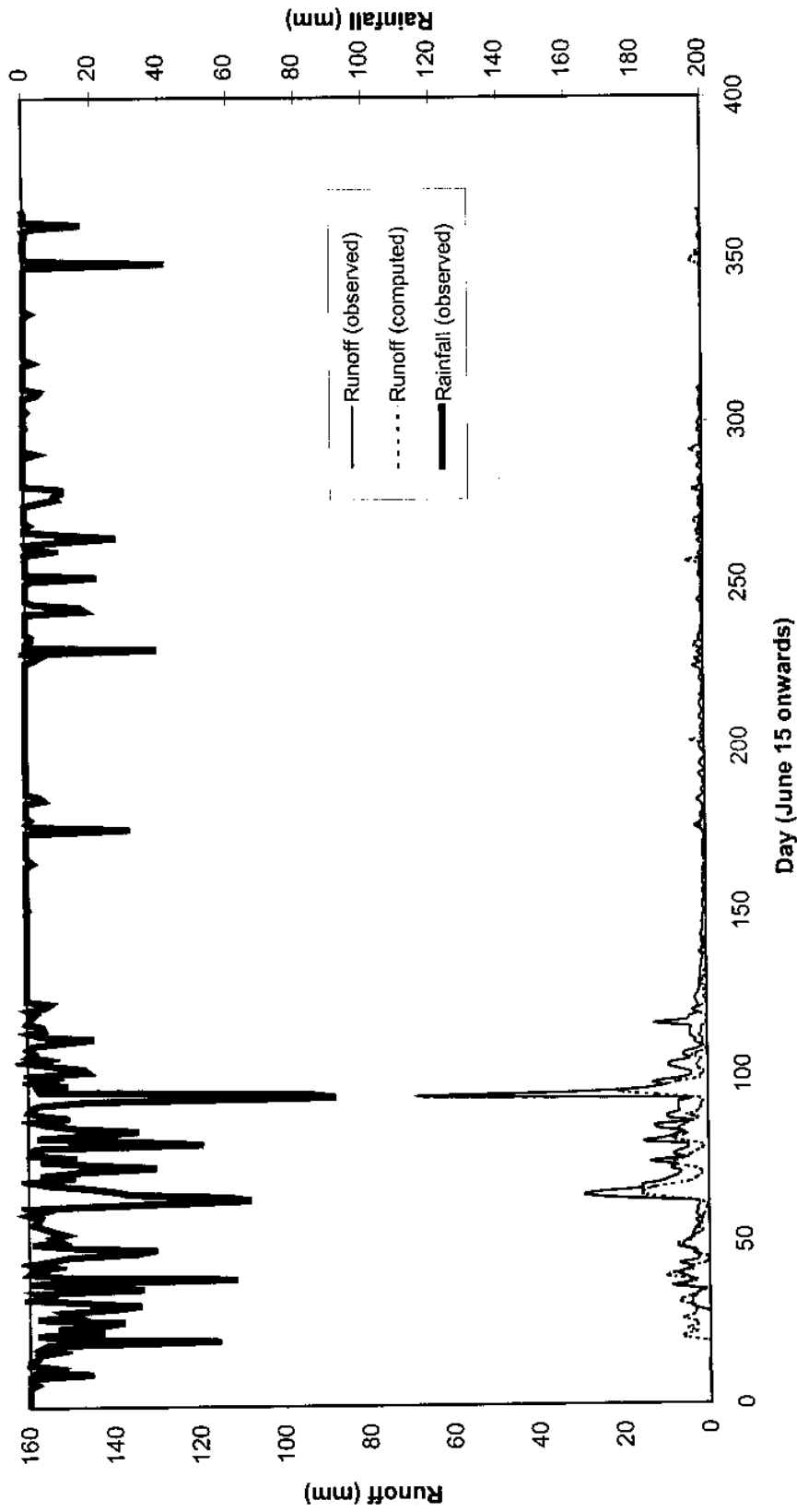


Fig. 9. Calibration of SCS-CN-based model on Ramganga data of the year 1978-79.

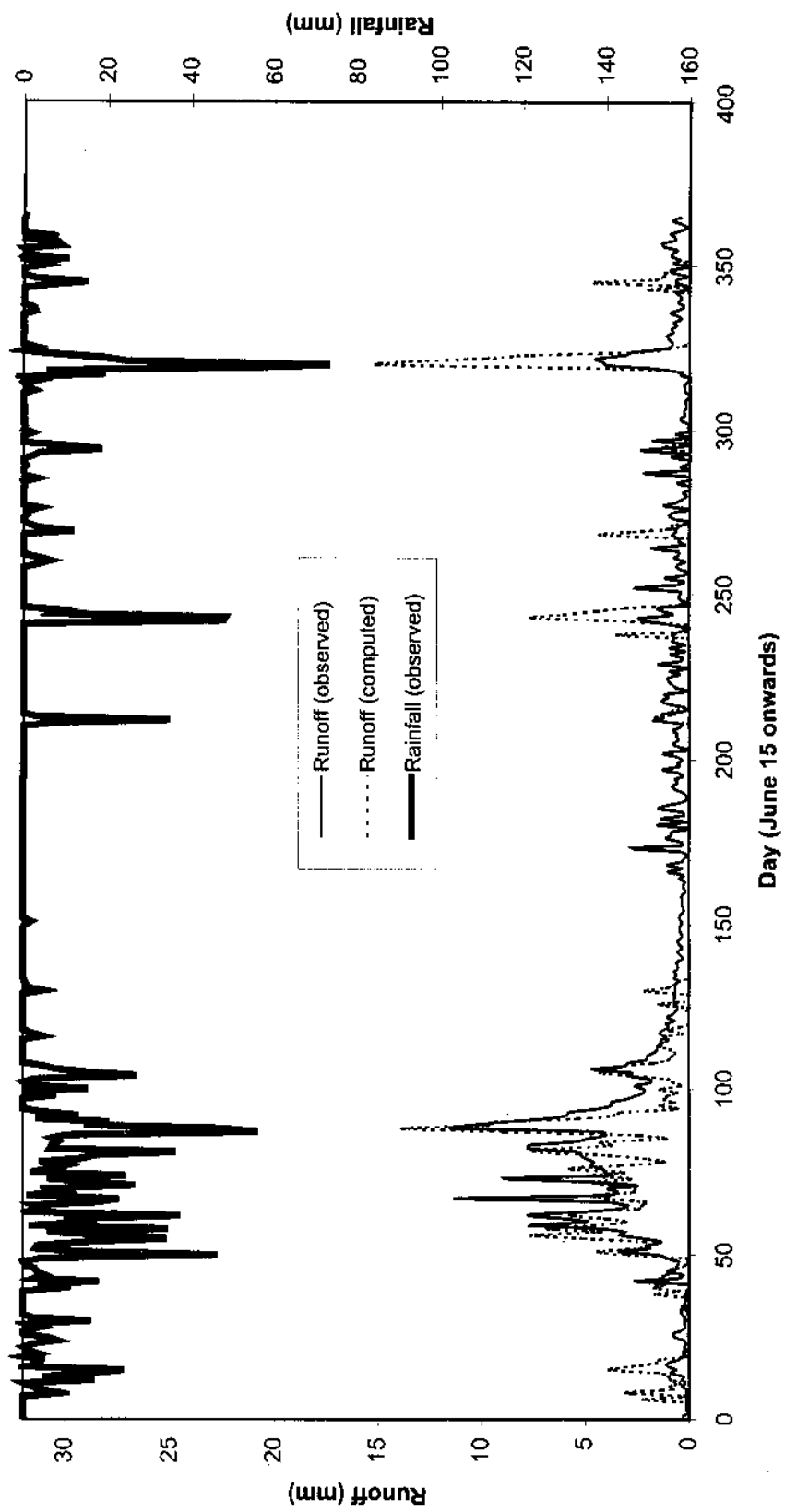


Fig. 10. Calibration of SCS-CN-based model on Ranganga data of the year 1982-83.



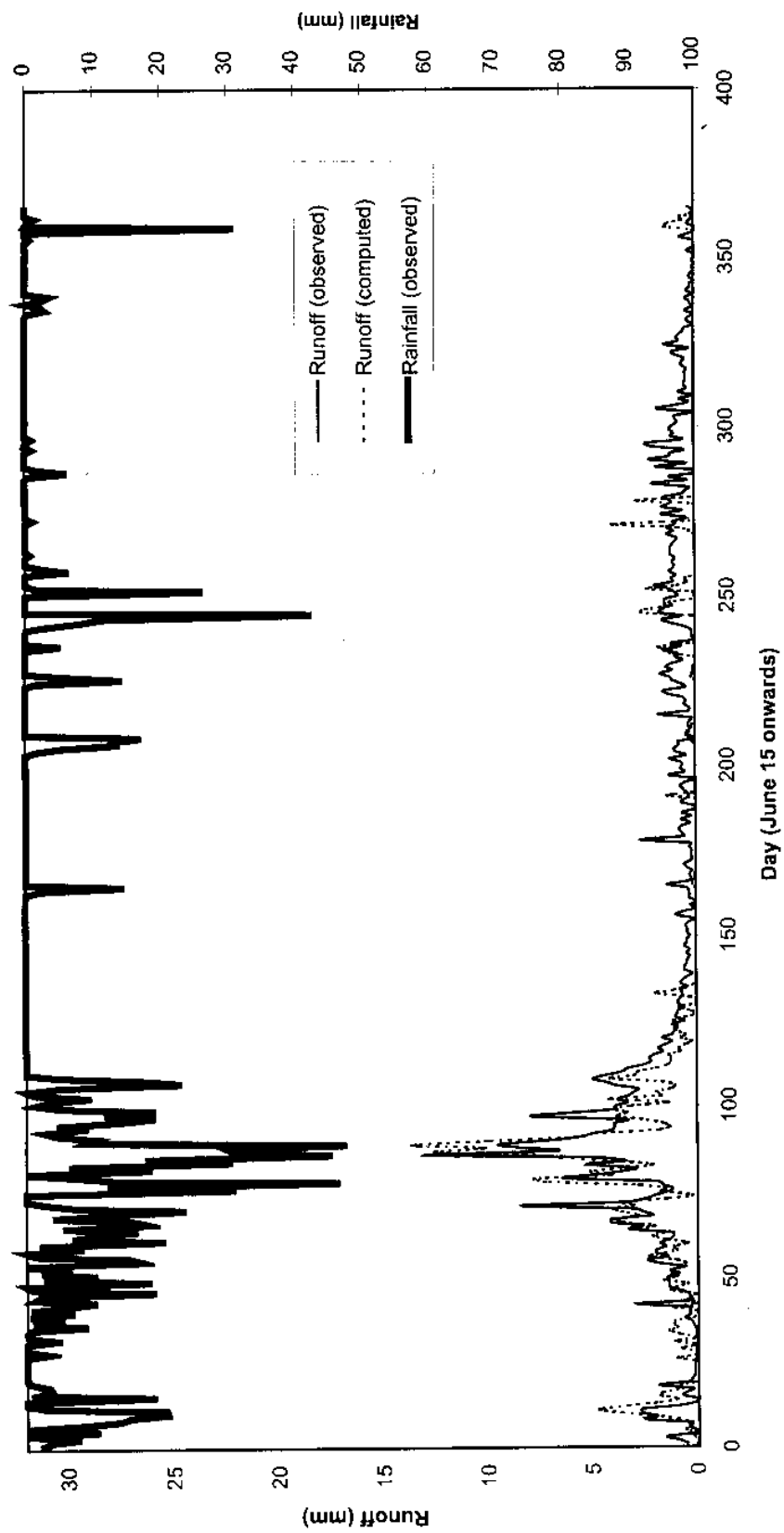


Fig. 11. Validation of SCS-CN-based model on Ramganga data of the year 1990-91.

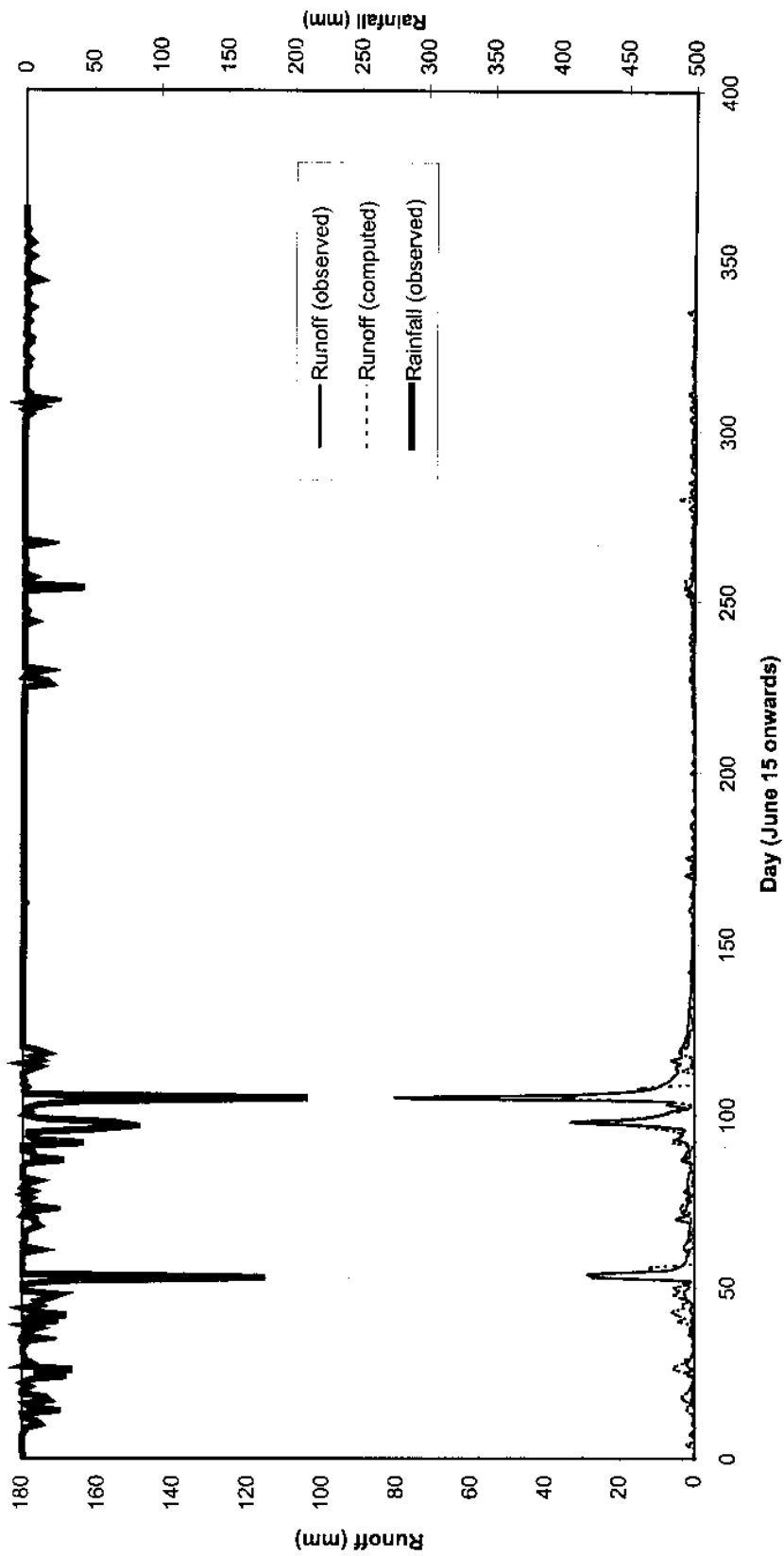


Fig. 12. Validation of SCS-CN-based model on Ramganga data of the year 1992-93.

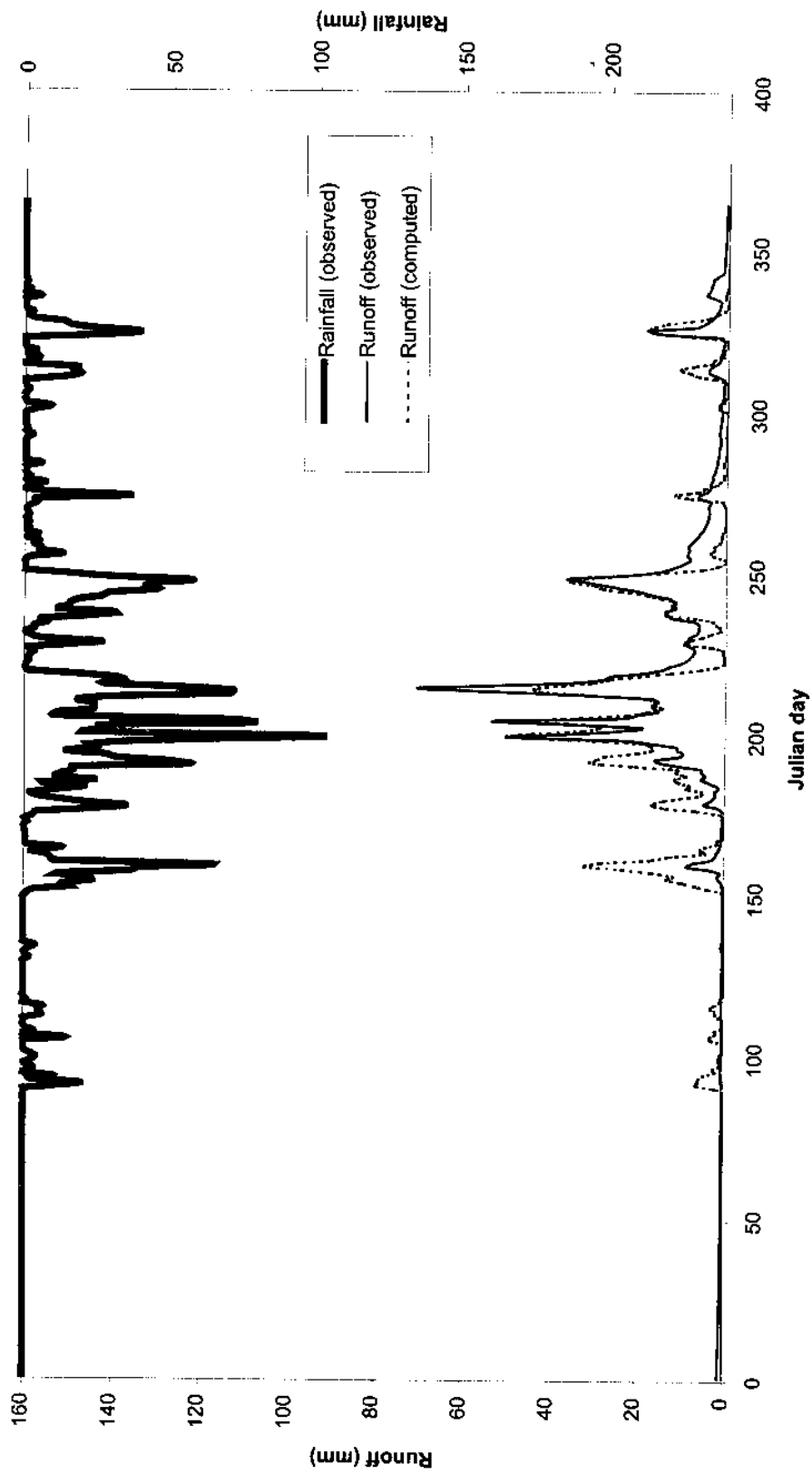


Fig. 13. Calibration of SCS-CN-based model on Hemavati data of 1975.

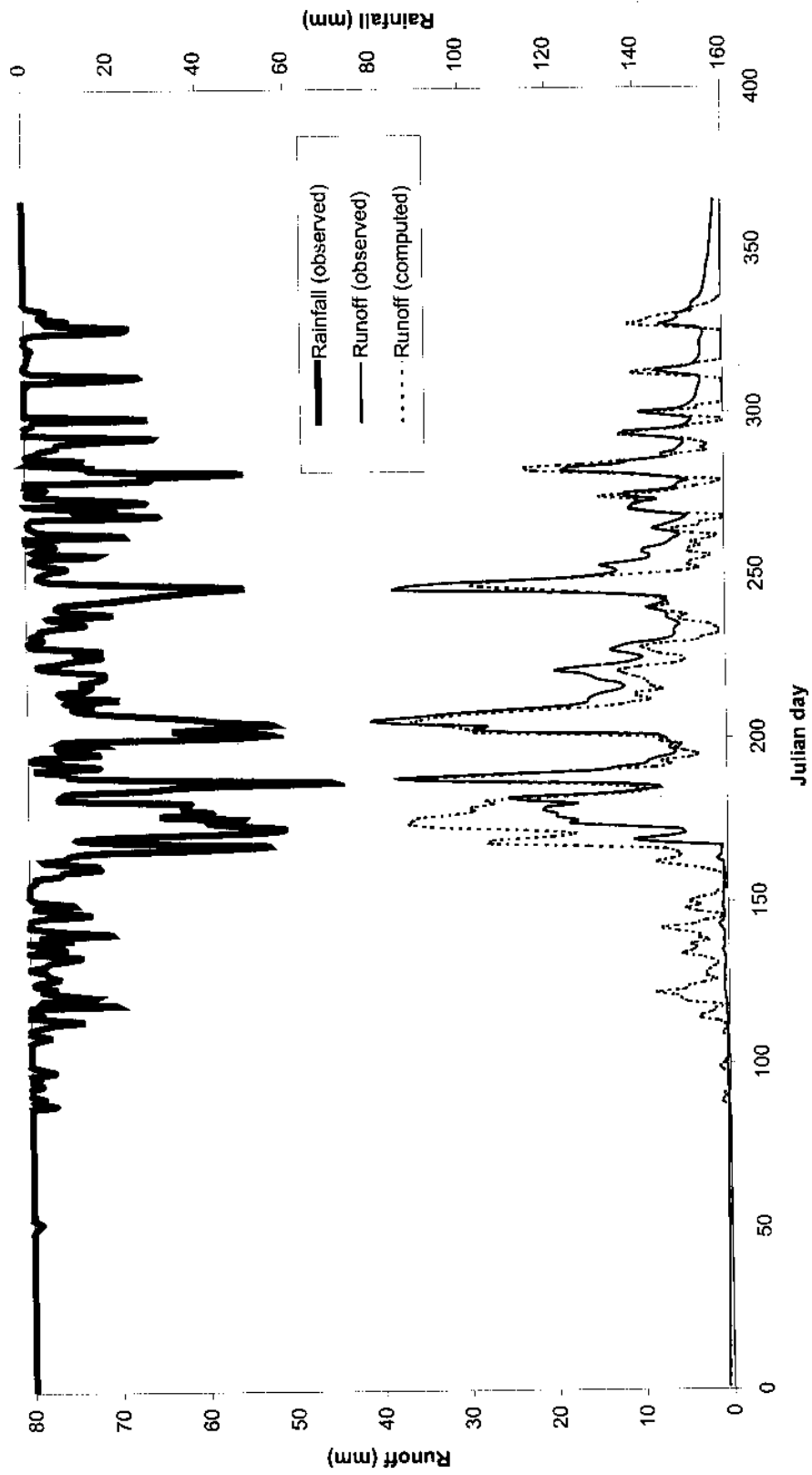


Fig. 14. Calibration of SCS-CN-based model on Hemavati data of 1976.

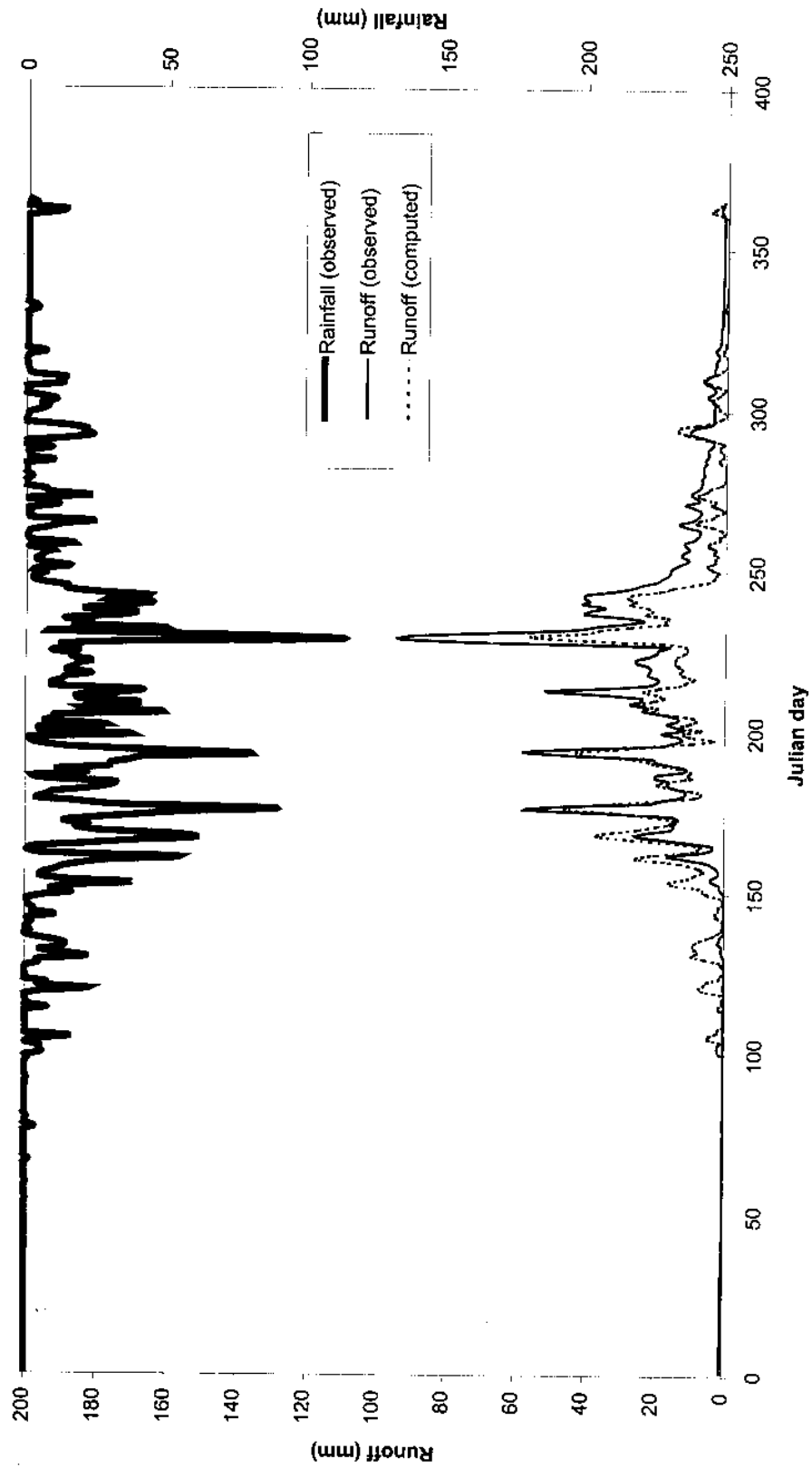


Fig. 15. Calibration of SCS-CN-based model on Hemavati data of 1977.

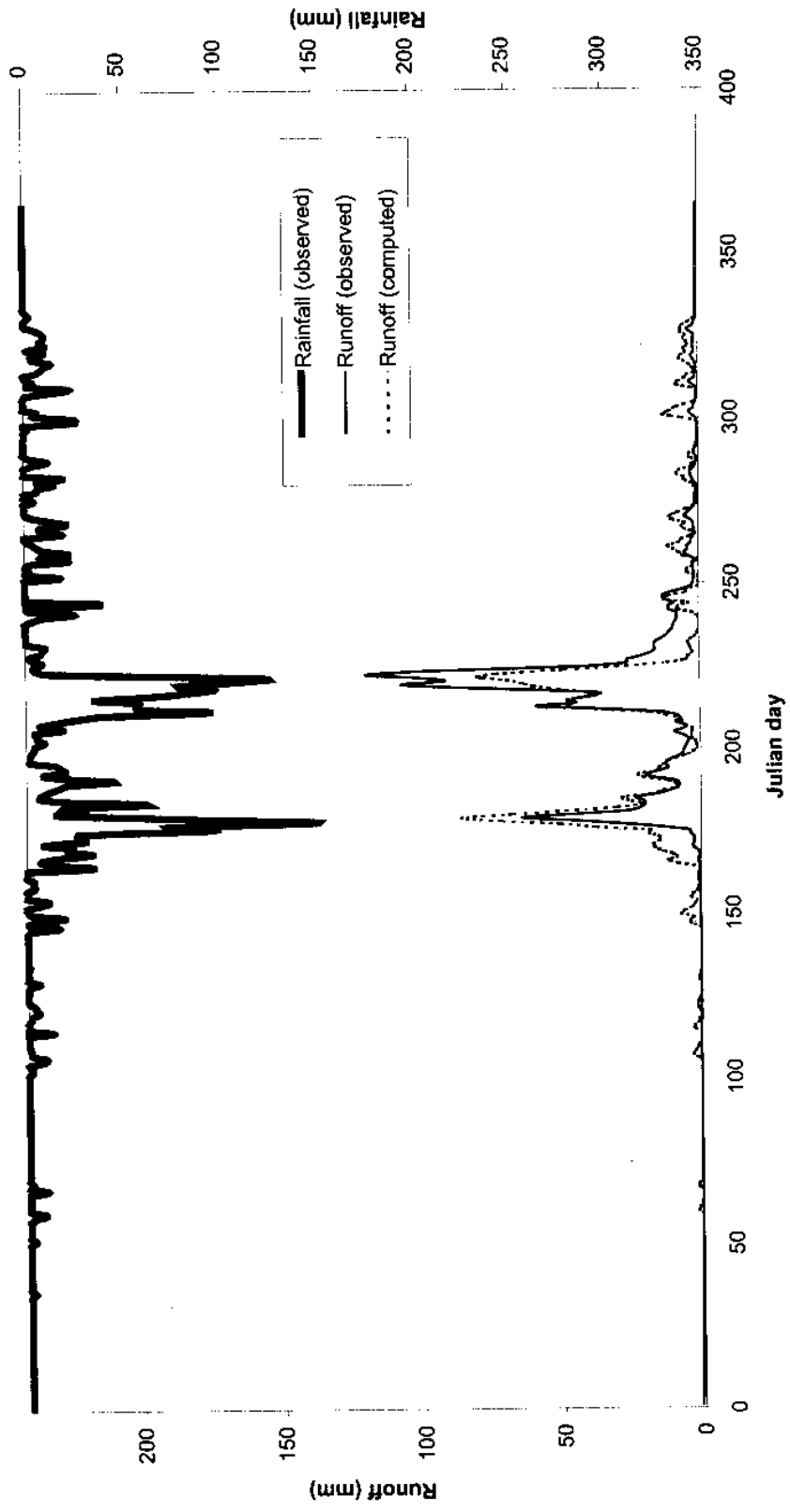


Fig. 16. Validation of SCS-CN-based model on Hemavati data of 1978.

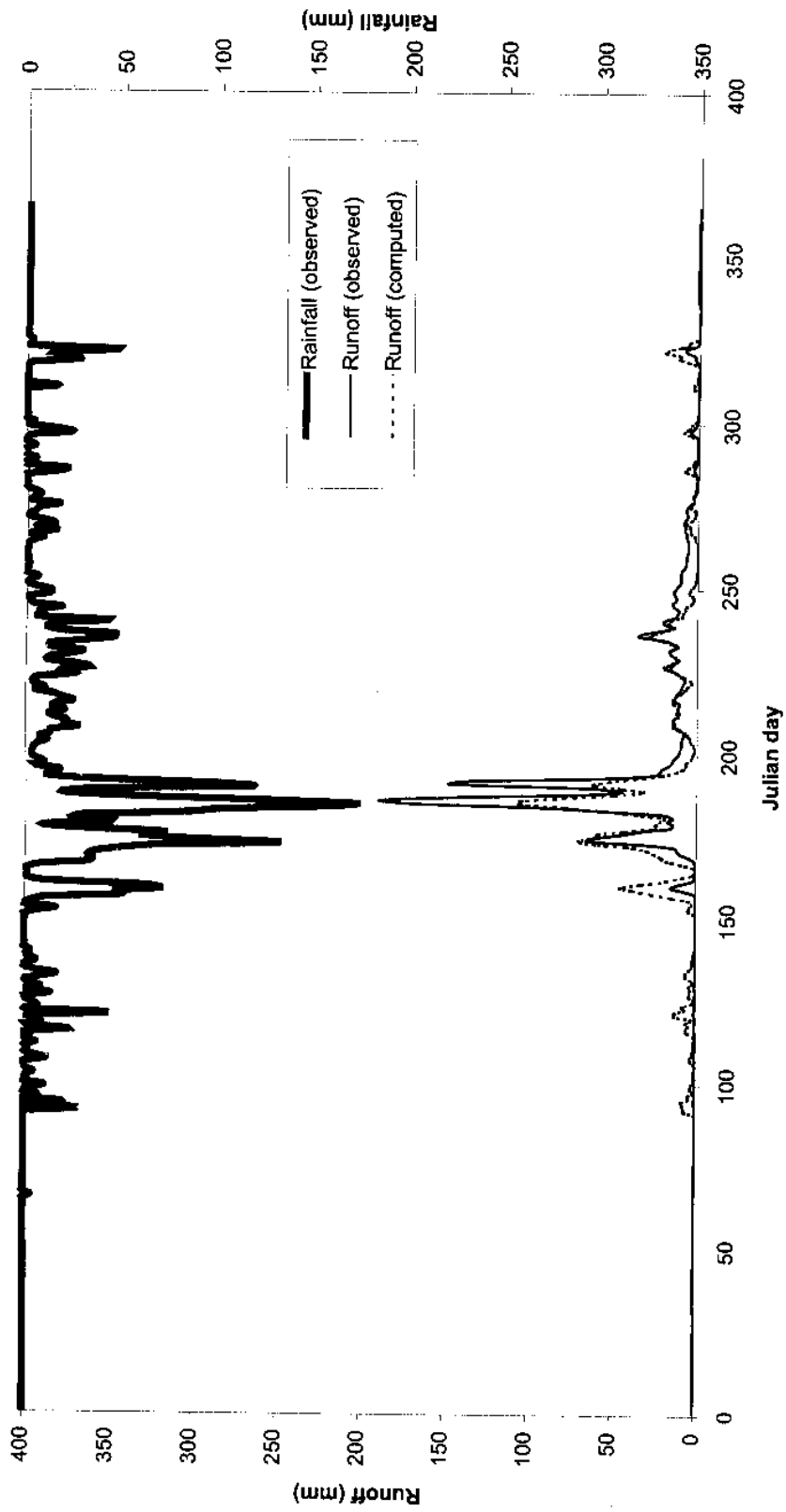


Fig. 17. Validation of SCS-CN-based model on Hemavati data of 1979.

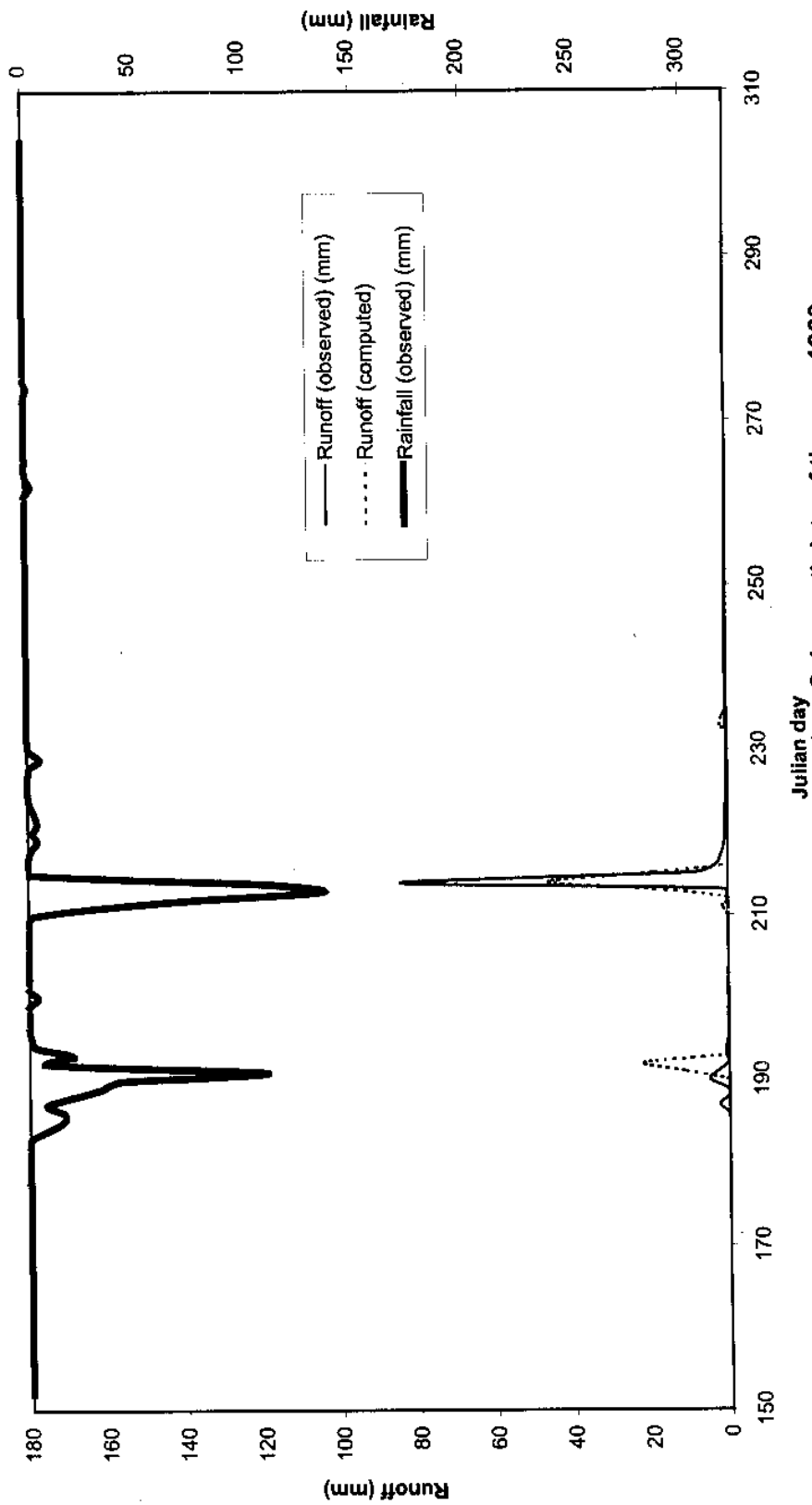


Fig. 18. Calibration of SCS-CN-based model on Sabarmati data of the year 1968.



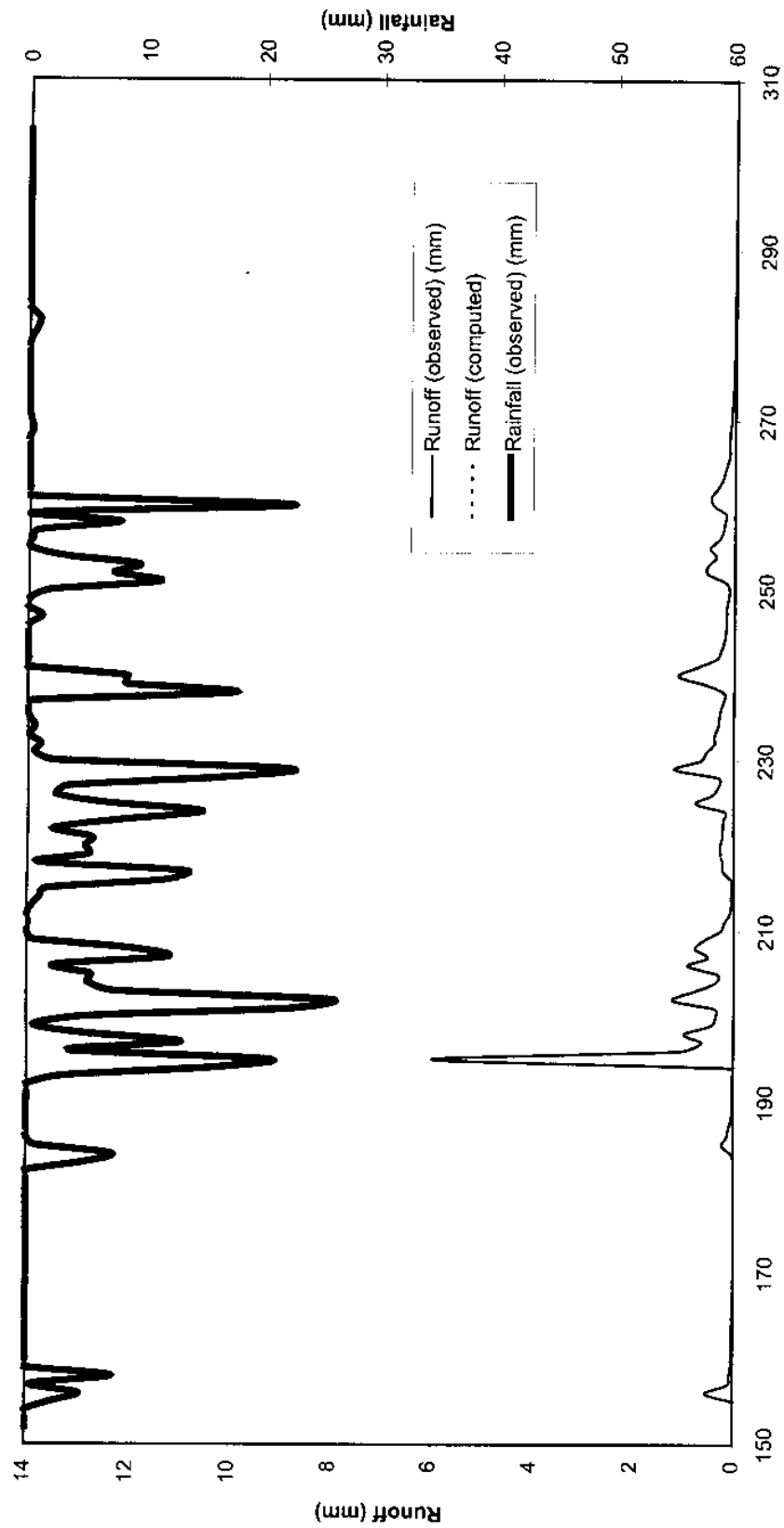


Fig. 19. Calibration of SCS-CN-based model on Sabarmati data of the year 1969.

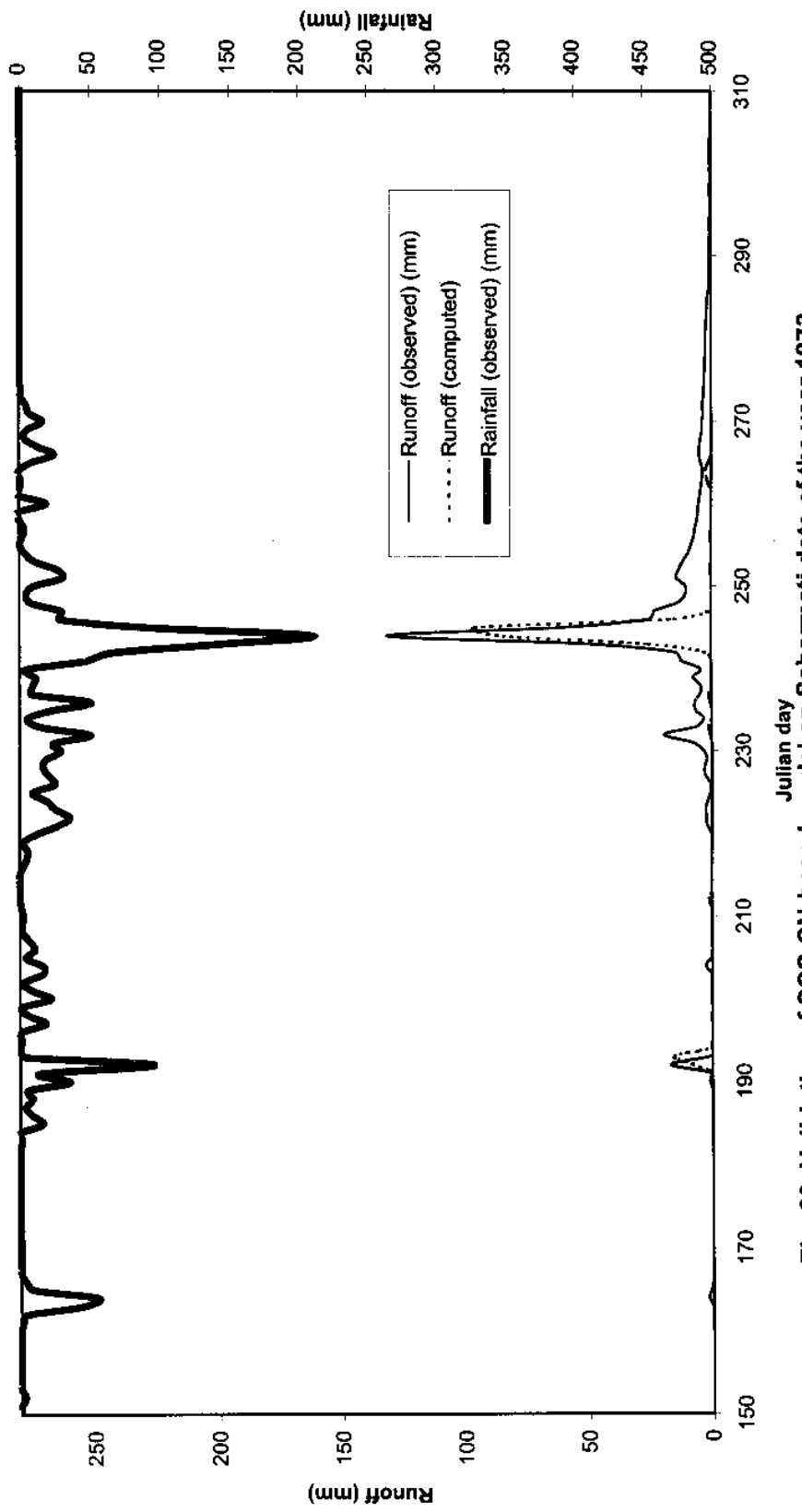


Fig. 20. Validation of SCS-CN-based model on Sabarmati data of the year 1973.

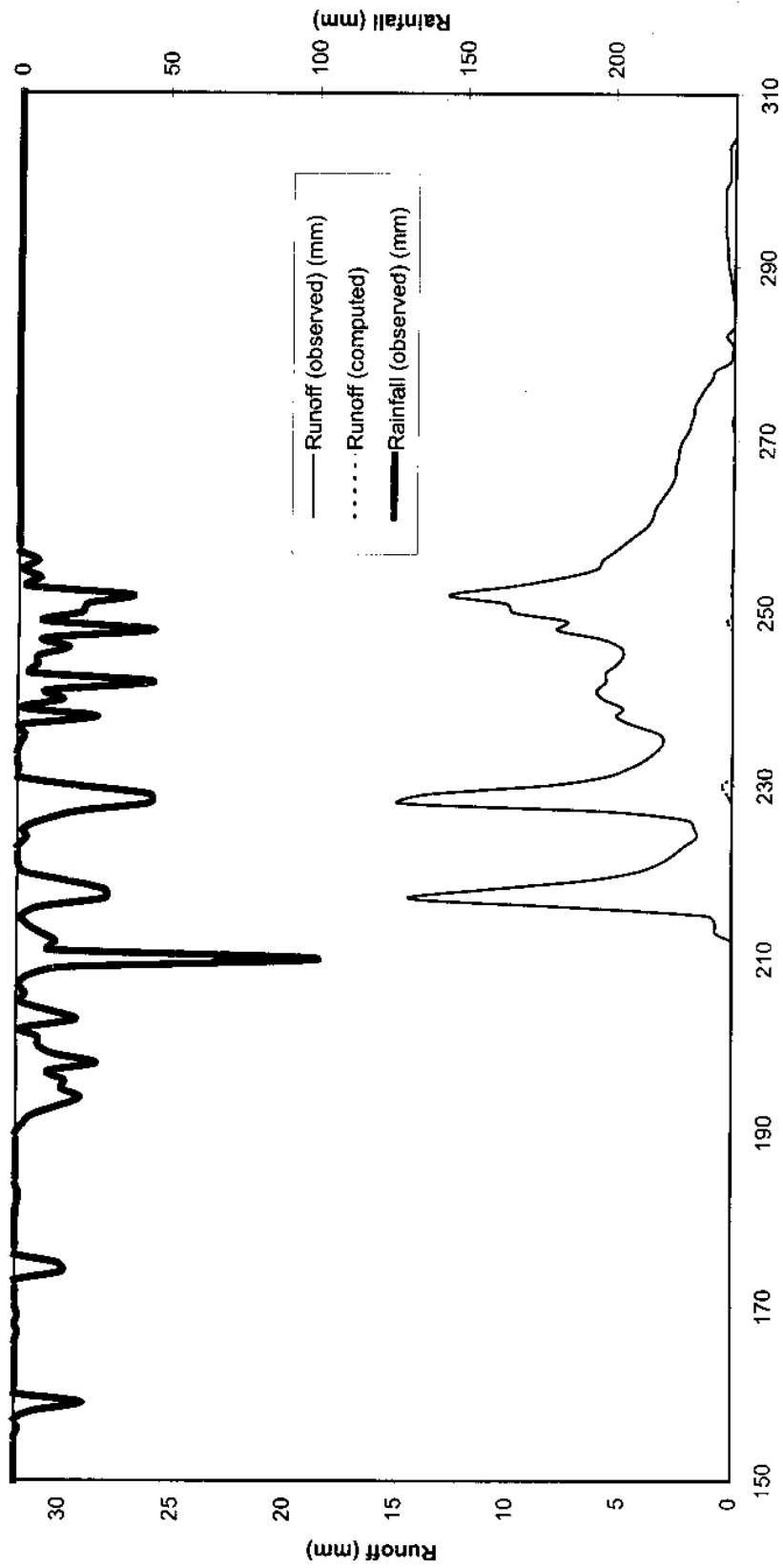
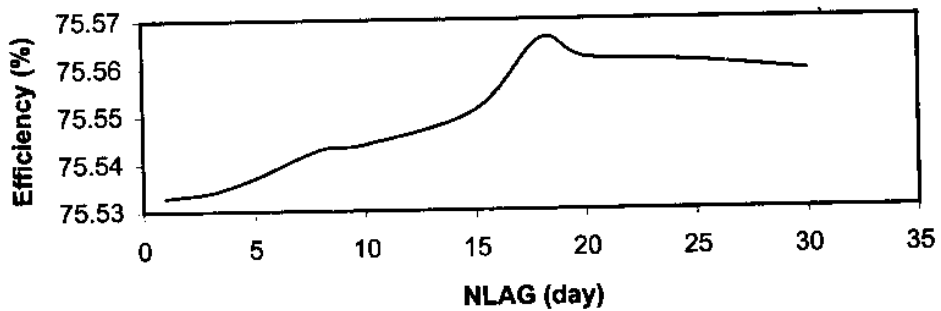
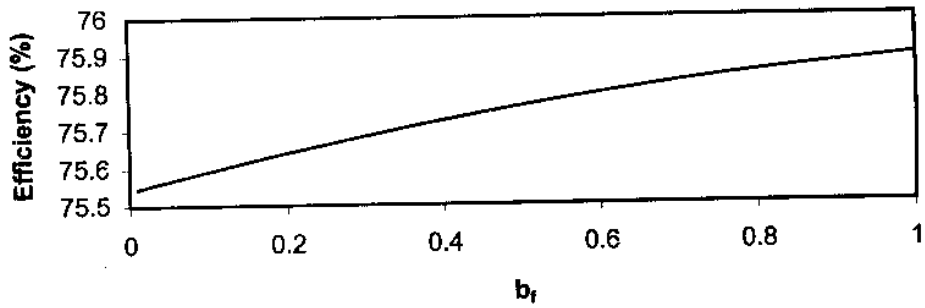
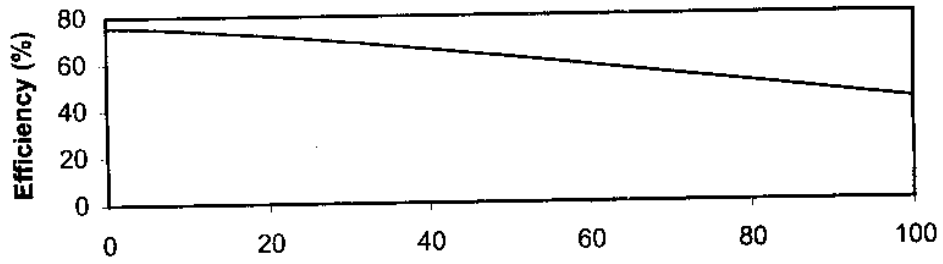
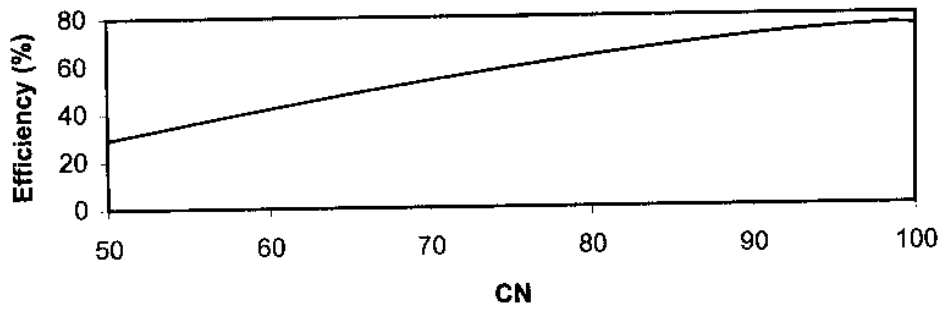
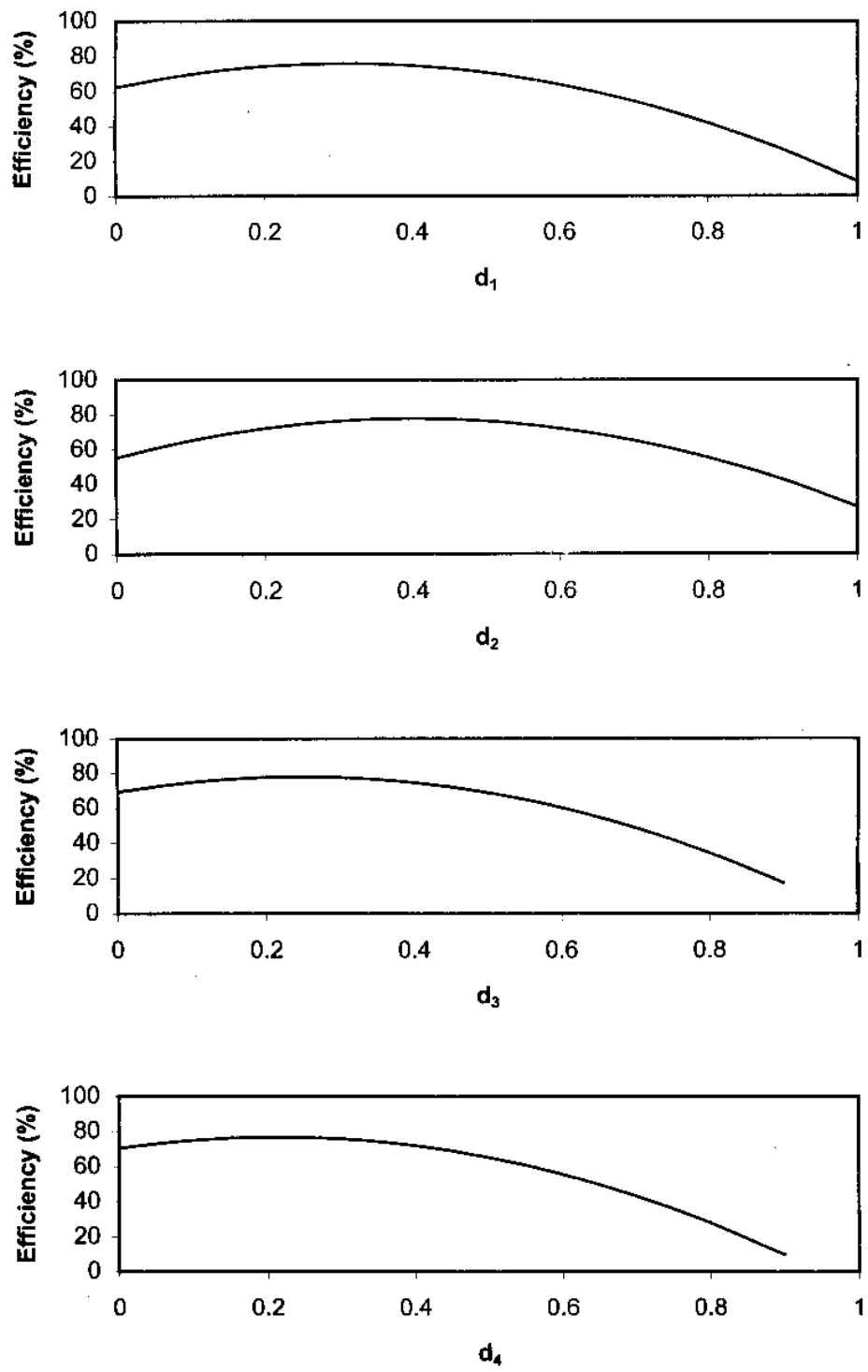


Fig. 21. Validation of SCS-CN-based model on Sabarmati data of the year 1976.



**Fig.22. Sensitivity of SCS-CN-based model parameters in validation on Hemavati data. (Contd.)**



**Fig.22. Sensitivity of SCS-CN-based model parameters in validation on Hemavati data.**

#### 4.6.3 Sensitivity of $b_r$

Fig. 22 shows that as  $b_r$  increases from 0 to 1, the efficiency increases, but only marginally, from 75.546% to 75.893%. As described earlier, the parameter  $b_r$  represents the fraction of the infiltrated amount of water that joins the runoff at the outlet of a basin as a delayed component. The higher the CN, the higher is the direct runoff or the lower is the infiltration. The excessively high CN-value yields excessively low infiltration. Therefore, the variation in  $b_r$ -value has shown only a marginal increase in the efficiency.

#### 4.6.4 Sensitivity of NLAG

Fig. 22 exhibits that as NLAG increases from 1 to 18 days, the efficiency increases almost continuously from 75.533% to 75.566%. After 18 days, which is the optimal parameter value for the given set of other parameters' values, efficiency shows a slowly decreasing trend with NLAG and attains a value of 75.559% at NLAG=30 days. Such a marginal variation in the efficiency is again attributed to the excessively high value of curve number or excessively low infiltration magnitude. Thus, NLAG has little bearing on the runoff computation of Hemavati catchment.

#### 4.6.5 Sensitivity of $d_1$ , $d_2$ , $d_3$ , and $d_4$

From Fig. 22 it is apparent that all the parameters exhibit convexity in variation with efficiency. The efficiency first increases with the increase in the parameter-value, attains maximum value, and then decreases as the parameter-value further increases. Within the range of parameters' variation between 0 and 1,  $d_1$  exhibits an efficiency of 62.522% at  $d_1=0$ , maximum efficiency of 76.052% at  $d_1=0.3$ , and a minimum efficiency of 8.438% at  $d_1=1$ . Similarly,  $d_2$  yields an efficiency of 55.235% at  $d_2=0$ , maximum efficiency of 77.828% at  $d_2=0.4$ , and a minimum efficiency of 26.742% at  $d_2=1$ . Parameter  $d_3$  yields an efficiency of 69.443% at  $d_3=0$ , maximum efficiency of 77.645% at  $d_3=0.2$ , and a minimum efficiency of 17.127% at  $d_3=1$ . Parameter  $d_4$  yields an efficiency of 70.502% at  $d_4=0$ , maximum efficiency of 76.841% at  $d_4=0.2$ , and a minimum negative efficiency at  $d_4=1$ . Negative efficiency

indicates that a mean model is better than the other model. Thus, the range of variation of efficiencies (%) are (8.438,76.052) for  $d_1$ , (26.742,77.828) for  $d_2$ , (17.127, 77.645) for  $d_3$ , and (0, 76.841) for  $d_4$ . Thus,  $d_4$  is the most sensitive, and  $d_1$  the least. Parameter  $d_2$  is less sensitive than  $d_3$ , and  $d_4$ .

## 5.0 SUMMARY

Long-term hydrologic simulation is useful for water balance and availability studies. Employing SCS-CN method runoff computation, a model is developed and applied to three catchments of India, viz., Ramganga, Hemavati, and Sabarmati; the first two catchments fall in the sub-humid region and the last in the arid region. The study was carried out with the following objectives: 1) To develop a SCS-CN-based hydrologic model. 2) To apply on Ramganga data using the data in its primitive form and perturbed data similar to the concept of linear perturbation model (LPM) and compare the results with the results of LPM in both calibration and validation. 3) To evaluate the performance of the SCS-CN-based hydrologic model on the data of the three watersheds and determine the model's suitability. 4) To carryout a sensitivity analysis of the model parameters. The results showed that the model when applied to perturbed data performed better than the model applied to the original rainfall-runoff data set and even better than the LM in validation on Ramganga data. The application of SCS-CN-based simulation model (using original data) to all catchments exhibited model's poorer performance on Sabarmati data and a very good performance on Hemavati catchment. Its performance was satisfactory on Ramganga data set. The results inferred that the model was more suitable to sub-humid catchments than the arid catchments. The sensitivity analysis on the data of Hemavati showed that the parameter CN was the most sensitive and  $\lambda$  and  $b_f$  were the least sensitive. The regression coefficients (parameters) were also found to be significantly sensitive to runoff computations. The sensitive parameters, thus, need to be determined more carefully and accurately than the less sensitive parameters.



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**LINEAR PERTURBATION MODEL**

The Linear Perturbation Model (LPM) (Nash and Barsi, 1983) is primarily composed of perturbation model (PM) and the error model (EM); the latter is used for updating. First, the perturbations about the smoothed (through harmonic analysis) mean runoff and rainfall are related through a regression equation the parameters of which are computed using the least squares approach. The runoff is computed as below:

$$y_i = h_1 x_i + h_2 x_{i-1} + \dots + h_m x_{i-m+1} + e_i \tag{I-1}$$

where  $x = P - p(d)$  and  $y = Q - q(d)$  are the departures of the rainfall and runoff from their seasonal means, respectively;  $P$  is the rainfall,  $Q$  is the runoff;  $p(d)$  and  $q(d)$  are the smoothed yearly daily means, computed using Fourier analysis, of rainfall and runoff, respectively;  $m$  is order of the perturbation model;  $e_i$  is the error term; and the subscript  $i$  represents the day. The computed errors ( $e_i$ ) are analysed for persistence as

$$e_i = b_1 e_{i-1} + b_2 e_{i-2} + b_3 e_{i-3} + \dots + b_n e_{i-n} + E_i \tag{I-2}$$

where,  $b_1, b_2, b_3,$  and so on are the regression coefficients computed using least squares approach;  $n$  is the order of the model; and  $E_i$  is a random component of the error which is ignored in the present study. During the calibration period, the model results are updated by coupling the identified error model (EM) with the perturbation model (PM) as

$$Q_t = q(d_t) + h_1(P_t - p(d_t)) + h_2(P_{t+1} - p(d_{t+1})) + \dots + h_m(P_{t-m+1} - p(d_{t-m+1})) + b_1 e_{t-1} + b_2 e_{t-2} + \dots + b_n e_{t-n} \tag{I-3}$$

The smoothing and statistical details of the model are given by Yevjevich (1984)

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