CASE STUDY

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SENSITIVITY ANALYSIS USING BATS

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PREFACE

Increasing knowledge about the processes responsible for global climatic change shows that the physical component of the earth system is intimately interwoven with both the global chemical cycles and the biosphere. The growing awareness of the importance of hydrological land-surface processes in models, that simulate global changes, has attracted the hydrologists to become an effective team member in this research area. It is essential to acquire a better understanding of the problems associated with climate change. Indian hydrologists have yet perceived the importance of global scale hydrology, and are showing keen interest to carry out studies in this emerging area.

The surface grid squares of an atmospheric general circulation model typically cover an area of the order of 10^4 to 10^5 Km^2. Regions of this size in nature are characterised by extensive spatial variability in precipitation, topography, vegetation, soil, ecological characteristics and other surface features. Assumption of internal homogeneity within a grid makes the modelling results questionable; and in many respects, solutions cannot in accordance with reality. Therefore, it is essential to carry out some studies to assess the effects of surface heterogeneity on land-atmosphere interactions.

The present study focuses on the effect of spatial variability at subgrid scale in precipitation and soil characteristics. An extensive sensitivity experiments are carried out using BATS (Biosphere Atmosphere Transfer Scheme, Dickinson et al. 1986) under different scenarios to assess the subgrid scale variability of forcing variables on moisture and energy fluxes. The effect of subgrid scale variability on the land-atmosphere interactions is demonstrated using the rainfall characteristics of the Sher sub-basin of Narmada basin. Besides, the study focuses on the accuracy of precipitation parameterization contained in the model. The study has been carried out by Dr. Divya, Scientist 'C' and Dr. Ashok K. Keshari, Scientist 'B' of this Institute. Shri Manoj Kumar, RA assisted the scientists during the preparation of this report.

(S. M. Seth)

DIRECTOR

ABSTRACT

It is observed that methodology coded in modified Biosphere Atmosphere Transfer Scheme (BATS) for simulating the inhomogeneous precipitation field is not applicable to the Sher sub-basin. A new methodology based on the concept of Thiessen Polygon, used in estimating average areal precipitation over the catchment, is proposed to generate the precipitation field. A large number of sensitivity experiments are carried out using BATS to assess the subgrid scale variability of forcing variables on moisture and energy fluxes. The Sher sub-basin of Narmada basin is considered for the study. The sensitivity analyses are based on the precipitation field, generated using the proposed methodology. The analyses are carried out for a time horizon of 20 days with a time step of one hour. The study mainly focuses on the sensitiveness of spatial variability of precipitation, soil texture, soil colour and soil temperature. Impact of inadequate spatial precipitation information on the moisture fluxes is also studied. The conclusions drawn in this study have the relevance for the qualitative assessment of the subgrid scale variability of forcing variables on land-atmosphere interactions. These conclusions should not be interpreted as actual findings for the Sher sub-basin, as many parameters regarding soil information are taken fictiously, because of nonavailability of complete data sets as per the model.

Sensitivity analyses reveal that there is no need to consider explicitly the precipitation variability at subgrid scale for the

computation of moisture fluxes, provided the average precipitation over the grid remains same. However, this finding is true only when a small degree of spatial variability exists within the grid, and if catchment response is linear. In such cases, precipitation can be represented on a basin scale for simulating the moisture fluxes. But, in case of nonlinear response, a high degree of spatial variability may cause profound effect on the fluxes. The fluxes are more sensitive to the size of the area within a grid on which a fixed volume of precipitation occurs. Any deviation in average precipitation over the grid causes significant change in the fluxes.

It is found that detailed spatial variability of soil information appears to be more critical than that of precipitation field. The hydraulically controlled processes like runoff and soil moisture are more sensitive to soil texture; whereas, the radiative and thermal conductive fluxes, such as net solar radiation, longwave radiation, and ground and subsurface temperatures are highly sensitive to soil colour. Rainfall-runoff parameterization in the BATS seems to be inadequate for most real-life situations, because of nonlinear behaviour. However, an exhaustive numerical experiments are needed to establish it. Use of remote sensing data and/or a decision support system to quantify the areal variability of the forcing variables may improve the findings.

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NOTATION

a_{ij}	area occupied by the polygon j within the subgrid i
$(a_s)_{ij}$	area of the subgrid i
A	grid area
A_j	area occupied by the polygen j within the grid
$f(x)$	probability density function
m	number of rain gauge stations
n	number of subgrids within a grid
P_{av}	average precipitation over the grid
P'_{av}	average precipitation over the grid using perturbed data
P_i	precipitation at subgrid i at time t
P^o_j	observed precipitation at gauge j at time t
P'_j	perturbed precipitation data for jth gauge
w_j	Thiessen weight for the gauge j
w_s	Subgrid weight
$(w_s)_{ij}$	weight assigned to j th gauge for the computation of precipitation at subgrid i
x	event
α_j	perturbation factor for j th gauge
λ	mean rate of occurrence of the events

1. INTRODUCTION

1.1 Global Scale Hydrology

Emerging problems of environmental change and of long range hydrologic forecasting demand knowledge of the hydrologic cycle at global rather than catchment scale. Changes in atmosphere and/or landscape characteristics modify the earth's metabolism through changes in its biogeochemical cycles. The most basic of these is the water cycle which directly affects the global circulation of both atmosphere and ocean, and hence is instrumental in shaping weather and climate. Defining the spatial extent of the environmental impact of a local land surface change, or identifying, for forecasting purposes, the location and nature of climatic anomalies that may be causally linked to local hydrologic persistencies require global scale dynamic modelling of the coupled ocean-atmosphere-land surface.

The land surface component of global hydrology has been an active research area for meteorologists and climate modellers, and only recently have hydrologists become actively engaged in this research area. The sensitivity of the climate to the near surface soil moisture and other hydrological processes, as pointed out by global climate models has lead the scientists to develop improved understanding of atmosphere-land surface interactions, so that more realistic future climate change scenarios may be obtained.

The representation of hydrological processes is one of the weakest and most challenging aspects of the present General Circulation Models (GCMs). A crucial role of the land surface is to partition incoming solar energy into fluxes of latent and sensible heat, and the processes by which this partitioning is determined are very complex. Not only is the surface energy balance at a point controlled by complicated interactions between vegetation, topography, and available soil moisture; but all of these quantities vary spatially, with varying degrees of spatial correlation between them. Despite this difficulty, the realistic modelling of land surface processes is critical. Our present understanding of land-surface-atmosphere interactions, and the processes and fluxes that define these interactions is still limited. Furthermore, current GCM's use grid sizes in the order of several hundred kilometers. These grid sizes are too coarse to resolve most hydrologic and biospheric processes, as fluxes of moisture and heat occur on much smaller spatial scales. Hence, these processes must be adequately parameterized to bridge the gap between the large and the small scales.

1.2 Land Surface Parameterization Schemes

The evolution of Land Surface Models (LSMs) has been guided by the desire to increase their realism with the ground truth, and thereby the accuracy of the GCM's climate. Understanding the importance of land-surface hydrology to climate has emerged as an important research area since mid 1960's when researchers at Geophysical Fluid Dynamics Laboratory (GFDL) put a land hydrology component into their GCM (Manabe et al., 1965; Manabe, 1969). Since then many meteorologists, climate modellers and hydrologists have shown interest in the problem of land surface parameterization in climate models.

However, most current GCMs still use some version of the bucket model for hydrological parameterizations. The bucket model considers the soil as a reservoir of fixed capacity of 15 cm. The soil moisture reservoir fills when precipitation exceeds evaporation, and after becoming full, the excess water runs off. Evaporation is computed using a wetness factor (evapotranspiration efficiency) which is a linear function of soil saturation. This is a very crude representation of land surface processes.

With the recent advances in plant physiology, micrometeorology and hydrology, and the ability to integrate to all of these small scale physical processes that control biosphere-atmosphere interactions, the scientists have been able to develop more complex land surface models. These models are BATS (Biosphere-Atmosphere-Transfer Scheme), SiB (Simple Biosphere model), and the model developed by Abramopolous et al. (1988). Recently, the acronym SVATS for Soil-Vegetation-Atmosphere-Transfer Scheme has been proposed for this group of parameterizations. The models attempt to separate the vegetation canopy from the surface, and to represent the energy and water fluxes from the canopy in detail. Thus, the resulting models have a complex representation of the soil-vegetation-atmosphere system which gives them the apperance of having tremendous vertical resolution and structure.

The BATS developed by Dickinson et al. (1986) accounts for vegetative control on evapotranspiration, canopy effects on net radiative budget at the surface, and includes an improved representation of soil and vegetative processes using several soil and canopy layers. The parameterization, SiB, developed by Sellers et al. (1986) consists of a two layer vegetation canopy whose elements and roots are assumed to extend uniformly throughout the GCM grid.

On the horizontal scale, BATS and SiB assume homogeneous conditions. That is, the parameters for the soil and vegetation properties are assumed constant within a GCM grid, thus ignoring spatial heterogeneity. The model by Abramopolous et al. (1988) considers spatial subgrid variability through an area-weighted compositing scheme for the soil and vegetation parameters. However, with respect to precipitation, they assume uniform spatial distribution of precipitation within the grid.

As the natural land surfaces are usually heterogeneous over the resolvable scales (a grid square of about 300 km x 300 km) considered in atmospheric numeric models, the researchers have also made attempts to develop the land surface models which take into account the subgrid variability in soil moisture, precipitation and other quantities (Avissar and Pielke, 1989; Entekhabi and Eagleson, 1989; Famiglietti and Wood, 1990). Wetzel and Chang (1988) developed a parameterization for evapotranspiration from nonuniform surfaces that can be used in short-term numerical weather prediction. A thorough review of current land surface modelling strategies has been presented by Avissar and Verstraete (1990), and Wood (1991). The parameterizations reviewed so far have been developed for inclusion within GCMs. Related research is also being carried out to develop more complex land-atmosphere models that can be used to further test current parameterizations. An example of this work is that of Choudhary and Monteith (1988) who developed a detailed four-layer model for the heat budget of vegetated land surfaces. Two layers are used to represent the vegetation and two layers for the soil system. The transpiration process from the vegetation is modeled in considerable detail. Koster and Eagleson (1990) developed interactive soil-atmospheric model that allows for testing different GCM land parameterizations.

1.3 BATS

The land surface-biosphere model used for the present study is a modified version of BATS. BATS incorporates most of the essential surface features including a vegetation canopy, surface and rooting zone soil layers, variable albedo, and hydrological characteristics. The treatment of canopy energy and moisture balance includes (i) interception of precipitation by vegetation and subsequent evaporative loss and leaf drip, (ii) moisture uptake by plant roots, distributed between the upper and full soil column, and (iii) stomatal resistance to transpiration. The soil column is divided into three nested layers: an upper layer, a root layer, and a deep layer. Only the upper two layers are thermally active. BATS calculates the transfers of momentum, heat and moisture between earth's surface and the atmosphere. It determines the values of wind, moisture and temperature within vegetation canopies and at the level of surface observations; and determines (over land and sea ice) values of temperature and moisture (moisture content of the soil, the excess rainfall that goes into runoff etc.) quantities at the earth's surface. Though BATS is more complex than many other land surface parameterization schemes, it does not consider the subgrid scale variability in precipitation and other soil and vegetation parameters. Ramírez (1991a,b) modified the BATS model in order to account for partial wetting and subgrid scale spatial variability of precipitation and other geomorphoclimatic forcing.

BATS recognises 18 dominant land types based upon wide variety of land surface, hydrological and vegetation properties; twelve texture classes of soil type; and eight color classes. The details are given in Appendices I, II and III.

Energy and water budgets are calculated for the land surface, and the vegetation canopy. The updated temperatures, soil moisture, and foliage transpiration are used to determine net fluxes of heat and momentum from the surface to the lowest atmospheric model layer. For further details on model structure, the reader is kindly referred to Dickinson et al. (1986), Ramirez, (1991a, b), Mehrotra and Divya (1994) and references given therein.

1.4 Objectives of the Present Study

Most parameterization schemes proposed for GCMs assume homogeneous conditions throughout the grid. Since GCMs involve a very large size grid, typically varying from 250 to 500 km, spatial heterogeneity can not be ignored in predicting the global change. For a reliable prediction, there is a need of adequate representation of spatial heterogeneity within the parameterization schemes developed for GCMs, and extensive studies are required to assess the effect of spatial variability of forcing variables at subgrid scale. To assess the effect of subgrid scale variability of precipitation and soil parameters on moisture and energy fluxes, a large number of sensitivity experiments have been carried out over the Sher sub-basin using BATS. The Sher sub-basin is one of the typical sub-basin of

Naramada basin.

The original version of the BATS assume homogeneous condition throughout the grid. Assumption of internal homogeneity within the grid makes the modelling results questionable. However, the BATS was modified by Ramírez (1991a, b) to account for the heterogeneities. But the methodology adopted by Ramírez for simulating the inhomogeneous precipitation within the grid can not hold true for all real-world settings. His assumption of exponential distribution for precipitation intensity, storm duration, and interval time between precipitation fluxes may be valid for some typical catchments. But his assumption of wetness of a subgrid that is, only one subgrid gets wet at a time, and the choice of wetting a grid is random, seems to be unrealistic. Since patterns of precipitation are highly variable, both spatially and temporally, its adequate representation is needed in the model to simulate the inhomogeneous condition. On account of these facts, specific objectives of the present study can be summarized as follows:

(1) To check whether quantification of precipitation variability as per the modified BATS is justified for the sub-basin under consideration,

(2) To develop a methodology for quantifying the areal variability in precipitation, if the methodology for simulating the inhomogeneous precipitation in modified BATS does not hold true for the study area under consideration,

(3) To assess the subgrid scale variability of precipitation on moisture fluxes; runoff and soil moisture,

(4) Numerical quantification of sensitivity of moisture fluxes to probable deviation in average precipitation over the grid,

(5) To assess the spatial variability of soil parameters; texture, colour and temperature, within a grid on the moisture and energy fluxes; runoff, soil moisture, radiation, evaporation, ground and subsurface temperatures.

The flow diagram of salient features of the BATS including the necessary modification is shown in Fig. 1.1, and the sequence of subroutines in the computer code developed for the BATS is shown in Fig. 1.2. A flexible grid system is considered for the analysis to bridge the gap between GCM scale and distributed physically based hydrologic model scale. This approach is proposed by Nemec (1988) for macroscale modelling. It is in accordance with the grid technique application in larger scale river basin modelling (Solomon et al., 1968). The schematic representation of such grid system is shown in Fig. 1.3.

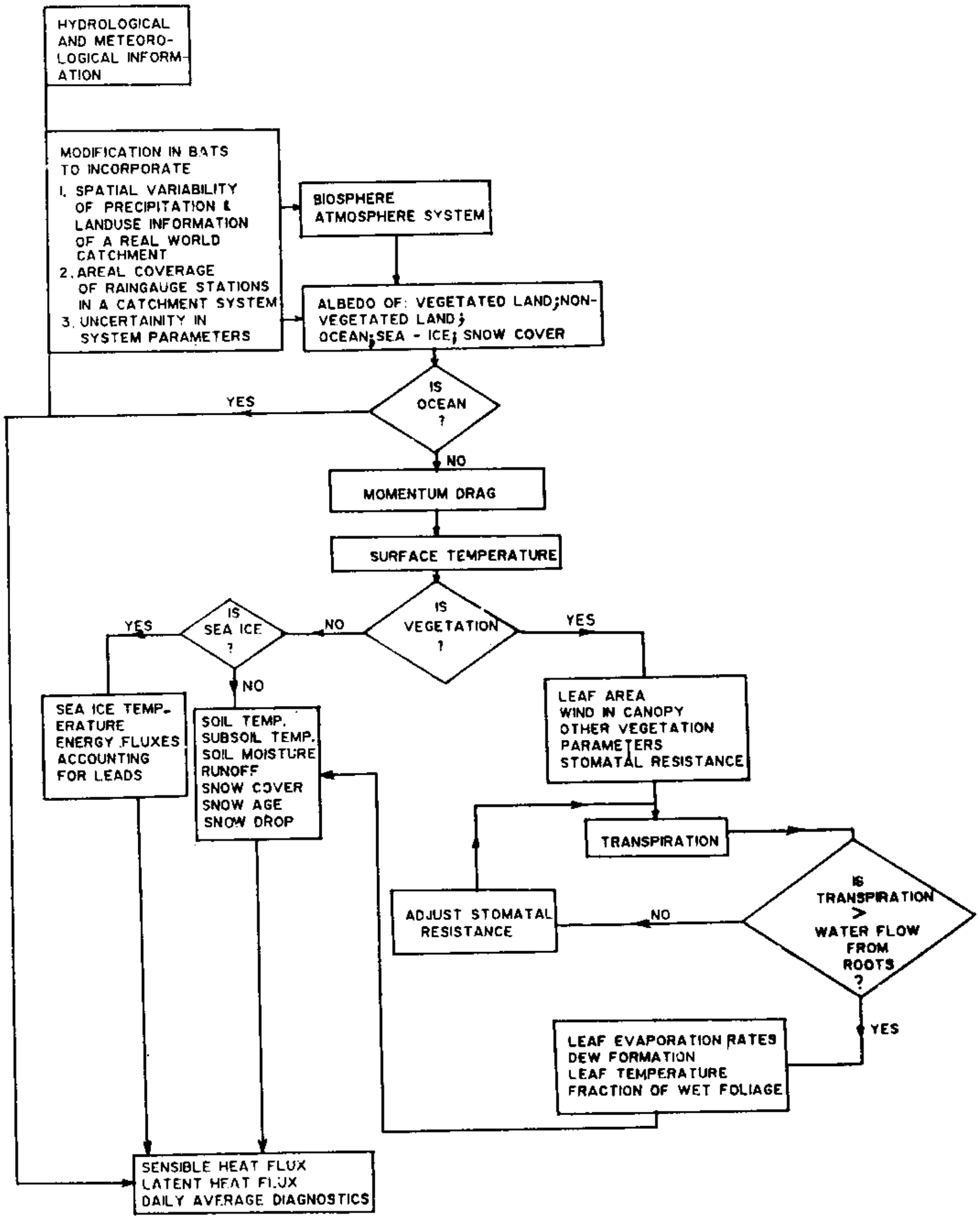

Fig. 1·1 Flow diagram of salient features in the model

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BDCON
BDPOINT
INITB            RAING_J
BMARCH  ====>    SOLBDC
OUTB             ALBEDO
                 ZENITH
                 BNDRY   ====>  DRAG    ====>  DRAGDN ====>  DEPTH
                 BUFOUT         SATUR
                                VCOVER

                                DRIP
                                LEFTEM ==================>  STOMAT
                                CO2     ====>  CARBON        FRAWAT
                                               TSEICE        ROOT
                                               TGRUND        SATUR
                                               SNOW          LFDRAG
                                               WATER         CONDCH
                                                             CONDCQ
                                                             DERIV
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Fig. 1.2 Sequence of subroutines in the model

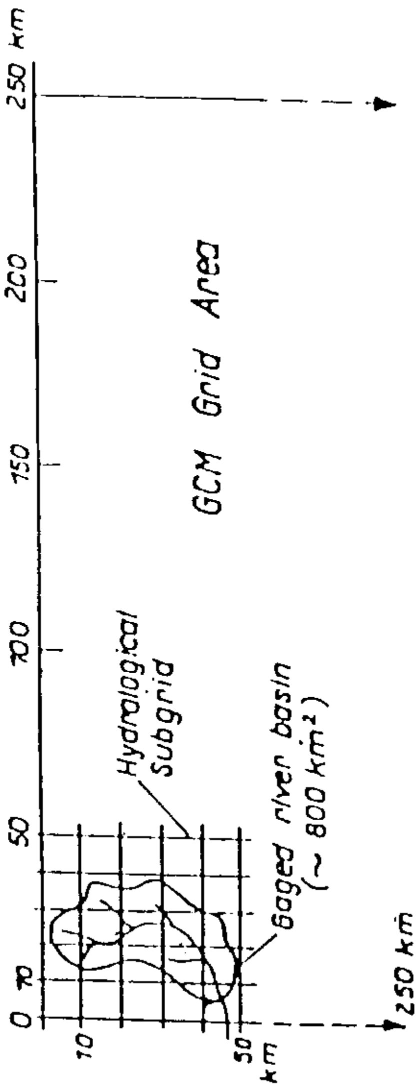

Fig. 1.3 Schematic representation of a river basin and of a hydrological subgrid within a GCM grid area

2. DESCRIPTION OF THE STUDY AREA

2.1 Narmada Basin

The river Narmada is a major west flowing river in Central India with a total length of 1312 km., which runs through the states of Madhya Pradesh, Gujarat and Maharashtra. The river emanates from the Amarkantak plateau in Shahdol district of Madhya pradesh (M.P.) at an elevation of 1057 m from mean sea level, and terminates at the Arabian sea. It has a huge potential for water resources development. The Narmada basin lies between longitude $72^{\circ}32'$ to $81^{\circ}45'$ and latitude $21^{\circ}20'$ to $23^{\circ}45'$; and has a catchment area of 98,796 sq. km. The climate is generally humid tropical, but ranges from subhumid in the east to semi-arid in the west. The average annual rainfall of the basin is about 1200 mm out of which 90% falls during the monsoon months (June-September).

The major part of the Narmada basin consists of a variety of black soils with a large content of clay. Mixed red and black soils, red and yellow soils, and skeletal soils are observed at isolated areas. The vegetation in the basin includes variety of agricultural crops in the plains, forest of varying density in the upland areas, and also the areas of scrub land and bare soils.

2.2 Sher Sub-basin

The Sher river rises in the southern Satpura range in the Durg district of M.P. at an elevation of 600 m from mean sea level. The catchment area upto the confluence point of Sher with

Narmada is about 2900 sq km. However, the Central Water Commission has established a gauging site, upstream of the confluence covering about 1500 sq km of Sher sub-basin.

The Sher sub-basin is characterized by hilly terrain, and is heavily intersected by streams and rivers. The vegetation of the sub-basin consists of forest of medium density, scrub land, spread pockets of cultivation on undulating land, and some denuded land. The land use study of the sub-basin shows that the percentage area of dense forest, medium forest, agriculture, and waste land are 26.2, 39.9, 30.9, and 3.0, respectively. At present, there is no major water resources activity in the Sher sub-basin.

The sub-basin lies in the districts of Narsingpur, Chhindwara and Seoni in Madhya Pradesh. The river Sher is fairly big tributory of river Narmada. About 40 km upstream of the confluence of river Sher with Narmada, the Narsingpur-Jabalpur road crosses the river Sher. At this point, the Belkheri gauging site is located at a distance of 16 km from Narsingpur. Fig. 2.1 shows the map of the Sher sub-basin within Narmada basin. The detail features of the Sher sub-basin is shown in Fig. 3.1

2.3 Land Surface Characteristics

The study area under consideration, having a grid size of 50 km x 50 km, which covers the Sher sub-basin, is assumed to be divided into 16 subgrids. The average land surface characteristics, taken for the study, are given in Table 2.1. The vegetation type, soil texture class, and soil colour class are defined as per BATS terminology. At initial condition, upper soil moisture, root zone soil moisture, and total soil moisture are assumed 30 mm, 500 mm, and 2500 mm, respectively. The soil

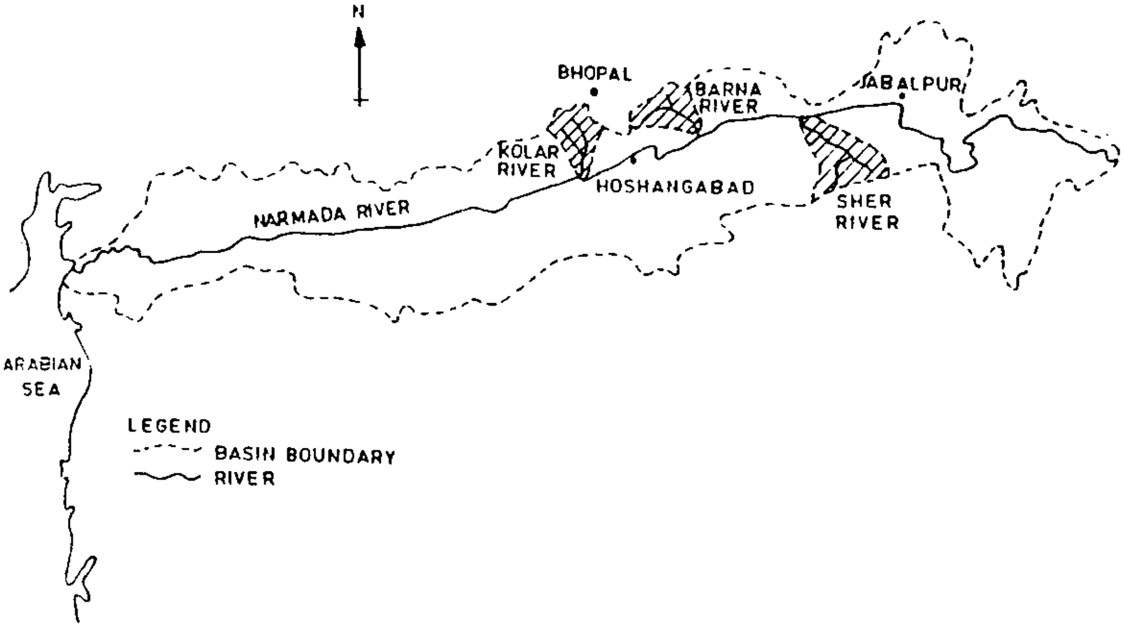

Fig. 2.1 Location map of Sher sub-basin within Narmada basin

characteristics considered for the study do not reflect the actual soil characteristics of the Sher sub-basin. The soil parameters have been assumed fictiously, because of nonavailability of complete data sets as per the model. These differences do not affect our objectives of the study, because emphasis is on the study of the sensitivity of the model to various forcing variables for the land-atmosphere interactions. However, precipitation data used in the study are the actual measurements made at various raingauge stations located within cr nearby the Sher sub-basin.

Table 2.1 Average land surface characteristics for the study

Land surface parameters	
1. Vegetation Type	5*
2. Snow Cover (mm of water)	0
3. Snow Age (non dimensional)	0
4. Relative Humidity	0.85
5. Diurnal Mean Anemometer Temperature (K)	303
6. Soil Texture Class	2**
7. Soil Color Class	7**
8. Diurnal temperature range factor	6
9. Noontime maximum radiation received at surface	8.9×10^2 W/m^2

* Pl. see Appendix I
** Pl. see Appendix III

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3. INCORPORATION OF AREAL CONCEPT FOR PRECIPITATION PARAMETERIZATION

The original version of the BATS considers homogeneous precipitation intensity throughout the grid. Assumption of internal homogeneity within a grid makes the modelling results questionable; and in many respects, solutions are not in accordance with reality. Basically, the fundamental differential equations of the continuum hydrodynamics and thermodynamics are applied to the modelling of the hydrological land surface processes at micro scale. At micro scale level, these equations can conserve a real world validity. The conditions of continuity, internal homogeneity, etc. can not hold true in case of atmospheric models because these conditions are forced to be fulfilled for much larger scales. In some cases like desert areas, large flat lands, etc. these assumptions may give satisfactory results. But especially in case of river basin modelling and in the mountainous regions, the spatial variability at subgrid scale must be treated explicitly in modelling.

The BATS was modified by Ramirez (1991a, b) to account the simulation of spatially inhomogeneous conditions in precipitation. He added a subroutine, RAING_J to account the variability in precipitation within the grid. The methodology assumes that the precipitation intensity, interarrival time between precipitation pulses, and storm duration follow an exponential distribution. These parameters are generated assuming random events. To compute the hydrologic and climatic fluxes for a real-life field problem, this assumption restricts its wide applicability. Because, the historical records of rainfall at various raingauge stations may show other types of distributions. Dealing with historical records, it is also observed that the distribution of rainfall data not only differs from one basin to other basin; but also for a particular basin, it differs from one season to other season. The distribution depends upon the basis of analysis for time; whether yearly, seasonal, monthly or daily. Moreover, one needs to first establish that the assumption of exponential distribution holds true for the area under consideration, and secondly to determine the precipitation parameters from the observed individual gauge measurements. The other assumption making the existing methodology questionable for the application on real world system is that in a given time step, only one subgrid gets wet, and the choice of the subgrid to get wet is random. The other 15 subgrids receive zero precipitation in that time step. In addition, fluxes at subgrid scales, obtained from distributed precipitation field, are lumped spatially by the simple arithmetic average. Therefore, it is realized that modification in the precipitation scheme is needed for real-life applications. Milly and Eagleson (1988) demonstrated the critical need to incorporate some representation of areal storm variability in large area hydrologic models.

3.1 Establishing Patch Domains

To assess the effect of subgrid scale spatial variability of relevant forcing variables on fluxes, the measurements of hydrologic and climatic data are needed at a large number of subgrid points. Although GCM grid is divided into a number of meso scale subgrids, the land surface characteristics and hydrologic parameters are not completely known even at such scales. There is a large discrepancy between the observed and model scales. In absence of extensive spatial data, some methodology is needed to assign the subgrid values for different parameters. In this study, the subgrid values for precipitation are obtained by establishing the domain of each raingauge located within or near the area under consideration. However, a better assessment of the effect of detailed spatial variability on land-atmosphere interactions can be achieved by utilizing remotely sensed areal information of land surface characteristics. A decision support system also could be a better tool to improve the understanding of land-atmosphere interactions provided an extensive field measurements are availabe to quantify the areal variability at subgrid scale.

The concept of areal average rainfall for the watershed is utilized here for the whole grid to establish the patch domains of raingauge stations. The domains of raingauges within or nearby the area under consideration are established by drawing the Thiessen polygon network. The region bounded by the perpendicular bisectors of the lines joining adjacent gauges indicate the domain of the gauge station located in this region. Here, it is assumed that precipitation is uniform throughout this region. Therefore, the precipitation values for the subgrids falling completely inside a polygon are assigned the same values as measured at the gauge located within that polygon. For the subgrids falling at the boundary of two or more polygons, the precipitation values are estimated from the following expression:

$$P_i = \sum_{j=1}^{m} (w_s)_{ij} \, P_j^o \quad ; \qquad i = 1, 2, \ldots . n \tag{3.1}$$

where P_i, P_j^o and $(w_s)_{ij}$ denote the precipitation at subgrid i at time t, observed precipitation at gauge j at time t, and weight assigned to the j th gauge for the computation of precipitation at subgrid i, respectively; n and m represent the number of subgrids and raingauge stations, respectively. Here w_s is termed as subgrid weight. It is computed by fractional area of the subgrid i occupied by the polygon within which rainfall is assigned identical to the observed rainfall at gauge j. Mathematically, it can be expressed as:

$$(w_s)_{ij} = a_{ij}/(a_s)_{ij} \tag{3.2}$$

Where $(a_s)_{ij}$ and a_{ij} denote the area of the subgrid i and the area occupied by the polygon j within the subgrid i, respectively.

Fig. 3.1 shows the Thiessen polygon network for the study area, based on 3 raingauge stations; namely, Mungwani, Lakhandon and Harai. The domains of all gauges are demarcated by the polygon lines. the subgrid weights for various subgrids corresponding to various gauge stations are obtained and tabulated in Table 3.1. The average precipitation over the grid is computed by the Thiessen polygon method (Chow et al., 1988). It is given by:

$$P_{av} = \sum_{j=1}^{m} w_j \, P_j^o \tag{3.3}$$

Where P_{av} and w_j represent the average precipitation over the grid and the Thiessen weight for the gauge j, respectively. The Thiessen weight for a station is estimated by:

$$w_j = A_j/A \tag{3.4}$$

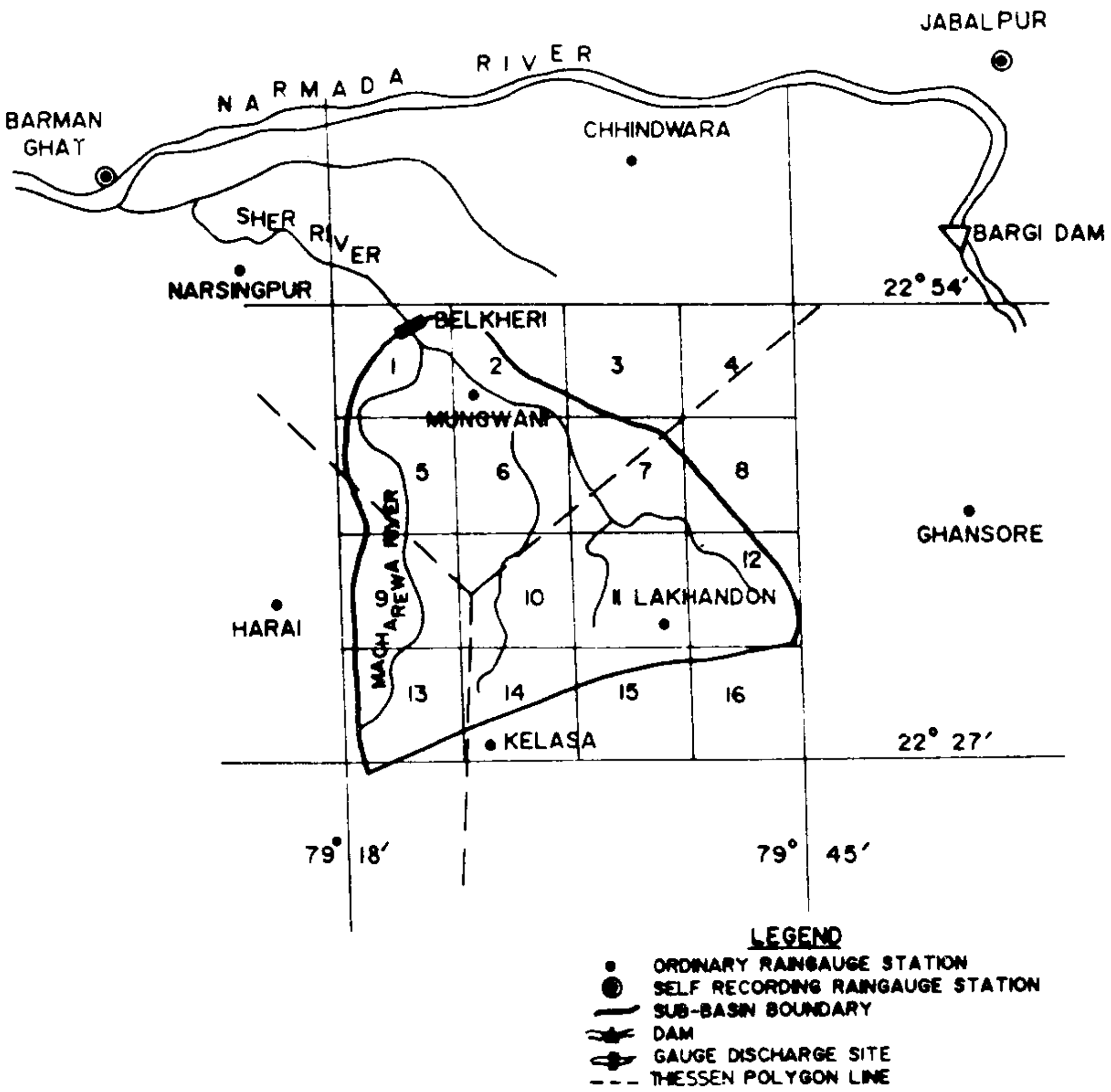


FIG 31 THIESSEN POLYGON NETWORK FOR THE STUDY AREA
(BASED ON 3 STATIONS)

Where A and A_j denote the grid area and the area occupied by the polygon j within the grid, respectively. The Thiessen weights for various stations are given in Table 3.2. The average precipitation over the grid can be computed also by the arithmetic mean of precipitation values generated at all subgrid points, because both methods yield the same value if the precipitation field is generated in the fashion outlined earlier.

Table 3.1 Subgrid weight
(Based on three stations)

Subgrid	Weight		
	Mungwani	Lakhandon	Harai
1	1.0	0.0	0.0
2	1.0	0.0	0.0
3	1.0	0.0	0.0
4	0.5	0.5	0.0
5	1.0	0.0	0.0
6	1.0	0.0	0.0
7	0.5	0.5	0.0
8	0.0	1.0	0.0
9	0.0	0.0	1.0
10	0.0	1.0	0.0
11	0.0	1.0	0.0
12	0.0	1.0	0.0
13	0.0	0.0	1.0
14	0.0	1.0	0.0
15	0.0	1.0	0.0
16	0.0	1.0	0.0

Table 3.2 Thiessen weight
(based on 3 stations)

Station	Weight
Mungwani	0.375
Lakhandon	0.500
Harai	0.125

3.2 Upscaling of Fluxes from Patch to Grid Scale

The subroutines RAING_J and BMARCH in the BATS software are modified to account for precipitation variability at subgrid scale in simulation, in accordance with the methodology described in section 3.1 for assigning precipitation values to various subgrid points within a modelling grid. However, generation of precipitation field to assess the subgrid variability on the fluxes using exponential distributions of generating parameters is retained in the BATS software as an alternate option. For comparison purpose, precipitation field is also generated using the concept of arithmetic mean for areal precipitation over the grid. The moisture and energy fluxes are computed using the generated precipitation fields.

To compute the hydrologic and climatic fluxes over the Sher sub-basin, rainfall records of three raingauge stations namely: Mungwani, Harai and Lakhandon are used to assign precipitation values at subgrids. The precipitation at various subgrids are computed using the Thiessen polygon concept as discussed in section 3.1 (Fig. 3.1). The analysis is carried out for 20 days simulation using hourly rainfall data of August 1986. The hourly rainfall data for these stations are obtained by converting the daily rainfall records using the hourly rainfall data of Jabalpur station (Lohani, 1989).

Fig. 3.2 shows the probability distribution functions for rainfall intensity, storm duration and interarrival time, obtained from the hourly rainfall data. The cumulative probabilities for the exponential distributions of these parameters are also shown for comparison. The exponential distribution of a random event is given as (Chow et al., 1988):

$$f(x) = \lambda\ e^{-\lambda\ x} \tag{3.5}$$

Where x, λ and $f(x)$ denote an event, mean rate of occurrence of the events, and probability density function, respectively.

It is evident from this figure that storm duration and inter-arrival time can be described by an exponential distribution. However, rainfall intensity, deviates from the exponential distribution. This comparison supports the assumption of modified BATS for precipitation field with little reservation. But, the comparison shown in Fig. 3.3 establishes that the hypothesis of modified BATS for precipitation field seems to be questionable for real-life applications. A large deviation occurs because of the assumption of wetness of only one grid at a time, and due to random location of wet grid. The average precipitation is computed by the arithmetic mean of rainfall records made at raingauge stations, Mungwani, Lakhandon and Harai. The average precipitation over the grid computed from the precipitation field generated using modified BATS deviates appreciably from the arithmetic mean of observed rainfall at 4, 5, 7, 8, 11, 12, and 14 th day (Fig.

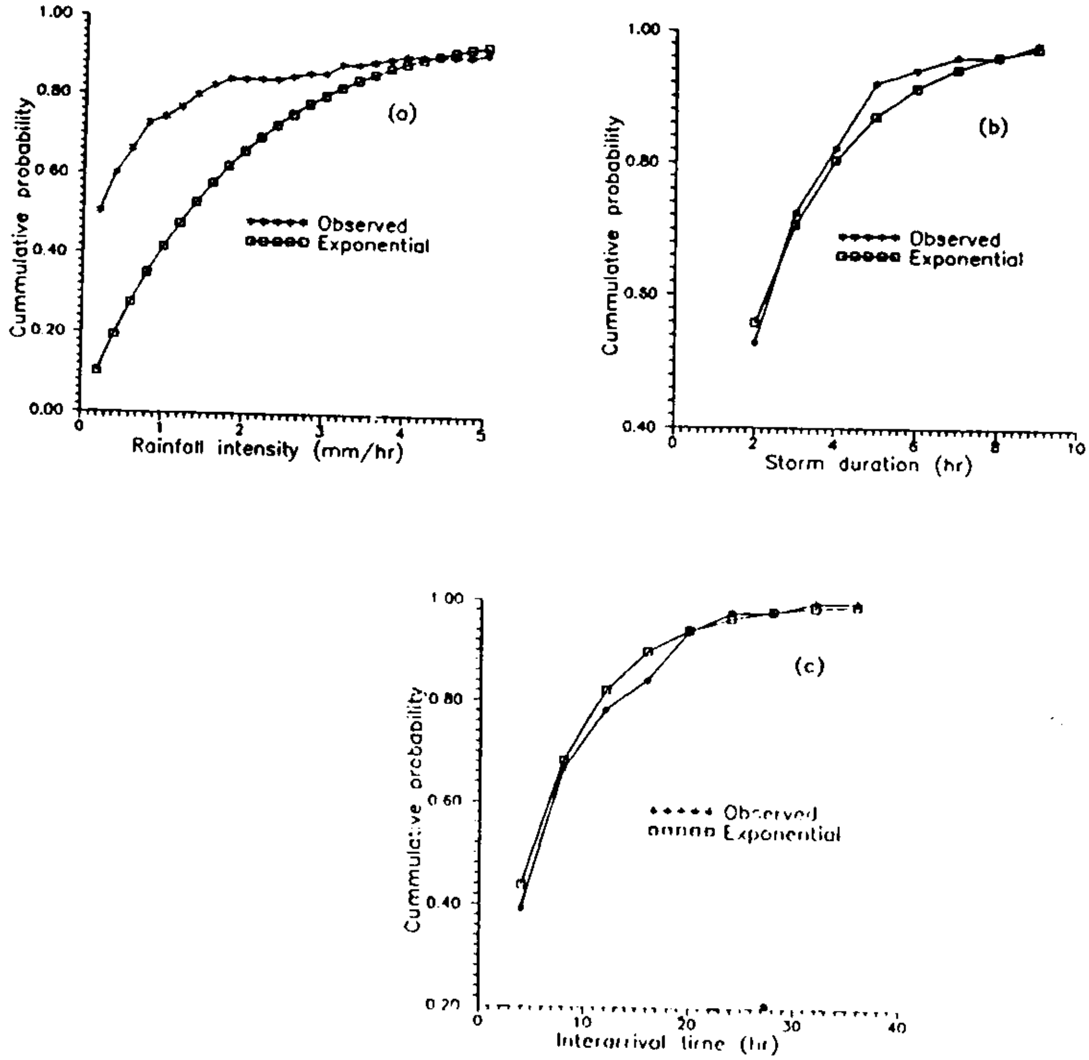


Fig. 3.2 Probability distribution function for (a) rainfall intensity (b) storm duration (c) interarrival time

3.3). Thus, precipitation field genarated from the modified BATS can not represent the ground truth for the study area under consideration. Fig. 3.3 shows that the proposed methodology for assigning the precipitation values to various subgrids is adequate.

Fig. 3.4 shows the comparison of different schemes of quantifying the precipitation variability at subgrid scales on computation of surface runoff and total runoff. In case of the hypothesis of modified BATS, peaks are of higher magnitude, and times to peaks are comparatively less. Fig. 3.5 shows time varying moisture fluxes for different schemes of quantifying the precipitation variability at subgrid scales. These comparisons depict that the fluxes obtained from the hypothesis of modified BATS for generating the precipitation field differ appreciably. In the beginning period, soil moisture in root zone decreases because of presence of a highly permeable soil. Due to very high hydraulic conductivity, soil moisture depletes to subsurface zone at a faster rate. It is observed that presence of clayey soil or less permeable soil causes a increasing trend in root zone soil moisture. This reflects that soil texture is a crucial parameter in estimating soil moisture fluxes. All the fluxes presented in Figs. 3.4 and 3.5 are spatially averaged by the simple arithmetic mean, as the BATS does.

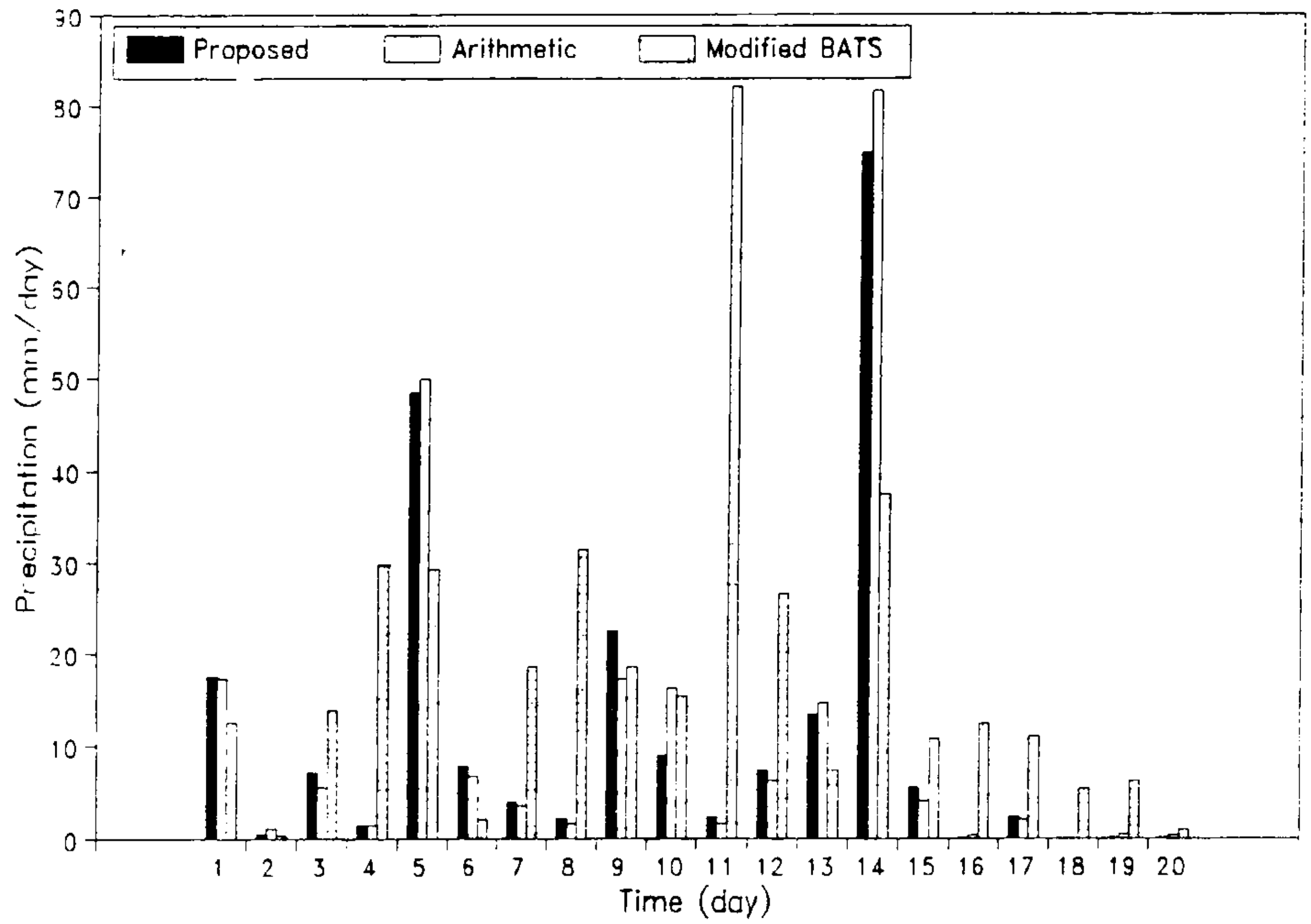


Fig. 3.3 Comparison of various schemes for precipitation field over the grid

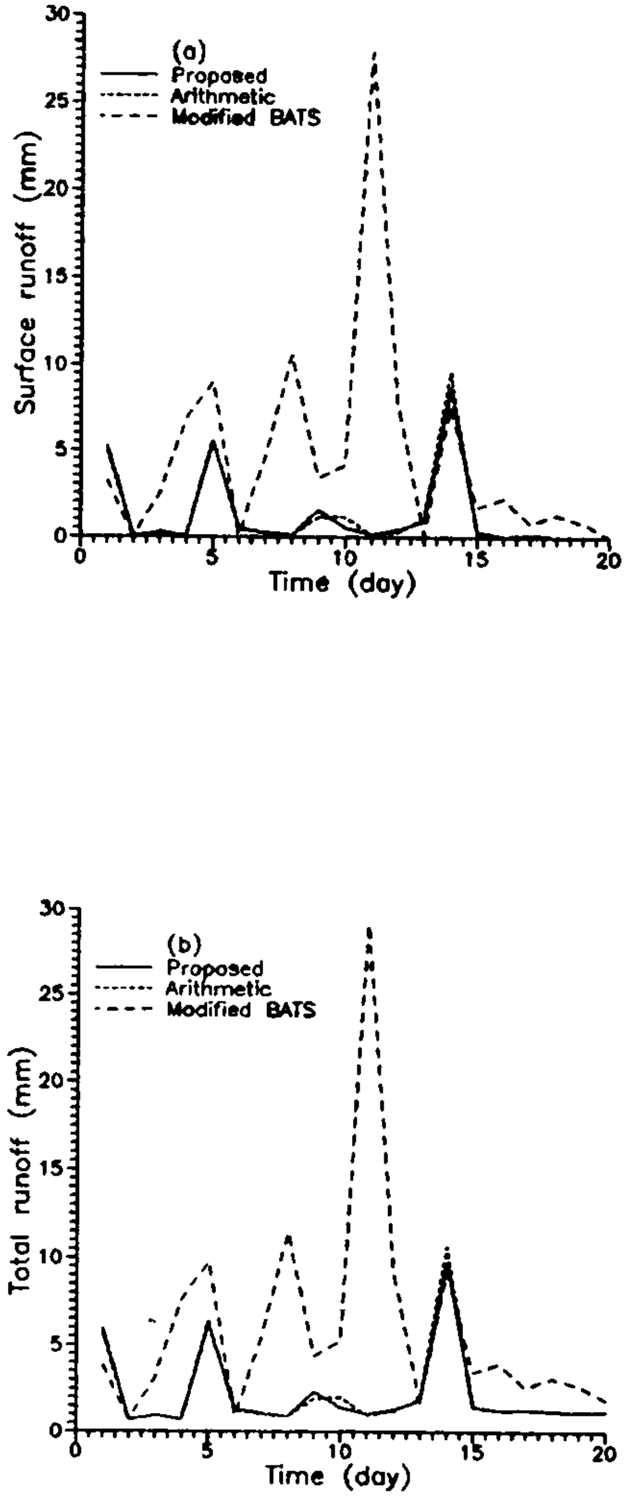


Fig. 3.4 Temporal variation of (a) surface runoff (b) total runoff

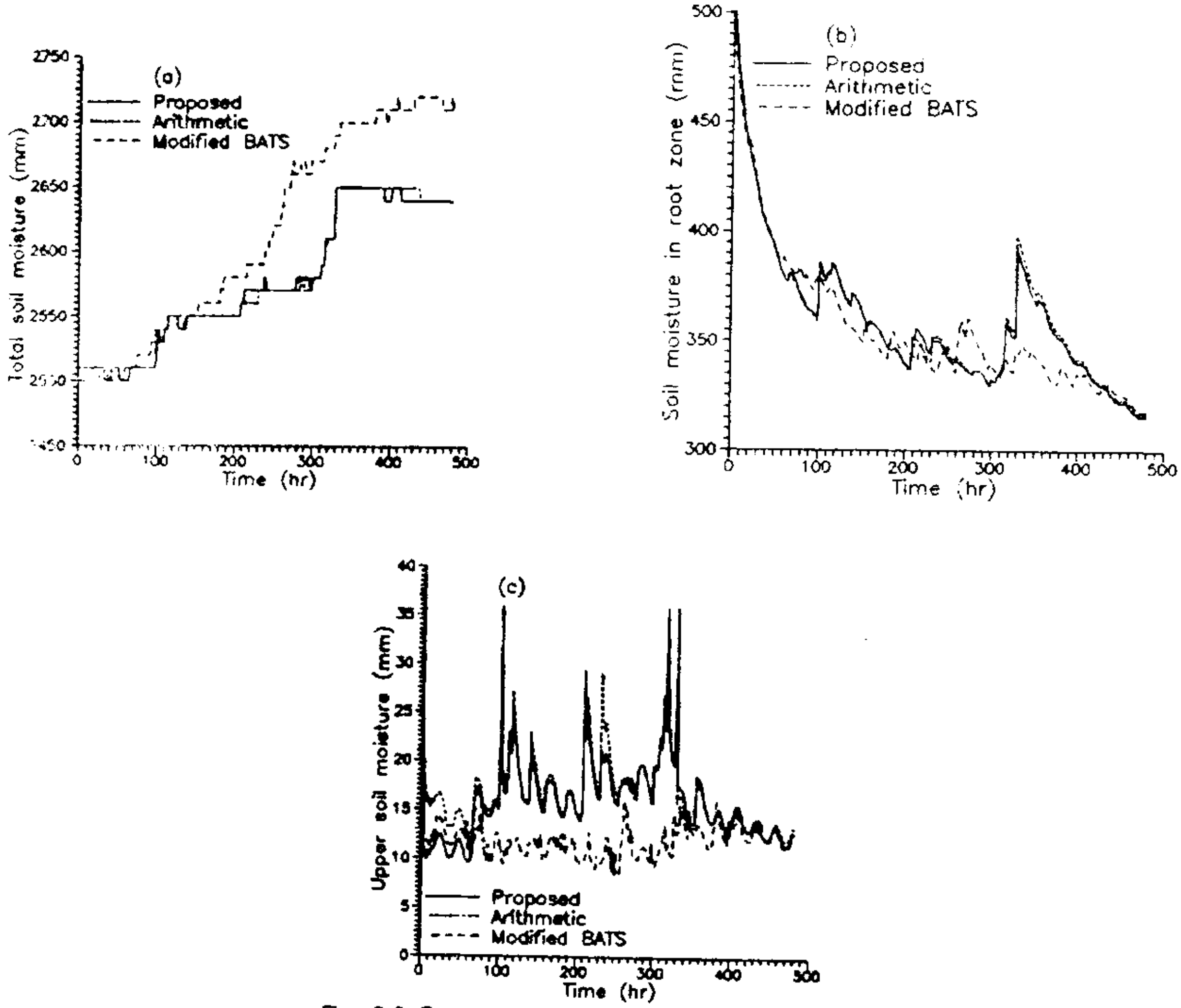


Fig. 3.5 Temporal variation of (a) total soil moisture (b) soil moisture in root zone (c) upper soil moisture

4. SENSITIVITY OF LAND-ATMOSPHERE INTERACTIONS TO CATCHMENT VARIABILITY

The surface grid squares of an atmospheric general circulation model typically cover an area of the order of 10^4 to 10^5 km^2, which is a macroscale for hydrological processes. Regions of this size in nature are characterized by extensive spatial variability in precipitation, topography, vegetation, soil, ecological characteristics and other surface features. Generally, the upper range of GCM grids for the computation varies from 250 to 500 km. However, for some purposes, finer grids are used with a lower limit of 10 km. For computational simplicity, most operational land surface models in GCMs assume a uniform surface within a grid square, thus ignoring spatial heterogeneity. Due to heterogeneities, parameters and processes controlling hydrologic response operate at many different time and length scales. The spatial and temporal variability of catchment characteristics may exert strong influence on the hydrologic and climatic fluxes at GCM scale. Therefore, an extensive sensitivity experiments are needed to assess the significance of the spatial variability of land surface characteristics and wide diversity of hydrologic processes at subgrid scale. Reliable predictions for global climate change can be made only when the fluxes occurring at subgrid scales are upscaled adequately at GCM scale on the basis of these sensitivity experiments, thus reflecting the realistic representation of subgrid variability.

To study the significance of the variability of precipitation, soil texture, and soil temperature; sensitivity experiments are carried out for a number of scenarios using the modified BATS. But, the precipitation field is generated on the basis of proposed methodology as described in section 3. The study is carried out for the Sher sub-basin of Narmada basin. The characteristics of different scenarios are described in Table 4.1. All runs are performed for 20 days simulation with a time step of one hour.

Table 4.1 Description of Scenarios

Scenario	Precipitation Characteristics		Soil Characteristics		
	No. of Gauges*	Average	Texture	Color	Temp.
1	3	n	HO	HO	HO
2	3	y	HO	HO	HO
3	5	n	HO	HO	HO
4	5	n	HE	HO	HO
5	5	n	HO	HE	HO
6	5	n	HO	HO	HE

y Average precipitation over the grid changes

n Average precipitation over the grid does not change.

* Average precipitation is computed on the basis of information available on these gauges.

HO Homogeneous with respect to particular soil characteristics within the grid.

HE Heterogeneous with respect to particular soil characteristics within the grid.

4.1 Effect of Spatial Variability of Precipitation

Precipitation varies widely in space and time according to the general pattern of atmospheric circulation, and local and regional factors. The effect of precipitation variability on hydrologic fluxes has been studied much at microscale, but little emphasis has been given on the study at mesoscale or macroscale.

Eagleson and Qinlang (1987) studied the effect of variation in storm size, relative to catchment size, using a kinematic wave based runoff model with a conceptual rainstorm model. They concluded that both the first and second moment of peak streamflow decrease rapidly with increasing values of the catchment to storm scale ratio. Milly and Eagleson (1988) demonstrated that a hydrologic model representing a sufficiently large area must incorporate some representation of areal storm variability. Loague (1988) concluded that the impact of soil information on runoff predictions at the hillslope scale appears to be more critical than spatial rainfall information. Divya (1993) carried out limited sensitivity experiments to assess the effect of subgrid scale variability in precipitation field on energy and moisture budget. She generated precipitation field using the modified BATS which allow the simulation of spatially inhomogeneous precipitation by an exponential distribution as discussed in section 3. The fluxes were computed using typical characteristics of central India in summer period. Basically the analysis is focused on the storm occurrence within the grid. The significant variation of fluxes were observed when a fixed volume of precipitation is concentrated over smaller area, instead of larger area.

To assess the significance of spatial variability of precipitation at subgrid scale, four runs of the scenario 1 are performed to compute moisture and energy fluxes over the Sher sub-basin. The fluxes are computed using BATS with the proposed methodology for quantifying the spatial variability in precipitation. The first run is taken with the actual precipitation data with zero percent perturbation in spatial values. Other three runs are carried out with linearly perturbed spatial precipitation values. The actual precipitation at subgrid points are perturbed linearly such that the average precipitation over the whole grid remains same at all times. Mathematically, this problem can be stated as:

Find α_j

such that

$$(P'_{av}) - P_{av} = 0 \tag{4.1}$$

Where

$$P'_{av} = \sum_{j=1}^{m} w_j\, P'_j \tag{4.2}$$

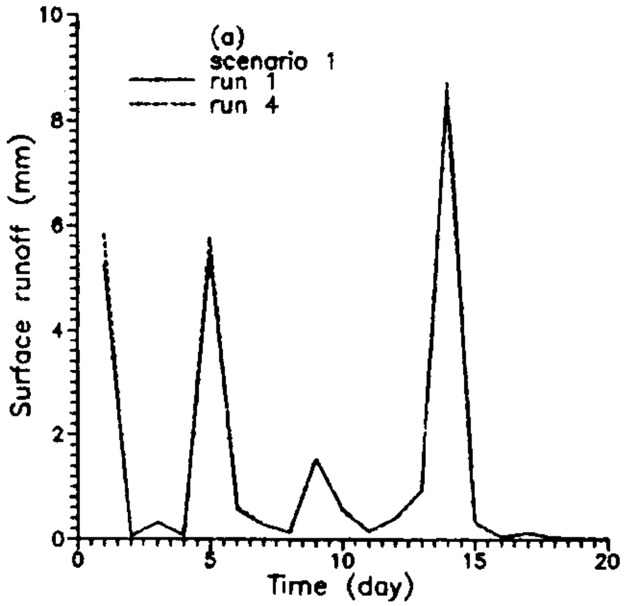
$$P'_j = P^o_j + \alpha_j\, P^o_j \tag{4.3}$$

Here P'_j, P'_{av}, and α_j denote perturbed precipitation data for j th gauge, average precipitation over the grid using perturbed data, and perturbation factor for j th gauge respectively. The above algorithm must hold true for all the time steps. A separate computer program is written to obtain perturbed data for various raingauges. The iterative technique has been used to estimate the values of α_j. The perturbation factors and relative errors in its estimation for all runs are given in Table 4.2.

Table 4.2 Perturbation Parameters

Run	α (in percentage) Station			Error in estimate of average precipitation (in percentage)
	Mungwani	Lakhandon	Harai	
1	0.00	0.00	0.00	0.00000
2	4.00	-3.00	-1.00	-0.00383
3	10.00	-8.00	-0.60	0.00762
4	18.00	-10.00	-16.75	0.00215

Fig. 4.1 shows the effect of precipitation variability at subgrid scale on surface runoff and total runoff. It is evident from this figure that the integration of subgrid fluxes shows almost no difference with variation in spatial precipitation values as long as the average precipitation over the grid remains same. Other runs, not shown in figure, also show similar behaviour. It reflects that rainfall-runoff relation can be described as a basin representation. However, this appears to be true only when the rainfall-runoff relation is linear, and a small degree of spatial variability exists within the grid. Fig. 4.2 establishes that there is almost linear relationship between surface runoff and precipitation. Here, it should be noted that if a high degree of spatial variability within the grid exists, and the sub-basin shows a nonlinear response; the moisture fluxes will vary significantly due to variation in precipitation at subgrid scale. The profound effect of precipitation variability at subgrid scale is observed when rainfall is assumed to be concentrated on much smaller area, instead of the whole grid,



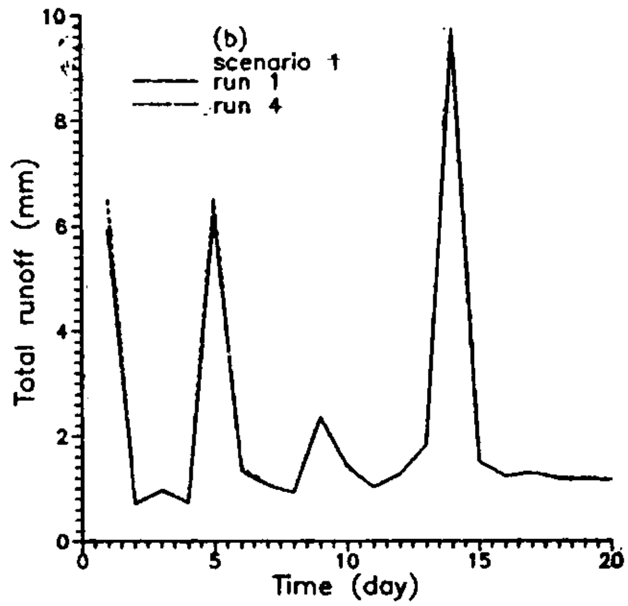


Fig. 4.1 Effect of precipitation variability on (a) surface runoff (b) total runoff

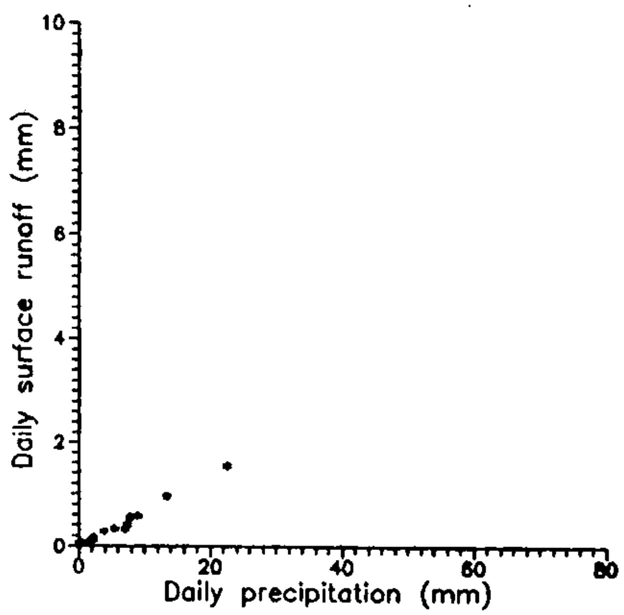


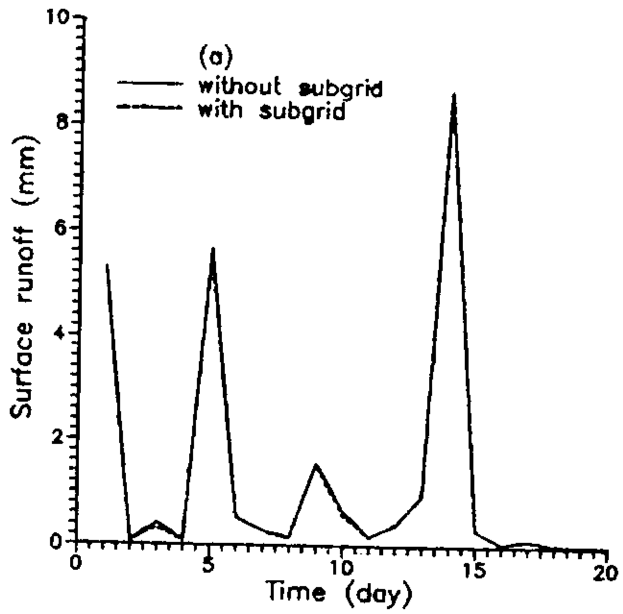
Fig. 4.2 Variation of surface runoff with average precipitation over the grid for scenario 1

having same volume of precipitation over the grid in both the cases. The similar characteristics are observed with other moisture fluxes.

Fig. 4.3 shows the effect of box grid assumption for the real landscape features. The moisture fluxes except upper soil moisture are unaffected if inhomogeneous precipitation within the grid is modelled by assuming a homogeneous precipitation throughout the grid provided the precipitation field is generated using the methodology described in section 3. However, these conclusions may not hold true if rainfall-infiltration and rainfall-runoff mechanisms for the considered area are governed by a highly nonlinear relations. In case of nonlinear response of the catchment, some description of areal variability will be needed to lessen the discrepancy in macroscale modelling, as these variability will act as highly sensitive forcing variables for simulation of global change.

4.2 Sensitivity to Spatially Averaged Precipitation

Fig. 4.4 shows the sensitiveness of surface runoff and total runoff to change in spatially averaged precipitation over the grid. Although only two deviations are shown in figure, the extensive computations show that peaks increase appreciably with increase in average areal precipitation over the grid. However, time to peak remains same. It shows that runoff appears to vary linearly with any change in average precipitation over the grid, however, its gradient vary widely with time. Here deviations in spatially averaged precipitation do not reflect random variations in spatial precipitation values. They denote linear variation in observed rainfall data for all three gauging stations.



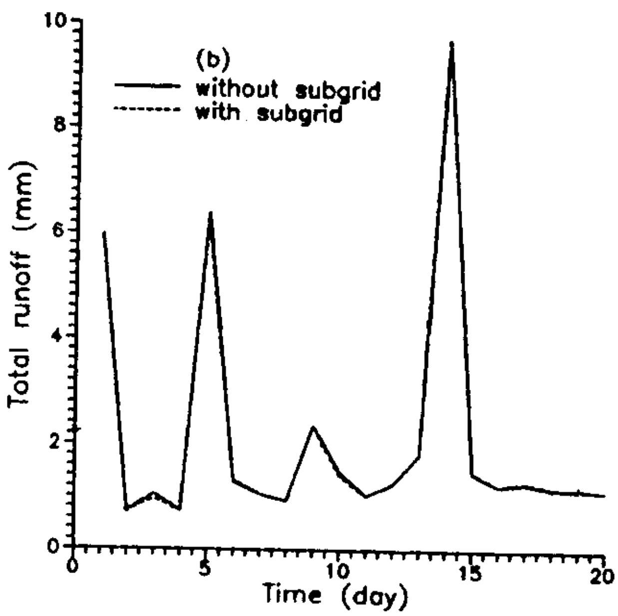
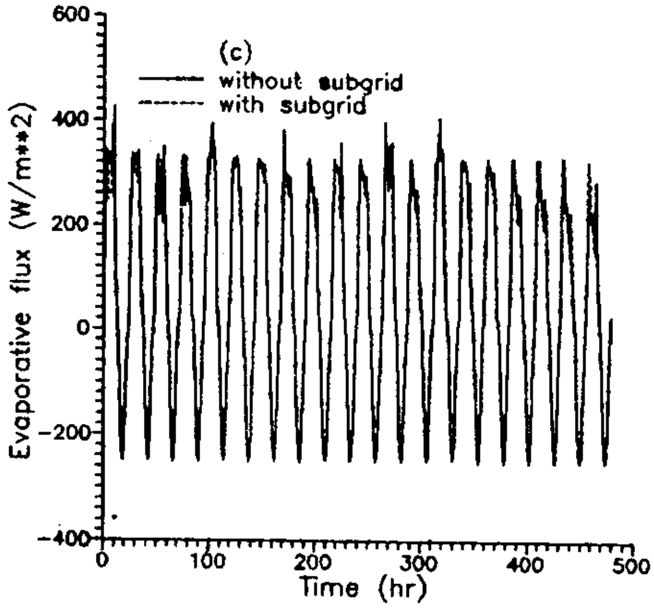


Fig. 4.3 Box grid versus distributed grid assumption for (a) surface runoff (b) total runoff



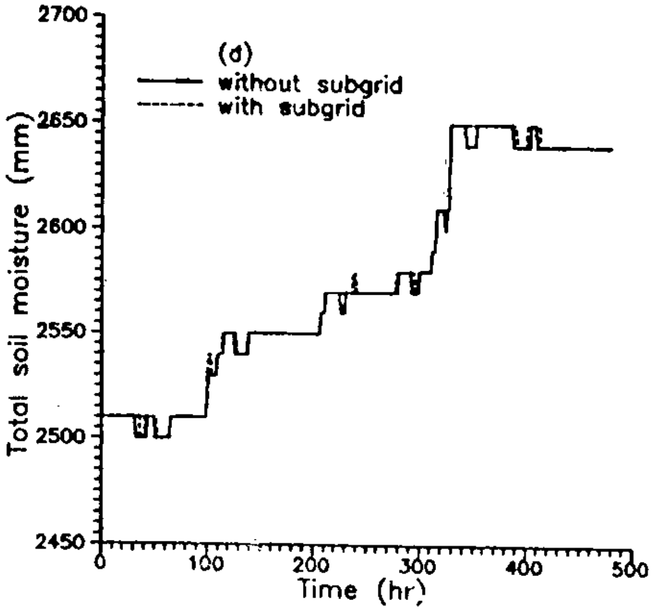
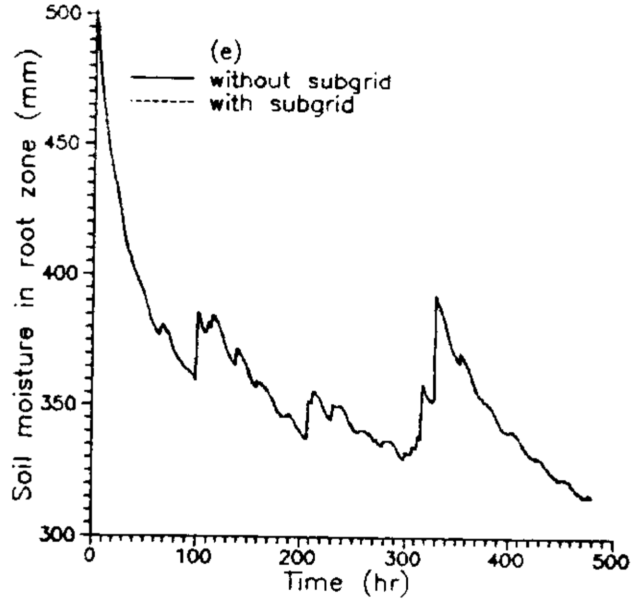


Fig. 4.5 Box grid versus distributed grid assumption for (c) evaporative flux (d) total soil moisture



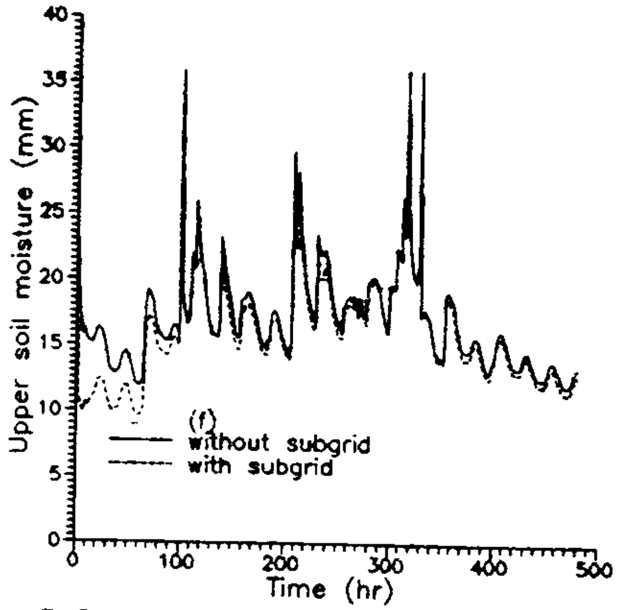
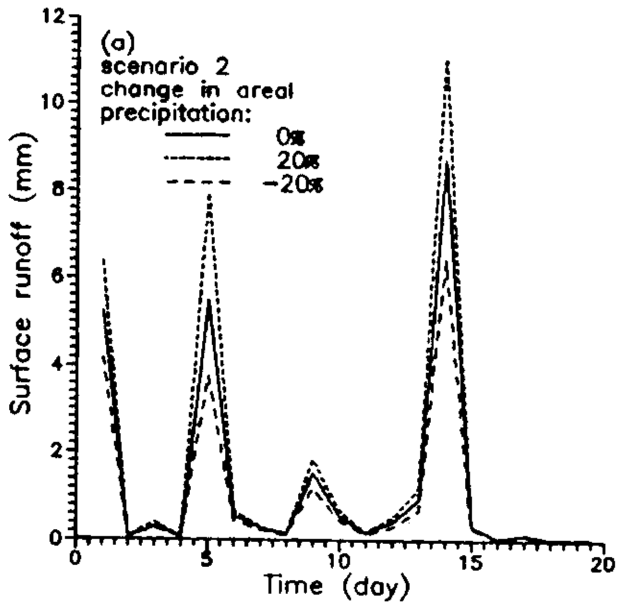


Fig. 4.3 Box grid versus distributed grid assumption for (e) soil moisture in root zone (f) upper soil moisture



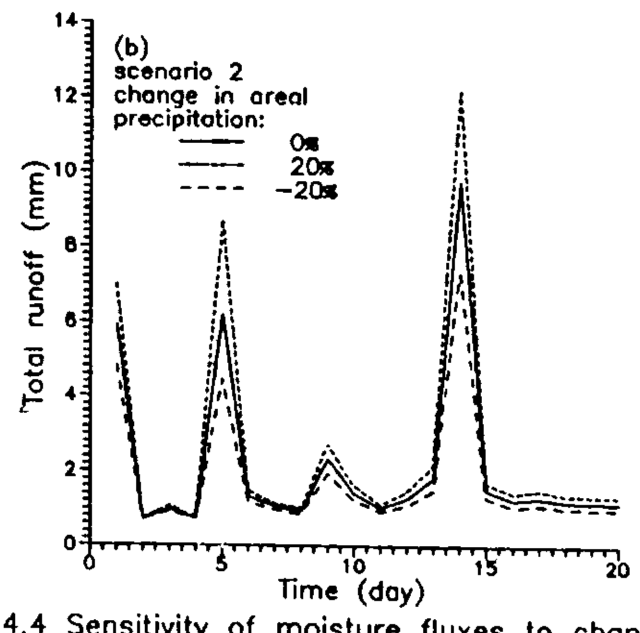


Fig. 4.4 Sensitivity of moisture fluxes to change in areal precipitation over the grid (a) surface runoff (b) total runoff

The similar characteristics are observed with soil moisture fluxes (Fig. 4.5). The total soil moisture is comparatively more sensitive to change in average precipitation. The soil moisture fluxes appear to vary linearly with any deviation in average precipitation.

4.3 Influence of Sparse Precipitation Data

Results reported in sections 4.1 and 4.2 are based on the rainfall measurements made at only three stations; Mungwani, Lakhandon and Harai. The precipitation values at all 16 subgrid points are obtained using these data, and the analysis is carried out on the basis of generated precipitation field. A closer vision on the study area reflects that the north-east area of the grid is not adequately represented in estimation of the precipitation values at subgrid points. If this zone will have a high degree of precipitation variability in contrast to adjoining stations, precipitation field and thus hydrologic fluxes may show significant difference to the predicted ones. Although, this zone can not be adequately represented because of nonavailability of raingauge station; the rainfall records of Narsingpur station, nearby this zone, are also considered for estimating the spatial precipitation values. In addition, rainfall records of Chhindwara are also considered for generating the precipitation field to assess the influence of incomplete precipitation information. The other stations, Ghansore and Kelasa (Fig. 4.6) are not included in the simulation study because of nonavailability of data.

Since the simulation study is based on hourly data, daily rainfall records of Chhindwara and Narsingpur must be converted into hourly basis. To employ statistical technique for conversion, an attempt is made to see the correlation between the

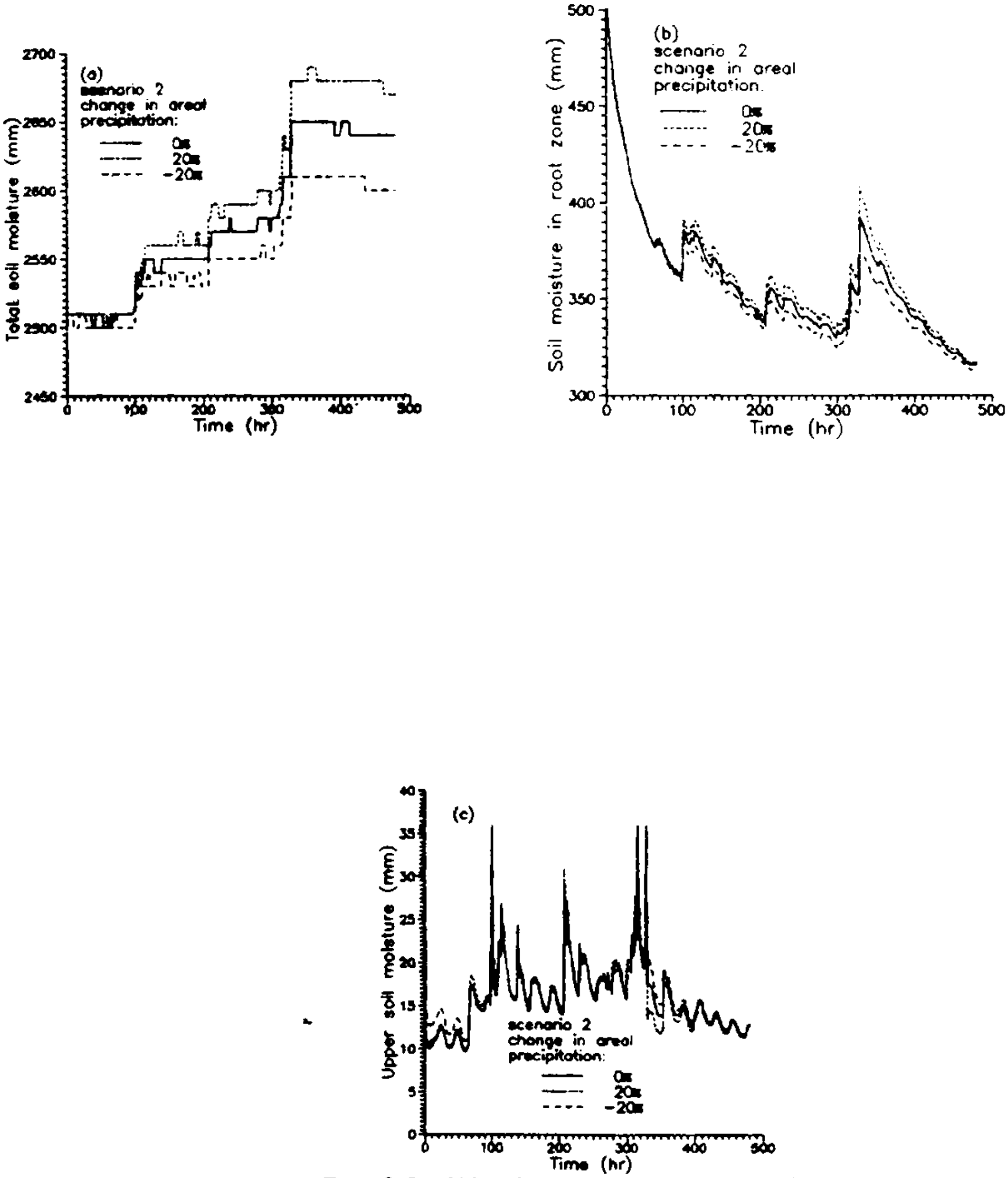


Fig. 4.5 Sensitivity of moisture fluxes to change in areal precipitation over the grid: (a) total soil moisture (b) soil moisture in root zone (c) upper soil moisture

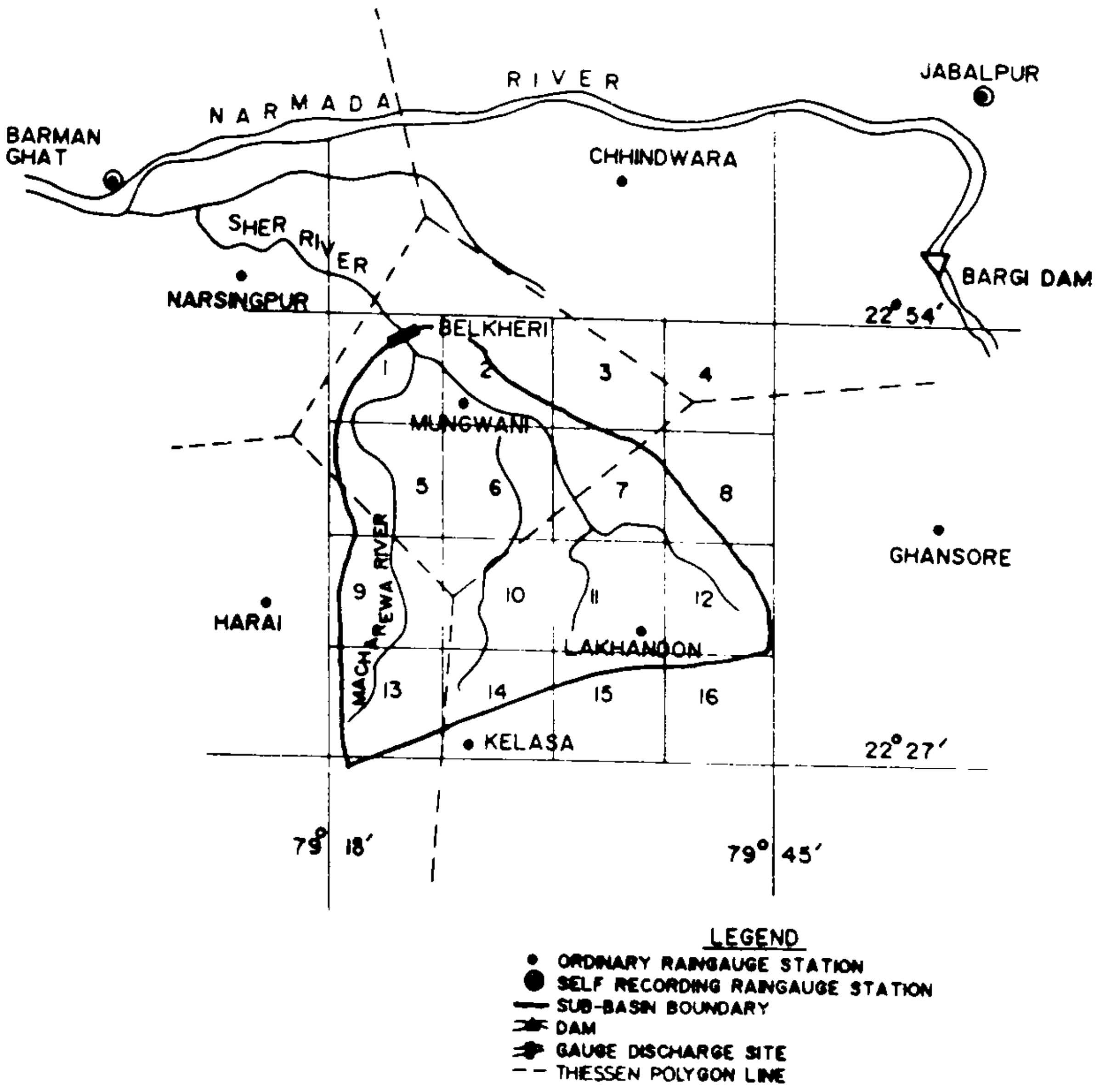


FIG. 4.6 THIESSEN POLYGON NETWORK FOR THE STUDY AREA (BASED ON 5 STATIONS)

rainfall data recorded at these two stations and Jabalpur station where records are available at hourly basis. The correlation coefficients for Jabalpur-Chhindwara, and Jabalpur-Narsingpur are obtained to measure the degree of association for linear dependency. The computed correlation coefficients for Jabalpur-Chhindwara, and Jabalpur-Narsingpur are 0.34 and 0.03, respectively. It establishes that rainfall records of Jabalpur and Chhindwara are poorly correlated; and there is almost no correlation between rainfall records of Jabalpur and Narsingpur. Due to nonapplicability of statistical technique, daily rainfall data of Chhindwara and Narsingpur are converted into hourly rainfall data using mass curve technique.

The precipitation field is generated using the converted hourly data of Mungwani, Lakhandon, Harai, Chhindwara, and Narsingpur, adopting the same methodology as described in section 3. The Thiessen Polygon network for the study area, based on 5 stations, is shown in Fig. 4.6. The subgrid weights for all 16 subgrids corresponding to each gauge station are given in Table 4.3. The Thiessen weights for the gauge stations are tabulated in Table 4.4.

Table 4.3 Subgrid weight
(based on 5 stations)

Subgrid	Weight				
	Station				
	Mungwani	Lakhandon	Harai	Chhindwara	Narsingpur
1	0.881	0.000	0.000	0.000	0.119
2	1.000	0.000	0.000	0.000	0.000
3	0.786	0.000	0.000	0.214	0.000
4	0.048	0.238	0.000	0.714	0.000
5	0.833	0.000	0.167	0.000	0.000
6	1.000	0.000	0.000	0.000	0.000
7	0.500	0.500	0.000	0.000	0.000
8	0.000	1.000	0.000	0.000	0.000
9	0.119	0.000	0.881	0.000	0.000
10	0.238	0.762	0.000	0.000	0.000
11	0.000	1.000	0.000	0.000	0.000
12	0.000	1.000	0.000	0.000	0.000
13	0.000	0.000	1.000	0.000	0.000
14	0.000	1.000	0.000	0.000	0.000
15	0.000	1.000	0.000	0.000	0.000
16	0.000	1.000	0.000	0.000	0.000

Table 4.4 Thiessen weight
(based on 5 Stations)

Station	Weight
Mungwani	0.337500
Lakhandon	0.468750
Harai	0.128125
Chhindwara	0.058125
Narsingpur	0.007500

Fig. 4.7 shows the effect of incomplete spatial precipitation information on average precipitation over the grid. It is evident from this figure that average precipitation over the grid, based on 5 stations (scenario 3) is less at 3rd, 9th, and 14th day; and for the rest of the days it is either more or equal to those based on only 3 stations (scenario 1). It reflects that moisture fluxes in scenario 3 will vary marginally from that in scenario 1. Fig. 4.8 shows the variation of surface runoff and total soil moisture with time for scenarios 1 and 3. Other moisture fluxes are not affected by this marginal change in precipitation field. The changes in fluxes would have been assessed more accurately if some gauges were present in north-east zone of the study area to represent the areal variability in precipitation more adequately.

4.4 Effect of Spatial Variability of Soil Parameters

Milly and Eagleson (1987) studied the effects of spatial variability of soil and vegetation on spatially and temporally averaged hydrologic fluxes. They concluded that because of typical nonlinear catchment response behaviour, spatial integration to the catchment scale is possible only in the case where a small degree of initial variability exists. Wilson et al (1987) carried out sensitivity studies using BATS with different soil and vegetation parameters. They analyzed five different bioclimatic regimes: a low latitude evergreen forest, low latitude sand desert, high latitude boreal forest, high latitude tundra, and a prairie grassland. Their results show that BATS is most sensitive to variations in soil texture, particularly to the associated variations in hydraulic conductivity and diffusivity parameters which control infiltration and evaporation. Wood (1991) pointed out that the results obtained by Abramopolous et

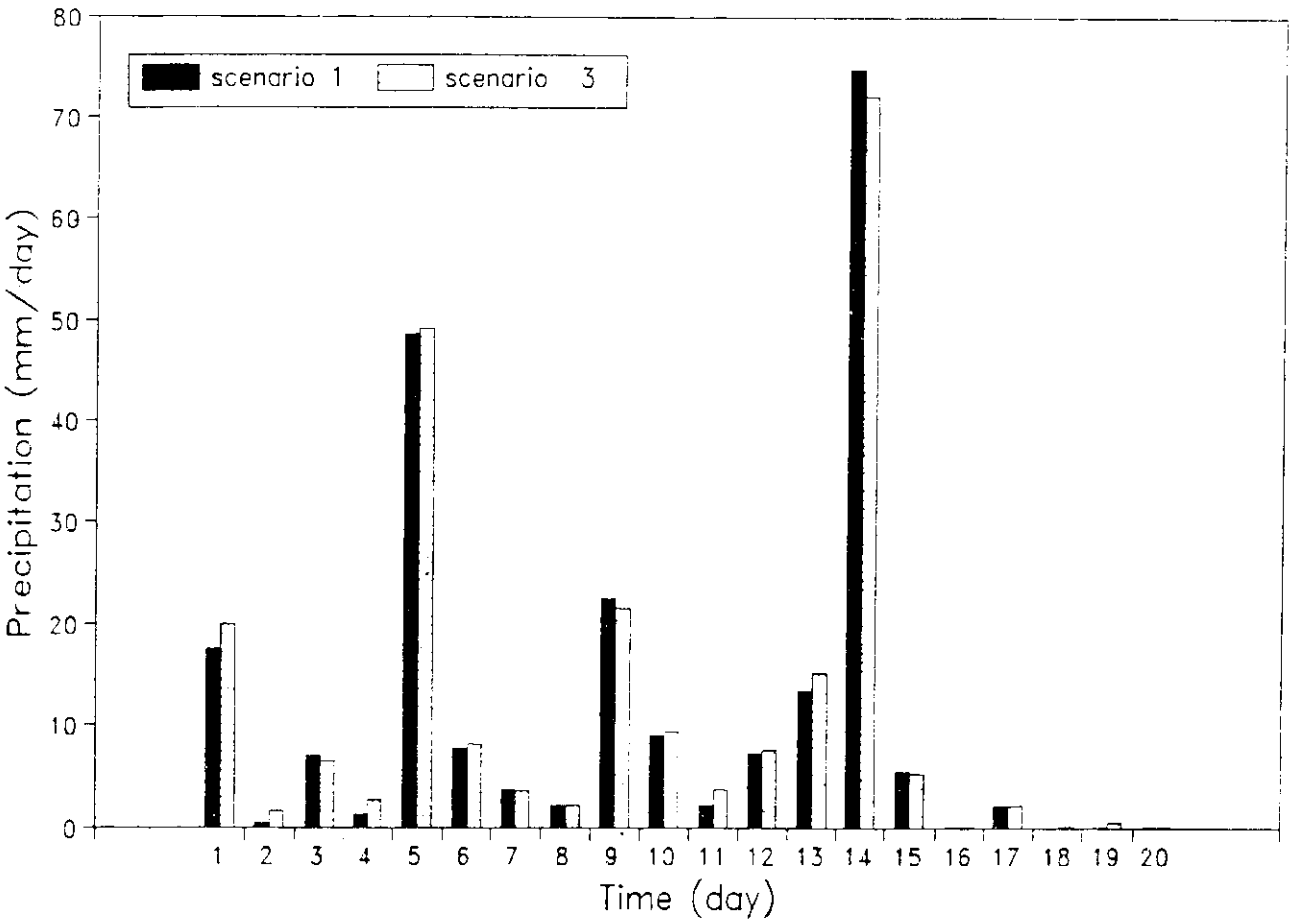
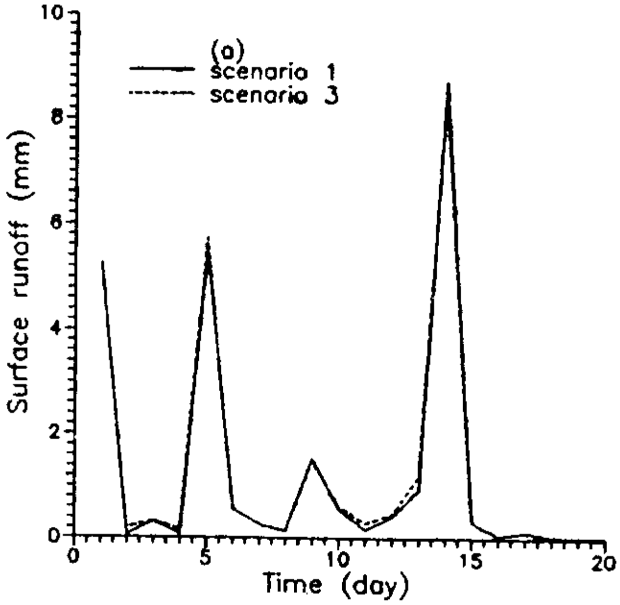


Fig. 4.7 Effect of incomplete spatial precipitation information on average precipitation



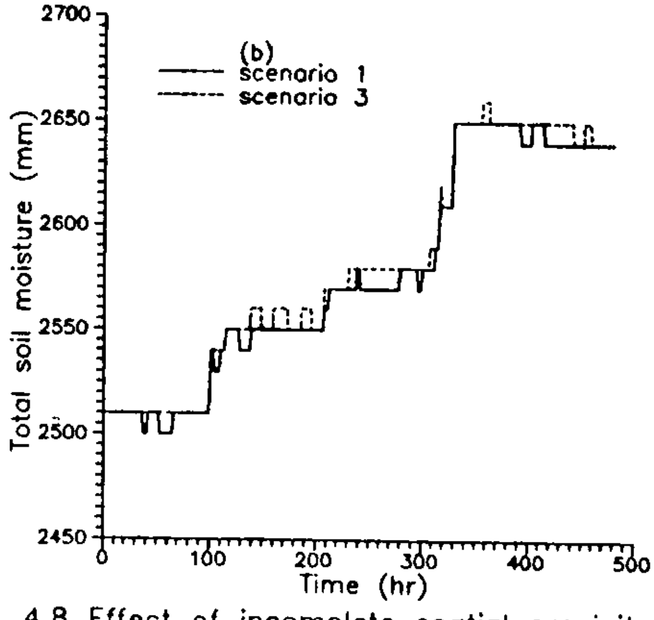


Fig. 4.8 Effect of incomplete spatial precipitation information on (a) surface runoff (b) total soil moisture

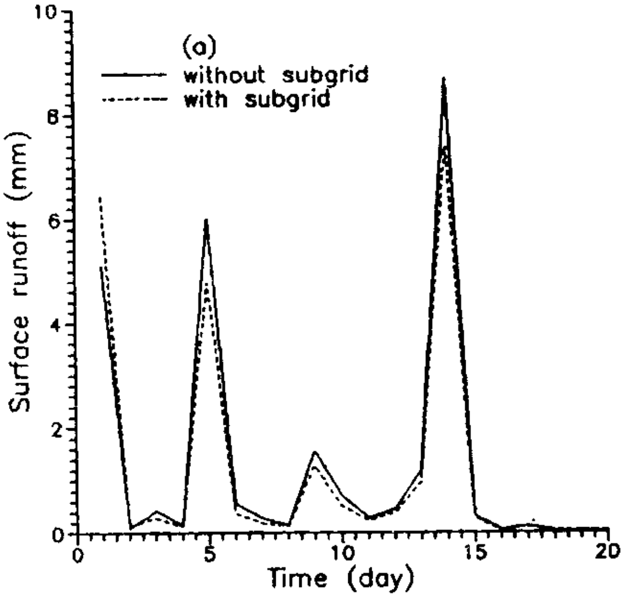
al. (1988) were odds to results of Wilson et al. (1987). They found from their land surface model that the fraction of land covered by vegetation is the most sensitive, and fluxes are the least sensitive to the soil hydraulic conductivity and matrix potential. However, these two studies cannot be compared strictly because their aims are not equivalent.

Wetzel and Chang (1987) examined the effect of natural soil variability on evapotranspiration, and found that soil variability is large enough to seriously alter the relationship between regional estimates based on homogeneous grid-box assumptions and for spatially variable conditions. Avissar and Pielke (1989) carried out regional mesoscale studies using land surface with patch heterogeneity and found that such heterogeneities can affect latent and sensible heat fluxes by upto 100%. In some cases, it may even exceed 100%. Entekhabi and Eagleson (1989) carried out sensitivity analyses using sub-grid variability in soil wetness, modeled with a gamma probability function to investigate sensitivities to soil type and climate forcing on runoff, soil evaporation and transpiration from vegetation.

In this study, sensitivity analyses are carried out using BATS to assess the subgrid scale variability of soil texture (scenario 4) and soil colour (scenario 5) for the Sher sub-basin. We have assumed that vegetation type is fixed and homogeneous within the study area. The vegetation type is a typical characteristic of the Central India. It is deciduous broadleaf type having a fractional vegetation cover of approximately 0.80. The study area can be typically represented by dark soil (7 or 8th class) in colour and sandy soil (1st or 2nd class) in texture. Two runs are performed to assess the subgrid scale variability in soil texture and soil colour.

Fig. 4.9 shows the effect of subgrid scale variability in soil texture on surface runoff and total runoff. Figs. 4.10 and 4.11 show the effect of natural soil variability in terms of inhomogeneous soil texture on moisture and heat fluxes, respectively. The inhomogeneous soil texture is characterized by two patches; first 6 sub-grids of texture class 1 and rest 10 subgrids of texture class 2. The average homogeneous soil texture class is assumed to belong to 2nd. It is evident from these figures that soil moisture fluxes (Fig. 4.10) are overestimated if a heterogeneous land surface is modelled by a homogeneous land surface, whereas it is reverse with energy fluxes (Fig. 4.11).The magnitude of peaks of runoff and total runoff are affected due to heterogeneities, however, times to peaks remain unaltered. It is observed from these figures that hydraulically controlled processes; infiltration-runoff and soil moisture transport mechanisms are highly sensitive to variations in soil texture. There is marginal effect of soil texture variability on the evaporation. Fig. 4.11 reveals that radiation budget, and ground and subsurface temperatures are also affected significantly due to soil texture variability.

Figs. 4.12 and 4.13 show the effect of natural soil variability in terms of inhomogeneous soil colour on moisture and energy fluxes. The inhomogeneity in soil colour is described by assuming two patches of colours in the study area. The first six subgrids are assumed to have dark colour (Class 7), and the rest 10 subgrids are assumed to have very dark colour (class 8). The homogeneous grid-box assumption is based on 7th class for soil colour. There is no effect of soil colour variability on runoff



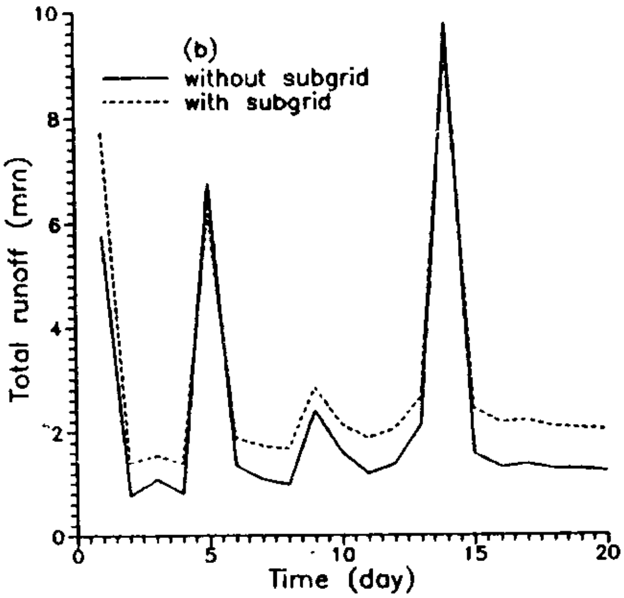


Fig. 4.9 Effect of subgrid scale variability in soil texture on (a) surface runoff (b) total runoff

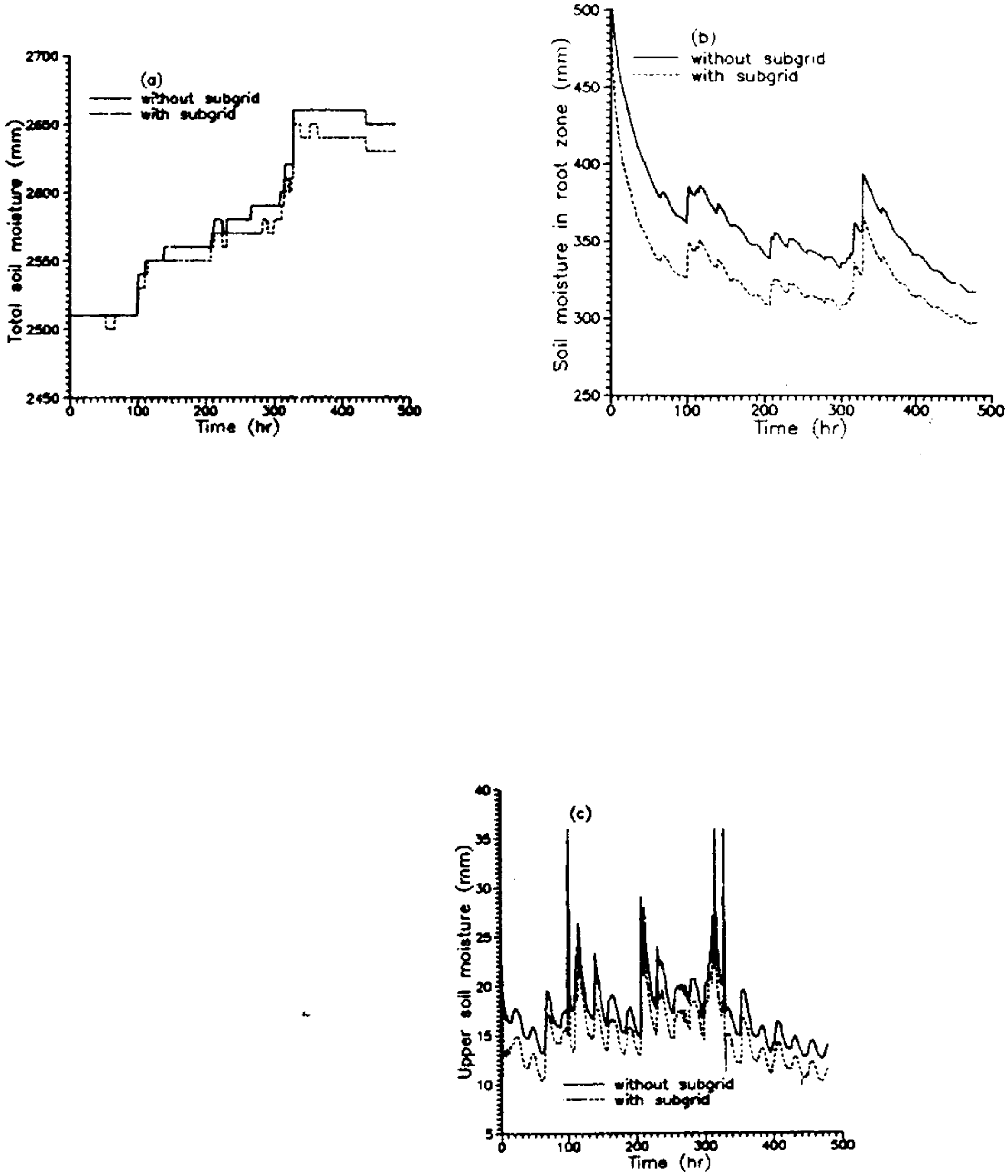


Fig. 4.10 Effect of subgrid scale variability in soil texture on (a) total soil moisture (b) soil moisture in root zone (c) upper soil moisture

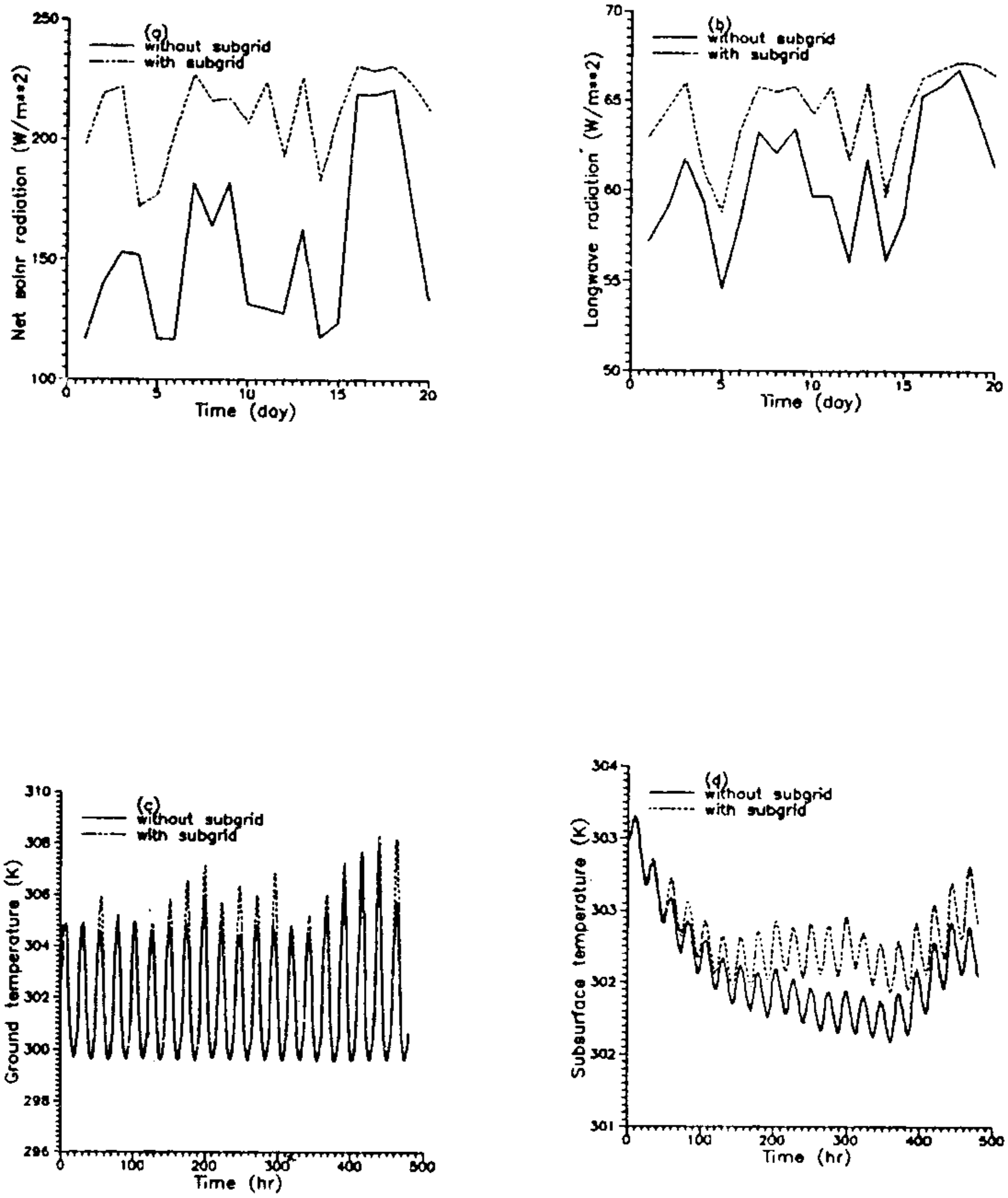
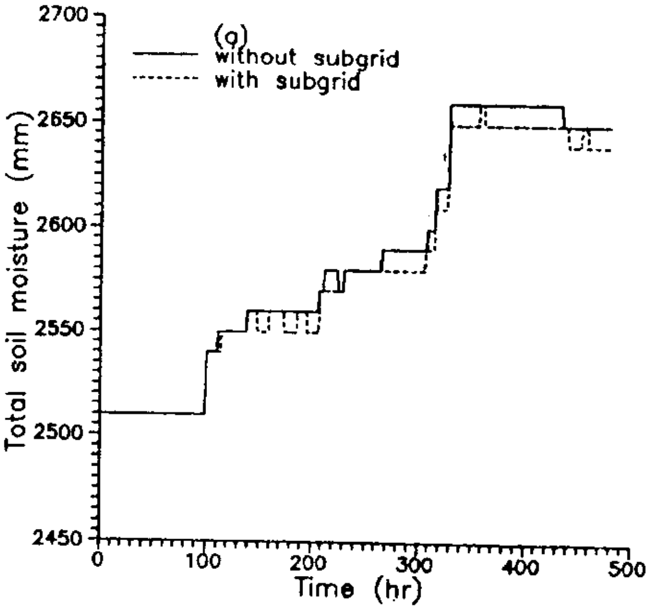


Fig. 4.11 Effect of subgrid scale variability in texture on
(a) net solar radiation (b) longwave radiation
(c) ground temperature (d) subsurface temperature



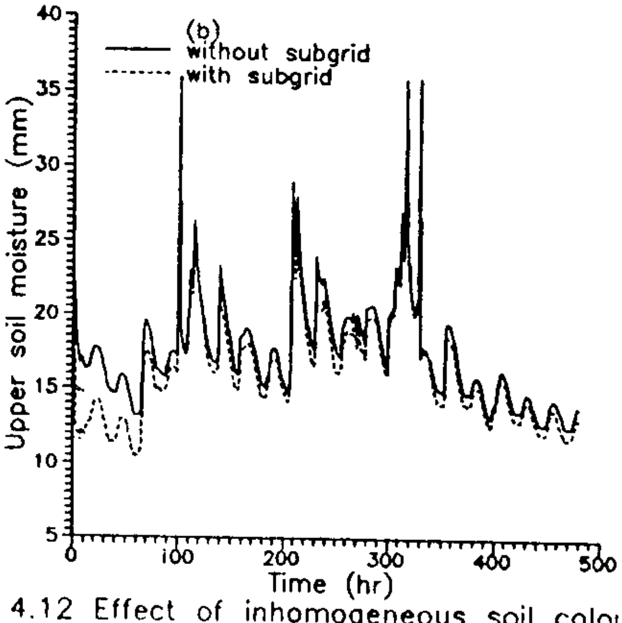


Fig. 4.12 Effect of inhomogeneous soil colour on (a) total soil moisture (b) upper soil moisture

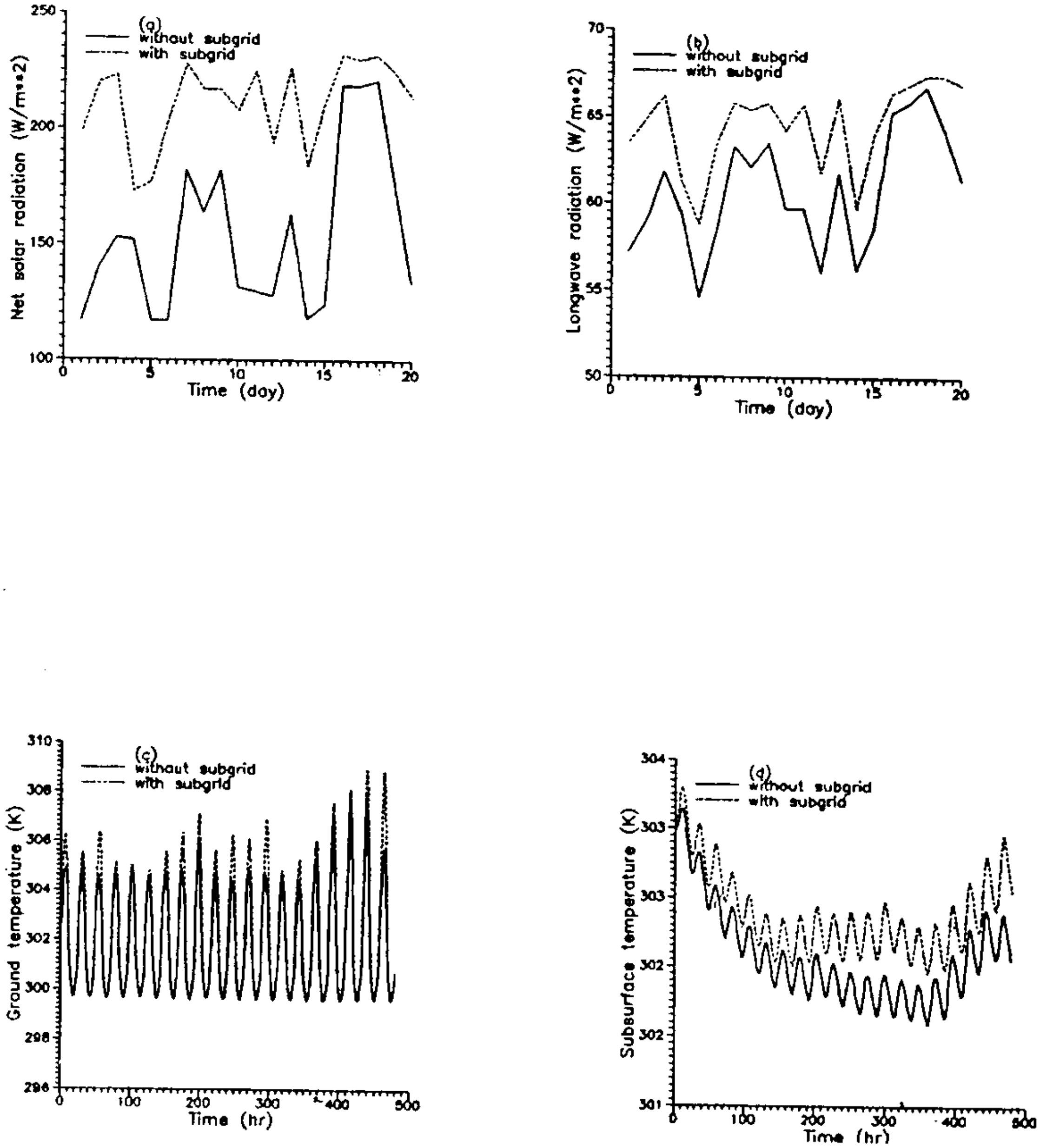


Fig. 4.13 Effect of inhomogeneous soil colour on
(a) net solar radiation (b) longwave radiation
(c) ground temperature (d) subsurface temperature

and soil moisture in root zone, and shows marginal effect on evaporation, because soil colour controls thermal processes, rather than the hydraulic processes. The energy fluxes are highly sensitive to spatial variability in soil colour (Fig. 4.13). Intercomparisons of corresponding figures for heterogeneities in soil texture and soil colour reveal that the infiltration and runoff processes are highly sensitive to soil parameters which control the hydraulic properties of the soil; whereas radiative and conductive fluxes show predominant variations due to any change in specular reflective, diffusive and thermally conductive parameters.

4.5 Effect of Spatial Variability of Soil Temperature

The scenario 6, which is described by the inhomogeneous condition of soil temperature within the study area, is analysed to assess the effect of varying temperature on evaporative, radiative, and conductive fluxes. Other parameters like vegetation, soil colour and soil texture are assumed homogeneous, and precipitation field is fixed. The inhomogeneity in soil temperature is characterized by the upgradient of two units from one subgrid to other subgrid in north to south direction. In horizontal direction, there is no temperature gradient. However, in the southern subgrid layer (last), there is a temperature drop of 3 units for subgrid nos. 13 and 14 and of one unit for subgrid nos. 15 and 16 in comparison to the just previous subgrid layer. The subgrid (first) layer is assumed to be at 301 $^{\circ}$K. The average temperature in a homogeneous grid-box assumption is 303 $^{\circ}$K.

Fig. 4.14 shows the effect of spatial variability of soil temperature on the radiative and conductive fluxes. The variation in soil temperature controls the albedo and thermal conductivity,

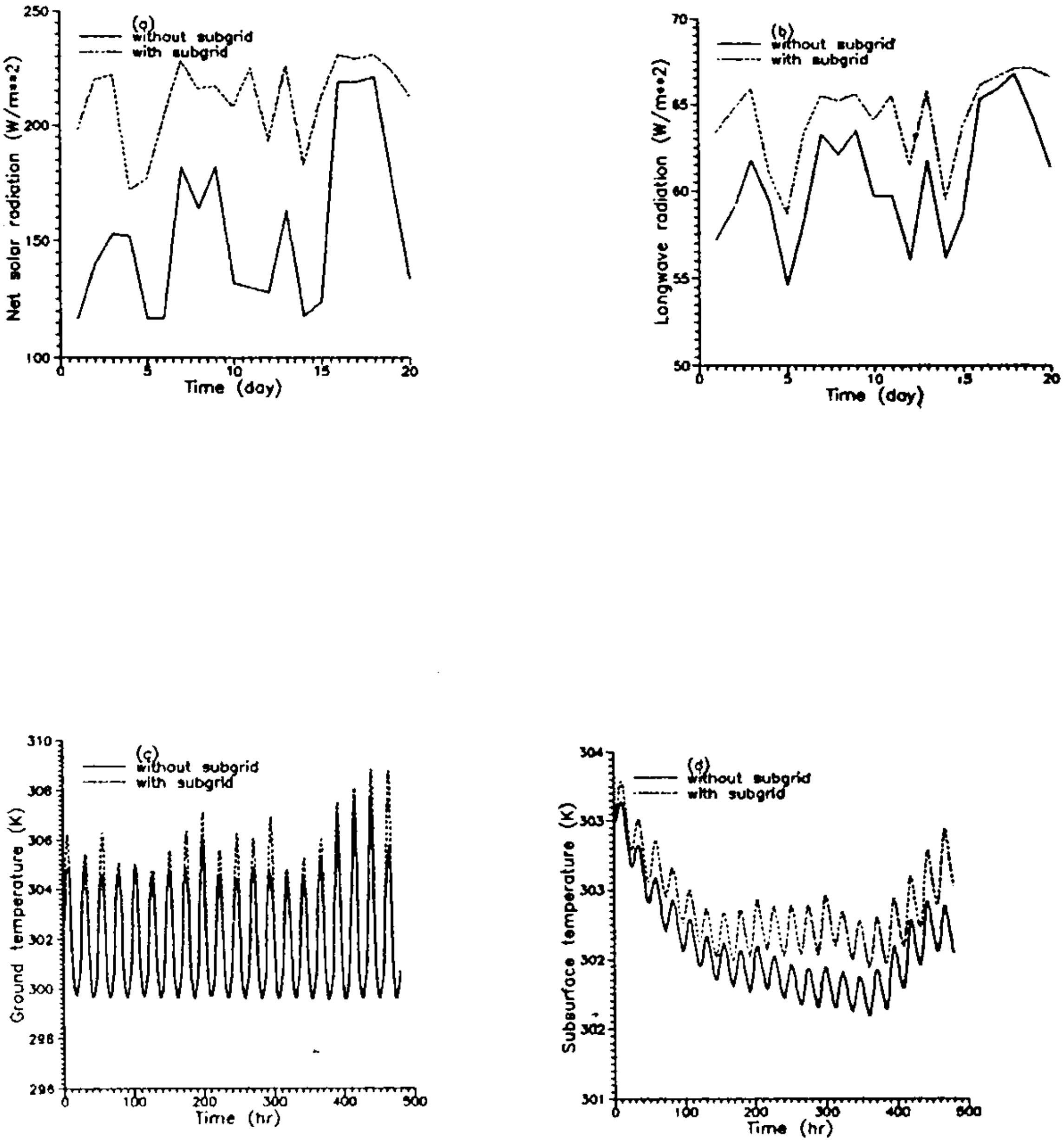


Fig. 4.14 Effect of spatial variability of soil temperature on (a) net solar radiation (b) longwave radiation (c) ground temperature (d) subsurface temperature

thus significantly affects the energy transfer between the land and atmosphere. The marginal effect is also observed on evaporative flux. The energy fluxes obtained by a homogeneous grid-box assumption for a heterogeneous land surface in terms of colour are overestimated.

5. SUMMARY AND CONCLUSIONS

The redistribution of solar energy over the globe is central to studies in climate. Water plays a fundamental role in this redistribution through the energy associated with evapotranspiration, the transport of atmospheric water vapor and precipitation. Land-atmosphere interactions are major components in the description of the GCMs. Parameterizations for GCMs in which the biosphere-atmosphere interactions are fully developed for calculating the transfer of energy, mass and momentum between the atmosphere and the vegetated surface of the earth have been developed by Dickinson et al (1986). It is referred as the Biosphere-Atmosphere Transfer Scheme (BATS). Other parameterizations are also reported in the literature. On the horizontal scale, BATS assumes homogeneous conditions. Since GCMs involve a very large sized grid, typically varying from 250 to 500 km; spatial heterogeneity cannot be ignored in simulating the global change. The BATS was modified by Ramirez (1991a, b) to account the subgrid scale variability. Ramirez (1991a, b) modified the BATS by adding a subroutine RAING_J to allow the simulation of spatially inhomogeneous conditions in precipitation field. He assumed that the precipitation intensity, storm duration and interarrival time between precipitation pulses follow an exponential distribution. The precipitation field is generated using these parameters and assuming that in a given time step, any one subgrid out of sixteen subgrids gets wet, and the choice of the subgrid to get wet is random, while the other 15 subgrids receive zero precipitation in that time step. The average precipitation over the grid is kept constant in both homogeneous and inhomogeneous cases.

To simulate the real-world systems at regional scales using the modified BATS to support the parameterization schemes for the inclusion within GCM, the observed rainfall records must follow an exponential distribution. However, it is observed that in real-life situations, the distribution of rainfall measurements vary from one basin to other basin; and also depends upon the basis of analysis, whether annual, seasonal, monthly or hourly. In such cases, there is need to first explore the type of distribution for the data being used in simulation by an exhaustive analysis or by employing a decision support expert system. In this study, precipitation intensity, interarrival time, and storm duration are obtained from the available data for the study area, and cumulative probability distributions of these parameters are derived. It is observed that data do not fit exactly with the exponential probability distribution. Therefore, in absence of extensive areal information, precipitation field is generated assuming the patchiness of precipitation in the study area. The domain of each patch is established using the Thiessen polygon method, and the spatial precipitation values are generated using the weighting techniques. The fluxes computed using the generated field are very close to the ones obtained by the homogeneous precipitation field, being equal to the arithmetic mean of the observed data at various stations. The fluxes computed from the exponential distribution parameters using the simulation procedure of modified BATS show off to the reality.

An extensive sensitivity analyses are carried out using BATS with the precipitation field generated by the proposed methodology, to assess the subgrid scale variability of precipitation, soil texture, soil colour and soil temperature. Impact of inadequate representation of areal variability and deviations in average precipitation over the grid on the hydrologic and climatic fluxes; runoff, evaporation, radiation, soil moisture, ground and subsurface temperatures. The specific conclusions observed in the study are enumerated below:

(1) There is no need to consider explicitly the precipitation variability at subgrid scale for the computation of moisture fluxes provided a small degree of spatial variability exists within the grid, and the catchment response is linear with respect to any deviation in precipitation field.

(2) The inadequate representation of areal variability in terms of precipitation may influence appreciably if spatial information differ much, and catchment response is nonlinear with respect to deviation in the precipitation field.

(3) Deviation in average precipitation over the grid causes significant change in the fluxes. The peaks of runoff increase or decrease linearly as the average precipitation increases or decreases, but the times to peaks remain constant.

(4) The detailed spatial information of soil parametes are more important than precipitation information, because hydraulically, and thermally controlled processes; infiltration, runoff, and energy transfer mechanisms are highly sensitive to soil characteristics. The precipitation information can be represented on a basin scale, rather than

at subgrid scale provided variability within the considered grid is of a small degree, and rainfall-runoff relation is not highly nonlinear.

(5) Runoff, evaporation and soil moisture are highly sensitive to soil texture as these processes are guided by the soil hydraulic parameters; whereas the radiative and thermally conductive fluxes are more governed by the soil colour anu soil temperature.

(6) Some more detailed sensitivity experiments are needed to examine the effect of vegetation and soil variability in vulnerable conditions.

(7) Use of remote sensing data and/or a decision support system to quantify the areal variability may improve the findings.

(8) Rainfall-runoff parameterization scheme appears to be inadequate for most real life-situations, because these are governed by nonlinear mechanisms. However, an extensive numerical experiments are needed to assess the adequacy of the parameterization schemes for different processes.

It should be noted here that absolute numerical values of fluxes reported in this study are not important for the sensitiveness of the Sher sub-basin, because many soil parameters are assumed hypothetically in absence of complete data sets as per BATS requirement. The conclusions drawn in this study mainly reflect the sensitivity of the model to various parameters, effect of subgrid scale variability of forcing variables on fluxes, and adequacy of the description of different hydrologic processes in the model for the real-life situations. The other important aspect is that the results reported here are based on the off line study. To assess the importance of subgrid scale variability for global climate change predictions and its implications, there is need to perform the sensitivity experiments coupled with either three dimensional GCM or one dimensional climate model.

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APPENDIX I

Vegetation/Land cover assignment

1. Crop/mixed farming
2. Short grass
3. Evergreen needle leaf tree
4. Deciduous needle leaf tree
5. Deciduous broad leaf tree
6. Evergreen broad leaf tree
7. Tall grass
8. Desert
9. Tundra
10. Irrigated crop
11. Semi-desert
12. Ice cap/glacier
13. Bog or marsh
14. Inland water
15. Ocean
16. Evergreen shrub
17. Deciduous shrub
18. Mixed woodland

Vegetation/Land cover parameters

Parameter	Land Cover/Vegetation Type 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
a) Maximum fractional vegetation cover	0.85	0.80	0.80	0.50	0.80	0.90	0.80	0.0	0.60	0.80	0.10	0.0	0.90	0.0	0.0	0.80	0.80	0.80
b) Difference between maximum fractional vegetation cover and cover at temperature of 269 K	0.6	0.1	0.1	0.3	0.3	0.5	0.3	0.0	0.2	0.6	0.1	0.0	0.4	0.0	0.0	0.2	0.3	0.2
c) Roughness length (m)	0.06	0.02	1.0	1.0	0.8	2.0	0.1	0.05	0.04	0.06	0.1	0.01	0.03	0.0024	0.0024	0.1	0.1	0.8
d) Depth of the total soil layer (m)**	1.0	1.0	1.5	1.5	2.0	1.5	1.0	1.0	0.5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	2.0
e) Depth of the upper soil layer (m)**	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
f) Rooting ratio (upper to total soil layers)	3	8	10	10	10	12	8	9	4	3	8	5	5	5	5	5	5	10
g) Vegetation albedo for wavelengths <0.7μm	0.10	0.10	0.05	0.05	0.08	0.04	0.08	0.20	0.09	0.08	0.17	0.80	0.06	0.07	0.07	0.05	0.08	0.06
h) Vegetation albedo for wavelengths >0.7μm	0.30	0.30	0.23	0.23	0.28	0.20	0.30	0.40	0.26	0.28	0.34	0.60	0.18	0.20	0.20	0.23	0.28	0.2[illegible]
i) Minimum stomatal resistance (s m^{-1})	150	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250	250
j) Maximum LAI	6	2	6	6	6	6	6	0	6	6	6	0	6	0	0	6	6	6
k) Minimum LAI	0.5	0.5	5.0	1.0	1.0	5.0	0.5	0.0	0.5	0.5	0.5	0.0	0.5	0.0	0.0	5.0	1.0	3.0
l) Stem (& dead matter) area index	0.5	4.0	2.0	2.0	2.0	2.0	2.0	0.5	0.5	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
m) Inverse square root of leaf dimension ($m^{-1/2}$)	10	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
n) Light sensitivity factor (m^2 W^{-1})	0.01	0.01	0.03	0.03	0.03	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.03

**Soil depths in code are in mm as are all water storages to make the conversion factor 1.0 between water amounts and SI energy fluxes.

Soil parameters

I/FUNCTIONS OF TEXTURE

Parameter	Texture Class (from sand (1) to clay (12))											
	1	2	3	4	5	6	7	8	9	10	11	12
a) Porosity (volume of voids to volume of soil)	0.33	0.36	0.39	0.42	0.45	0.48	0.51	0.54	0.57	0.60	0.63	0.66
b) Maximum soil suction (m)	0.03	0.03	0.03	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
c) Saturated hydraulic conductivity (mm s^{-1})	0.2	0.08	0.032	0.013	8.9×10^{-3}	6.3×10^{-3}	4.5×10^{-3}	3.2×10^{-3}	2.2×10^{-3}	1.6×10^{-3}	1.1×10^{-3}	0.8×10^{-3}
d) Ratio of saturated thermal conductivity to that of loam	1.7	1.5	1.3	1.2	1.1	1.0	0.95	0.90	0.85	0.80	0.75	0.70
e) Exponent "B" defined in Clapp & Hornberger (1978)	3.5	4.0	4.5	5.0	5 5	6.0	6.8	7.6	8.4	9.2	10.0	10.8
f) Moisture content relative to saturation at which transpiration ceases	0.095	0.128	0.161	0.266	0.300	0.332	0.378	0.419	0.455	0.487	0.516	0.542

II/FUNCTIONS OF COLOR

Parameter	Color (from light (1) to dark (8))							
	1	2	3	4	5	6	7	8
a) Dry soil albedo								
< 0.7 µm	0.23	0.22	0.20	0.18	0.16	0.14	0.12	0.10
≥ 0.7 µm	0.46	0.44	0.40	0.36	0.32	0.28	0.24	0.20
b) Saturated soil albedo								
< 0.7 µm	0.12	0.11	0.10	0.09	0.08	0.07	0.06	0.05
≥ 0.7 µm	0.24	0.22	0.20	0.18	0.16	0.14	0.12	0.10

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