Predicting the spatio-temporal variation of run-off generation in India using remotely sensed input and Soil Conservation Service curve number model

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The Soil Conservation Service curve number (SCS CN) model has been used in the GIS environment to compute run-off at spatio-temporal scales using remote sensing-derived rainfall for 2004 and climatic normal (1951–80) rainfall data. The SCS CN model takes into account land use/land cover, antecedent soil moisture condition and hydrological soil groups. Temporal 10-day composite Normalized Difference Vegetation Index images of SPOT–VGT sensor, and daily remote sensing-derived rainfall data at 10 km resolution from the NOAA Climate Prediction Centre have been used to generate the land cover and antecedent moisture condition (degree of saturation) respectively. Hydrological soil groups were prepared using the soil texture and their infiltration and drainage characteristics. Run-off coefficient maps were generated using the CN-based rainfall excess run-off. Wetland rice-growing areas of West Bengal, India were used to calculate threshold run-off coefficient (0.2) to identify run-off potential areas for major river basins of India during the monsoon season (June to September). There was a large difference in the spatial pattern of run-off estimated for the year 2004 compared to using normal climatic rainfall data. Area estimates for run-off potential were also found to vary significantly for the climatic normal and in-season (2004) data. The spatial variability showed high run-off potential in the western India river basins like Mahi, Luni, rivers of Saurashtra and Sabarmati in 2004. Run-off potential areas over India have been found to increase abruptly from June (158,700 km^2) to July (712,300 km^2), and decrease from August (633,400 km^2) to September (142,000 km^2) during 2004.

Keywords: Curve number, remote sensing, river basin, run-off.

INFORMATION about the spatial distribution and temporal variation of run-off potential areas at a regional scale is essential to understand its influence on conservation and development of land and water resources. Conventional techniques (installing stage recorder, current meters, etc.) of point run-off measurement are accurate and useful. However, in most cases such measurements are expensive, time-consuming and difficult. Therefore, rainfall–run-off models (empirical and physically based) are commonly used for computing run-off. There are distributed hydrological models which describe the physical rainfall–run-off processes controlling the transformation of rainfall to run-off[1–3]. The advantage of these models is the accuracy of their predictions. But a major disadvantage is that they require extensive database, time and expertise to be used effectively. A good run-off model includes spatially variable parameters such as rainfall, soil, land use/land cover, etc.[4,5]. Therefore, in this study the Soil Conservation Service curve number (SCS CN) method[6] was used, which is a versatile and popular approach for quick run-off estimation, is relatively easy to use with minimum data and gives adequate results[7–11]. It is used extensively in various hydrologic, erosion and water quality models, including CREAMS[12], EPIC[13], AGNPS[14] and SWAT[15]. Generally, this model is well suited for small watersheds of less than 250 km^2, as it requires details of soil physical properties, land use and vegetation condition[16,17]. Therefore, so far it has been used mostly as lumped (taking the average value of the study area) model at watershed scale[18–23]. However, advances in computational power and the growing availability of spatial data from remote sensing techniques have made it possible to use hydrological models like SCS CN in spatial domain with Geographic Information System (GIS)[24,25]. The SCS CN model has been used extensively on various watersheds of varied sizes. The model has been found to perform well without much calibration.

In the Indian subcontinent, run-off is generated mostly during the monsoon season (June to September) during a year. In this aritcle, the SCS CN model has been used to estimate run-off for major river basins of India at 10 km cell size during the monsoon period of 2004. Run-off coefficient (RC) maps were also prepared considering the wetland rice areas of West Bengal as a mask on the estimated run-off to identify the run-off potential areas.

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Study of the run-off potential areas has also been done using monthly climatic normal rainfall (1951–80) data (weather station measurements) and deviation in the run-off potential area pattern in a particular year (2004) from the normal climatic has been observed.

Study area

Major river basins of India were taken as the study area for run-off potential area estimation. There are 17 major drainage basins (Figure 1). Three of these basins, i.e. Indus, Ganga and Brahmaputra are snow-fed in summer and the remaining basins are purely monsoon rainfall-dependent[26,27]. The Ganga and Brahmaputra–Barak (BH–BRK) basins cover 34% of the area of the country and form the largest drainage area. The basin of the Indus river flows in a southwesterly direction to Pakistan, covering 10% area. Basins of the Godavari, Krishna and Mahanadi rivers draining to the sea in the east cover 22% of the total drainage area. Seven other medium-sized basins of the Sabarmati, Mahi, Narmada and Tapi rivers flowing west and the Subarnarekha, Brahmani–Baitarani and Cauvery rivers flowing east togeather cover 15% of the total drainage area of India. Dependable rainfall (75% of total annual rainfall) is high (1657 mm) for West South Coast Rivers (WSCR), while it is low (296 mm) for the Indus river[28].

Data used

Rainfall

Rainfall data (monsoon period: June to September) from two different sources were used in this study. Satellite-derived daily rainfall data of 10 km resolution have been downloaded from the NOAA Climate Prediction Centre (CPC) website (ftp.cpc.ncep.noaa.gov/fews/S.Asia) for the year 2004. CPC rainfall product gives semi real-time analysis of daily precipitation on a 0.1° lat./long. grid over South Asia (70°–110°E; 5°–35°N). Raw rainfall data (HDF format) were stored and prepared using the image processing (EASI PACE) and GIS (Arc-Info) software. Climatic normal point rainfall data (1951–80) available at a monthly scale, from 376 weather stations throughout India were collected from India Meteorological Department[29]. The climatic rainfall data were interpolated using inverse square distance interpolation technique with cell size of 10 km to obtain the spatial rainfall distribution pattern.

Land use/land cover

In general, Normalized Difference Vegetation Index (NDVI), which is based on differential absorption, transmittance and reflectance of energy by the vegetation in the red (0.61–0.68 μm) and near infra-red (0.78–0.89 μm) regions, is widely accepted and used in many research studies. It is sensitive to the phenology of vegetation[30–33] and is least affected by topographic factors. The discriminant power of multi-temporal NDVI observations is based on their characterization of dynamics of vegetation growth. Therefore, land use/land cover map has been prepared using the multidate (15 dates, May to September 2004) SPOT-VEGETATION 10-day composite NDVI data. The SPOT data are available in HDF format, which was later imported to PCIDISK format to analyse using the EASI/PACE software. NDVI profiles for different land covers were prepared. The training sites for these classes were spotted with the help of land use and crop regions map of Survey of India[34] and land use map prepared by Agrawal *et al.*[32]. A hierarchical logical model (Figure 2) for land-cover classification[35,36] was prepared by studying the pattern of NDVI profiles. In the beginning, non-vegetation classes were classified, viz. wasteland, fallow, urban and water bodies. The second step was to discriminate forest areas and lastly crop areas were classified. In each stage classified areas of the previous stage were masked out while classifying the next land-cover class. Land use/land cover classification was done keeping in mind the hydrological requirement of the crop and land-cover classes. In the case of hydrological vegetation class, vigour is more important than the type of vegetation/crop. The rating of good, poor and fair crop was done based on a combination of factors that affect interception, infiltration and canopy of vegetative areas. Misclassification among land-cover classes found to be

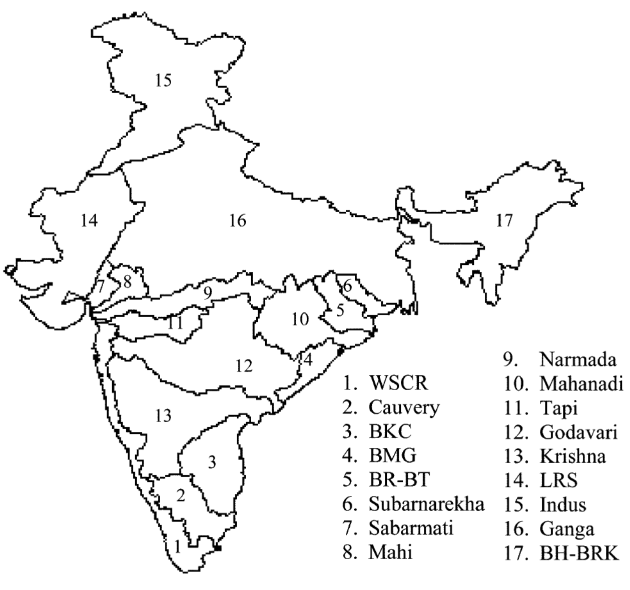

Figure 1. Major river basins of India (study area). WSCR, West south coast rivers; BKC, Between Krishna and Cauvery; BMG, Between Mahanadi and Godavari; BR–BT, Brahmini Baitrani; LRS, Luni river of Saurastra; BH–BRK, Brahmaputra, Barak and others.

between related hydrological land-cover classes (good, fair or poor), thereby not affecting the curve number for run-off calculations.

Soil

Soil texture map for 1 : 6 million scale was taken from Survey of India[37]. This map was first scanned and then digitized in Arc Info. There are fourteen soil textures over India. Soil texture map was used to prepare Hydrological Soil Groups (HSGs) map.

Run-off potential area estimation

SCS CN model

The SCS CN model developed by the United States Department of Agriculture (USDA) computes direct run-off through an empirical equation that requires rainfall, HSG and land use/land cover. CN is a computed variable, which is based on the antecedent moisture condition (AMC), land use/land cover class and HSG. CN represents the run-off potential of the hydrological soil cover complex (HSCC). This model involves relationship between land use/land cover, HSG and antecedent soil moisture to assign CNs. The following required layers were prepared for CN calculation.

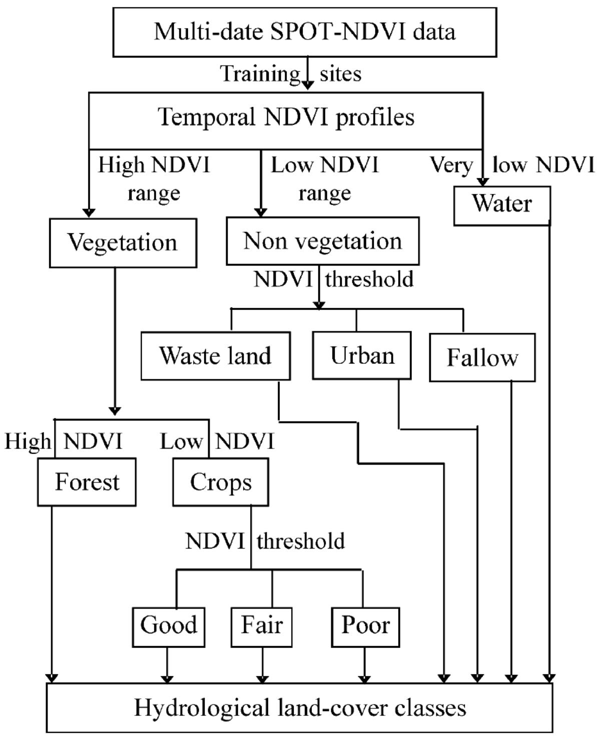

Figure 2. Methodology for hierarchical logical model for hydrological land-cover classification.

HSG: Soil textures obtained from the Survey of India maps were used to prepare the HSG map considering the soil infiltration and drainage characteristics of different soil textures[6]. Sandy and loamy sand were designated as HSG-A, sandy loam and loam as HSG-B, clay loam as HSG-C and clay as HSG-D. Area under different hydrological soil groups (A–D; high to low infiltration) was calculated and validated with the reported area[38]. In the present study, area under different soil groups was 8.3, 51.5, 17 and 23.2% (calculated considering total 319 mha area, which is exclusive of extreme northern and western areas beyond 35°N and before 70°E respectively) for the A, B, C and D groups of soil respectively. While the reported areas were 11.1, 53.7, 16.8 and 18.4% (calculated considering total 328 mha area) for the A, B, C and D types of soils respectively.

AMC: This was determined using cumulative last five days daily rainfall. The AMC was used as an index of wetness in a particular area. Three levels were:

AMC-I: Lowest run-off potential. The soils are dry enough for satisfactory cultivation (AMC rainfall <35 mm).
AMC-II: Average condition (AMC rainfall between 35 and 52.5 mm).
AMC-III: Highest run-off potential. The soils are wet from antecedent rains (AMC rainfall >52.5 mm).

Normal climatic rainfall data were available at a monthly scale. Therefore, antecedent rainfall ranges to identify AMC conditions were upscaled from cumulative last five days to the month period[39].

HSCC: Land use/land cover and HSG maps were combined in the GIS environment to prepare combinations of land-cover type and HSGs. The combined map had 32 combinations (for four HSG classes and eight land use/land cover classes). These combinations are termed HSCC and used to assign the CN along with antecedent moisture condition. Tabulated CN values were used for these 32 combinations of HSCC for AMC-II[40].

Since a standard table for CN values (ranging from 1 to 100), considering land use/land cover and HSG are given for AMC-II, the following conversion formulas were used to convert CN from AMC-II (average condition) to the AMC-I (dry condition) and AMC-III (wet condition).

For dry condition (AMC-I):

$$\mathrm{CN\ (AMC\text{-}I)} = \frac{4.2\mathrm{CN\ (AMC\text{-}II)}}{10 - 0.058\mathrm{CN\ (AMC\text{-}II)}}. \tag{1}$$

For wet condition (AMC-III):

$$\mathrm{CN\ (AMC\text{-}III)} = \frac{23\mathrm{CN\ (AMC\text{-}II)}}{10 + 0.13\mathrm{CN\ (AMC\text{-}II)}}. \tag{2}$$

Potential maximum retention: The potential maximum retention for a given HSCC is related to the CN and expressed as follows:

$$S = \left(\frac{25400}{\mathrm{CN}} - 254\right), \tag{3}$$

where S is the potential maximum retention (mm), and CN is dimensionless.

Initial abstractions: Losses due to infiltration, detention storage and interception were considered as initial abstractions[38]. Vandersypen *et al.*[40], developed the following relationship between initial abstractions and potential maximum retention for Indian conditions, for the black soil region with AMC-I and for all other regions:

$$I_a = 0.3\,S, \tag{4}$$

where I_a is the initial abstraction which includes interception, surface depression storage, and infiltration into the soil.

For black soil region (AMC-II and AMC-III):

$$I_a = 0.1\,S. \tag{5}$$

Run-off coefficient: The equation of run-off can be derived from the water balance equation under the critical assumption that the ratio of the predicted run-off to the potential run-off (rainfall-less initial abstraction) is equal to the ratio of the actual retention to the potential retention[41]:

$$Q = \frac{(P - I_a)^2}{(P - I_a + S)}, \tag{6}$$

$$\mathrm{RC} = \frac{Q}{P}, \tag{7}$$

where Q is the run-off depth (mm), P the rainfall depth (mm) and RC the run-off coefficient (fraction).

Threshold run-off coefficient

Rice is grown under wetland conditions where fields are bunded and water is retained at a certain depth during the crop growth period. Depending upon the landform, the standing water depth in rice fields varies from 10 cm (shallow) to more than 50 cm (deep). Thus, traditional rice fields, which are rainfed and having inherent soil properties, act as a suitable site for calculating threshold run-off coefficient to identify run-off potential areas. Rice area map of West Bengal was generated using multidate Radarsat SAR data. Rice-area mapping was based on the contrast dielectric constant of water (80) and dry soil (4). Distinct signature of rice crop in temporal microwave SAR data was observed due to the initial water background in the field which helps to discriminate it from other land-use classes. The methodology is elsewhere[42]. Daily RC maps were aggregated to prepare the seasonal (June to September) RC map for 2004. The rice mask of West Bengal was overlaid on the seasonal RC maps (for 2004 and normal climatic) in Arc-Info. The zonal statistics function, which calculates mean value for the area under mask, was used to calculate mean RC values. These mean values for 2004 and normal climatic period were again averaged to identify the threshold RC. Finally, run-off potential areas were identified using the threshold RC value for the major river basins of India using the logical analysis (RC > threshold value) in the GIS environment. The methodology for the threshold RC calculation is presented in Figure 3.

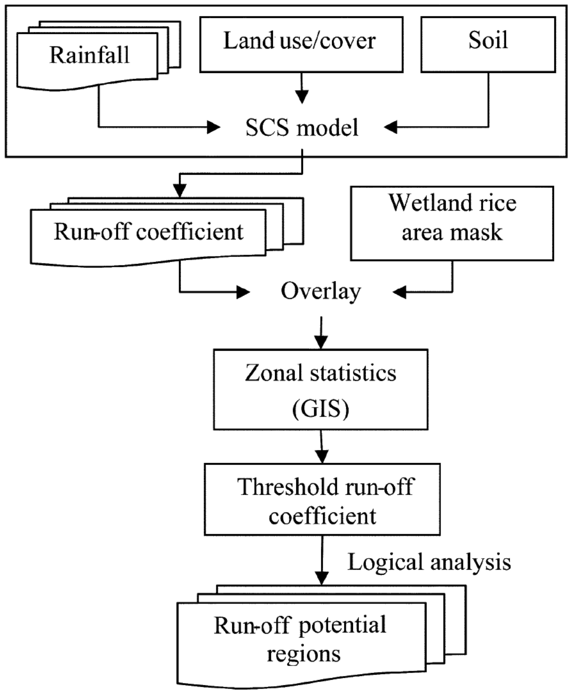

Figure 3. Methodology for identification of run-off potential areas.

Results and discussion

Run-off potential areas identified using the threshold RC for the year 2004 and normal climatic rainfall data have been presented.

Run-off potential areas (normal rainfall data)

The threshold RC value of 0.2 was obtained using the wetland rice area of West Bengal and seasonal run-off coefficient map. Areas having greater than threshold

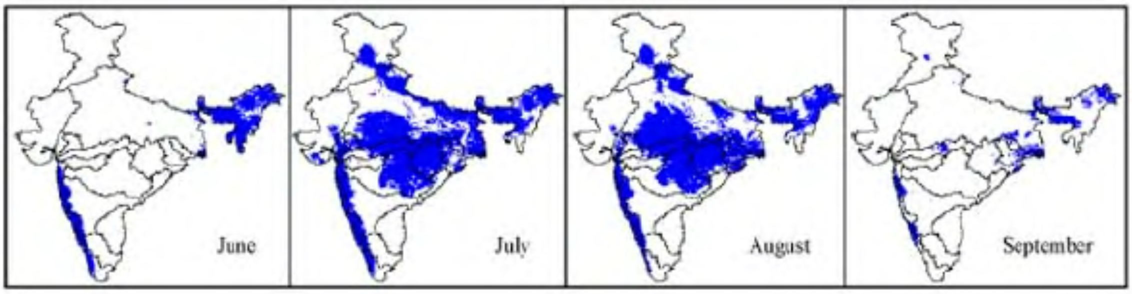

Figure 4. Month-wise run-off potential areas over India using normal climatic rainfall along with basin boundaries.

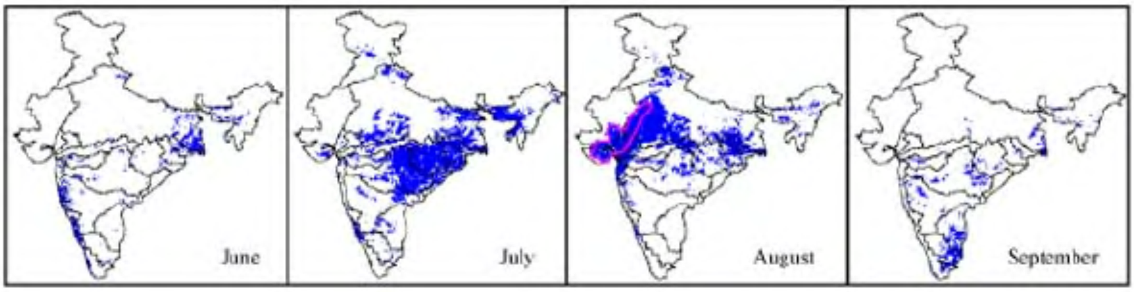

Figure 5. Month-wise run-off potential areas over India using remote sensing-derived rainfall along with basin boundaries for 2004.

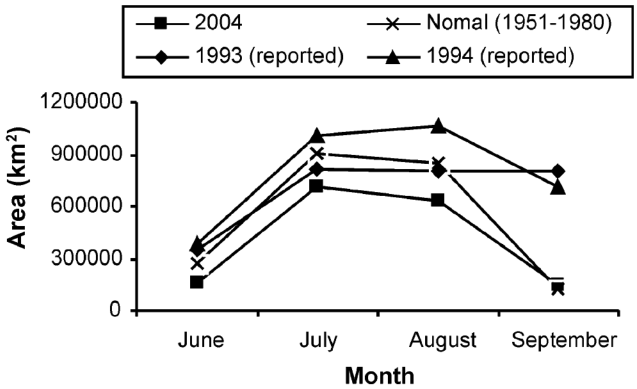

Figure 6. Seasonal variation of monsoonal run-off potential areas estimated during 2004 and normal climatic year along with those reported for 1993–94.

value of RC were identified as the run-off potential areas. Monthly spatial pattern of run-off potential areas in India from June to September months is presented in Figure 4. It was observed that the spatial pattern of run-off potential areas differed largely for each month. Monthly spatial run-off trends were found to match the corresponding rainfall pattern. Analysis showed that the run-off potential areas were of 334,800, 1,274,200, 1,159,500 and 194,500 km^2 during June, July, August and September, respectively, in the Indian mainland. Run-off potential areas occurred mainly during July and August in BH–BRK, Ganga, Mahanadi, WSCR, Subarnarekha, BR–BT and parts of Narmada and Godavari basins. During June run-off potential was observed in the BH–BRK and WSCR basins, while during September it was found in Subarnarekha, part of BH–BRK, WSCR, Ganga and BR–BT basins.

Basin-wise common run-off potential areas (mha) during July and August were also estimated. An area of 1,049,700 km^2 was found to have run-off potential during two months (July and August). The WSCR, BH–BRK, Mahanadi, Godavari, Subarnarekha, Narmada and BR–BT basins were found to have more than 50% of their total area under run-off potential during July and August. Highest run-off potential area was obtained for the Ganga basin (35.7 mha).

Run-off potential areas for 2004

Run-off potential regions were also calculated for the monsoon period of 2004. Month-wise spatial extent of run-off potential over the Indian mainland in 2004 is presented in Figure 5. During July and August run-off potential area was high, 712,300 and 633,400 km^2 respectively, compared to a low run-off potential area of 158,700 and 142,000 km^2 during June and September respectively. High run-off potential regions were mainly observed in BH–BRK, part of Ganga and WSCR basins during June; BH–BRK, part of Ganga, Subarnarekha, BR–BT, Mahanadi and Godavari during July; Ganga, Subarnarekha, BR–BT, Sabarmati, Mahi and Narmada during August and Godavari, BKC, Krishna and Cauvery during September.

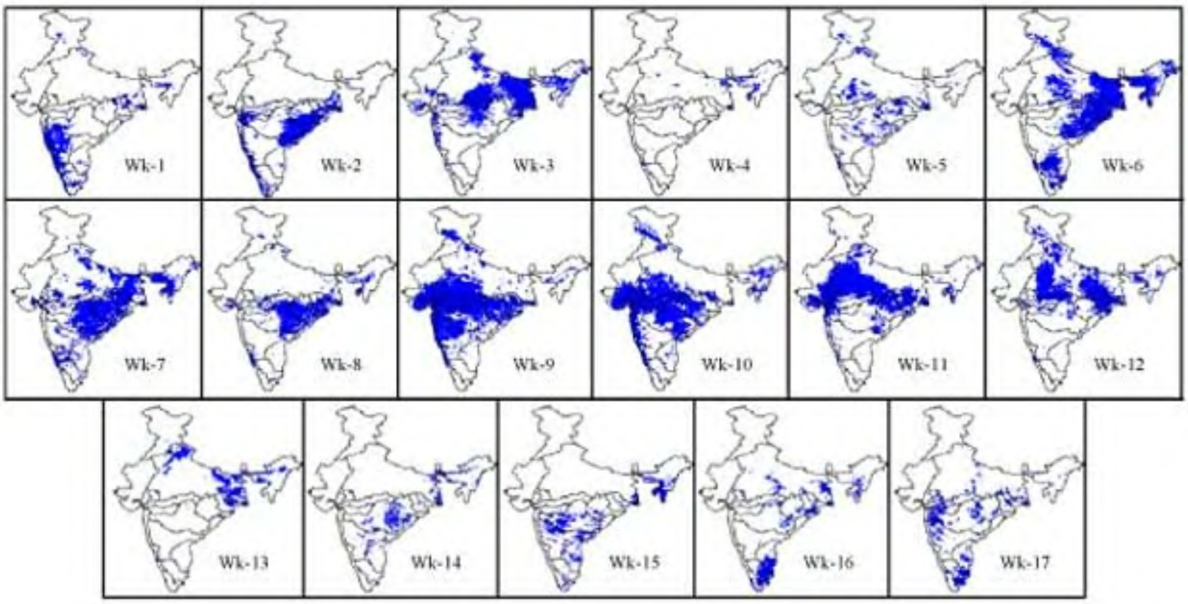

Figure 7. Weekly run-off potential areas over India along with river-basin boundaries (starting from 1 June 2004).

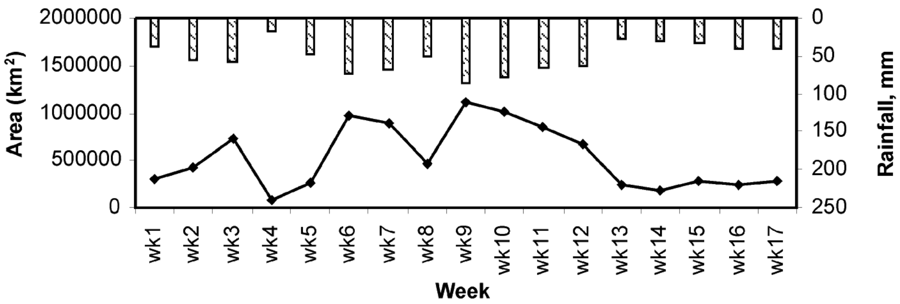

Figure 8. Week-wise run-off potential area variation along with weekly mean total rainfall over India (starting 1 June 2004).

Analysis of run-off potential areas for 2004 showed significant change from the normal climatic results both in the area estimation and spatial pattern, especially in the western regions, BH–BRK and WSCR. In August there was a major shift in the run-off potential region (area marked by the polygon in towards the west and northwest directions. These results show that there was significant variation in both total run-off potential areas as well as their location between normal climatic and the present scenario (2004). Similar seasonal fluctuations have been reported for the inundated areas over India during 1993 and 1994 using multi-temporal remote sensing data[43]. Run-off potential regions estimated for monsoon season of 2004 and normal climatic year were compared with the reported estimates (Figure 6). Reported wetness regions[44] (in % of the basin area) for six major river basins (Ganga, Mahanadi, Godavari, Krishna, Cauvery and Narmada) of India were compared with the estimated run-off potential regions. A good agreement ($r = 0.91$) was found between the estimated and reported wetness regions.

Basin-wise run-off potential areas were estimated for 2004 and normal climatic year, and are presented in Table 1. Comparative analysis showed significant differences in potential areas for most of the basins. Mahi, LRS and Sabarmati basins showed high run-off potential observed in August and a low value in July for 2004 compared to climatic normal period. This matched well with the flood events reported in these basins during 2004. Run-off potential areas were low for the BH–BRK and WSCR basins during the monsoon period of 2004. The low potential run-off estimates were due to hilly area and good vegetation coverage in the above-mentioned basins. Satellite data for the hilly regions (>750 m from msl) underestimated the rainfall due to negligence of orographic effect in the CPC algorithm[45]. Also, good vegetation like forest cover in the basins reduces the CN and eventually run-off.

Further, dynamics of run-off potential regions was carried out at weekly intervals. Weekly spatial behaviour of run-off potential area is presented in Figure 7. Spatial ex-

Table 1. Basin-wise run-off potential areas for different months

Basin	Run-off potential area (mha) with 2004 rainfall				Run-off potential area (mha) with climatic normal rainfall			
	June	July	August	September	June	July	August	September
Ganga	5.26	17.27	29.26	1.60	1.89	44.45	40.54	3.34
LRS	0.00	0.79	5.75	0.00	0.00	2.03	0.68	0.00
Sabarmati	0.00	0.24	2.07	0.00	0.00	1.23	0.93	0.00
Mahi	0.00	0.24	2.80	0.00	0.00	1.86	1.63	0.00
Narmada	0.32	3.07	4.62	0.10	0.06	6.65	6.62	0.83
BR–BT	0.57	4.02	2.68	0.14	0.00	3.07	4.28	0.80
Subarnarekha	0.81	2.06	2.30	0.12	0.03	1.94	2.56	1.39
Mahanadi	0.37	10.45	2.63	0.64	0.00	11.04	10.90	0.57
Godavari	0.79	15.40	3.22	2.45	0.02	16.34	15.65	0.04
Tapi	0.31	1.01	1.84	0.43	0.02	0.76	0.79	0.00
WSCR	3.37	1.42	2.47	0.93	6.74	7.58	5.96	2.38
BMG	0.06	2.53	0.02	0.02	0.00	0.66	0.25	0.00
Krishna	1.87	3.12	0.65	1.34	2.60	5.47	3.59	1.22
BKC	0.14	1.09	0.00	3.02	0.00	0.02	0.00	0.00
Cauvery	0.22	0.74	0.03	2.40	0.56	0.99	0.62	0.03
Indus	0.00	0.89	0.25	0.00	0.00	4.70	4.55	0.32
BH–BRK	1.78	6.89	2.75	1.01	20.53	17.20	15.39	7.90

tent of run-off potential areas varied significantly for each week over India and also among the major river basins. Week-wise run-off potential area and mean total rainfall over India are presented in Figure 8. Highest area of 1,117,600 km^2 under run-off potential has been obtained for the ninth week, while lowest area of 30,100 km^2 was observed for the fourth week (Figure 8).

Conclusion

Spatio-temporal information on run-off potential areas is required for many applications related to sustainable water use, including management of rainfed agriculture, surface water harvesting, etc. The present study provides an integrated approach to model the spatio-temporal pattern of run-off potential areas using the SCS CN model with remote sensing-derived inputs and ancillary data in GIS domain. In this study threshold value of run-off coefficient derived from the wetland rice fields was estimated and used to model the run-off potential areas. Run-off analysis using long-term climatic normal rainfall data showed that the run-off potential area in India was 334,800, 1,274,200, 1,159,500 and 194,500 km^2 during June, July, August and September respectively. Use of daily spatial rainfall data (satellite-derived) for 2004 showed that there was a large difference in the spatial pattern as well as in the area estimate of run-off potential compared to climatic normal run-off potential pattern. The run-off potential area in 2004 was 158,700, 712,300, 633,400 and 142,000 km^2 for June, July, August and September respectively. The study has shown excess run-off potential in some parts of the country and deficit run-off potential in other parts. For example, high run-off potential was observed in the western India river basins of Mahi, LRS and Sabarmati in 2004, which otherwise were low in climatic normal run-off potential pattern. The methodology proposed opens up the feasibility of real-time run-off potential area estimation at spatial scale.

1. Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connel, P. E. and Rasmussen, J., An introduction to the European hydrological system – systeme hydrologique Europeen. 'SHE', 2: Structure of a physically-based, distributed modelling system. *J. Hydrol.*, 1986, **87**, 61–77.
2. Al-Sabbagh, M., Surface runoff modeling using GIS and remote sensing. M Sc thesis, International Institute for Aerospace Survey and Earth Science, Enschede, The Netherlands, 2001.
3. Reggiani, P. and Rientjes, T. H. M., Flux parameterization in the representative elementary watershed approach: Application to a natural basin. *Water Resour. Res.*, 2005, **41**, W04013.
4. Shih, S. F., Integration of remote sensing and GIS for hydrologic studies. In *Geographical Information Systems in Hydrology* (eds Singh, V. P. and Fiorentino, M.), Kluwer, Dordrecht, The Netherlands, 1996.
5. Melesse, A. M. and Shih, S. F., Remote sensing and GIS database for runoff curve number change assessment. *Soil Crop Sci. Soc. Fla. Proc.*, 2000, **59**, 141–146.
6. SCS, *Hydrology National Engineering Handbook, Supplement A*, Soil Conservation Service, USDA, Washington, DC, 1956, 1964, 1971, 1972, 1975, 1985, 1993.
7. USDA, Urban hydrology for small watersheds. Technical Release 55, National Technical Information Service, Springfield, VA, 1986.
8. Schulze, R. E., Schmidt, E. J. and Smithers, J. C., SCS–SA User Manual, PC-based SCS design flood estimates for small catchments in southern Africa. Report No. 40, Department of Agricultural Engineering, University of Natal, Pietermaritzburg, South Africa, 1992.
9. Chatterjee, C., Jha, R., Lohani, A. K., Kumar, R. and Singh, R., Runoff curve number estimation for a basin using remote sensing and GIS. *Asia Pacific Remote Sensing GIS J.*, 2001, **14**, 1–7.
10. Ashish, P., Dabral, P. P., Chowdary, V. M. and Mal, B. C., Estimation of runoff for agricultural watershed using SCS curve num-

ber and Geographical Information System. 2003; http://www.gisdevelopment.net
11. Bhuyan, S. J., Mankin, K. R. and Koelliker, J. K., Watershed scale AMC selection for hydrologic modeling. *Trans. Am. Soc. Agric. Eng.*, 2003, **46**, 237–244.
12. Kinsel, W. G., CREAMS: a field-scale model for chemical, runoff and erosion from agricultural management systems. Conservation Research Report No. 26, South East Area, US Department of Agriculture, Washington, DC, 1980.
13. Sharpley, A. N. and Williams J. R., EPIC – Erosion/Productivity Impact Calculator: 1. Model documentation. US Department of Agriculture Technical Bulletin No. 1768, US Government Printing Office, Washington, DC, 1990.
14. Young, R. A., Onstad, C. A., Bosch, D. D. and Anderson, W. P., AGNPS: a nonpoint-source model for evaluating agricultural watersheds. *J. Soil Water Conserv.*, 1989, **44**, 168–173.
15. Arnold, J. G., Srinivasan, R., Muttiah, R. S. and Wiliams, J. R., Large area hydrological modeling and assessment part I: Model development. *J. Am. Water Resour. Assoc.*, 1998, **34**, 74–89.
16. Ponce, V. M. and Hawkins, R. H., Runoff curve number: has it reached maturity? *J. Hydrol. Eng., ASCE*, 1996, **1**, 11–19.
17. Sharma, T., Satya Kiran, P. V., Singh, T. P., Trivedi, A. V. and Navalgund, R. R., Hydrological response of watershed to landuse changes: Remote sensing and GIS approach. *Int. J. Remote Sensing*, 2001, **22**, 2095–2108.
18. Miloradov, M. and Marjanovic, P., Geographic information system in environmentally sound river basin development. In Third Rhine-Danube Workshop, Delft, The Netherlands, 7–8 October 1991.
19. Demayo, A. and Steel, A., Data handling and presentation. In *Water Quality Assessments, A Guide to the Use of Biota, Sediments and Water in Environmental Monitoring* (ed. Chapman, D.), WHO, UNESCO, UNEP, Chapman and Hall, London, 1996, 2nd edn.
20. Rao, K. V., Bhattacharya, A. K. and Mishra, K., Runoff estimation by curve number method – case studies. *J. Soil Water Conserv.*, 1996, **40**, 1–7.
21. Kumar, P., Tiwari, K. N. and Pal, D. K., Establishing SCS runoff curve number from IRS digital database. *J. Indian Soc. Remote Sensing*, 1997, **19**, 246–251.
22. Pandey, V. K., Panda, S. N. and Sudhakar, S., Curve number estimation watershed using digital image of IRS–1D, LISS III, 2002; www.gisdevelopment.net
23. Nayak, T. R. and Jaiswal, R. K., Rainfall–runoff modelling using satellite data and GIS for Bebas River in Madhya Pradesh. *IE (I) J.*, 2003, **84**, 47–50.
24. Moglen, G. E., Effect of orientation of spatially distributed curve numbers in runoff calculations. *J. Am. Water Resour. Assoc.*, 2000, **36**, 1391–1400.
25. Gumbo, B., Munyamba, N., Sithole, G. and Sevenije, H. H. G., Coupling of digital elevation model and rainfall runoff model in storm drainage network design. In Second WARFSA Water Net Symposium: Integrated Water Resources Management – Theory, Practice, Cases. Capetown, 30–31 October 2001.
26. Rao, A. L., *India's Water Wealth. Its Assessment, Uses and Projections*, Orient Longman Limited, 1975.
27. Nag, P., *National School Atlas*, National Atlas and Thematic Mapping Organization, Department of Science and Technology, New Delhi, 1999.
28. Water and related statistics. Water Planning and Projects Wing, Central Water Commission, New Delhi, 2002.
29. Climatological tables of observation in India 1951–1980, Indian Meteorological Department, New Delhi, 1989.
30. Knyazikhin, Y., Martonchik, J. V., Myneni, R. B., Diner, D. J., and Running, S. W., Synergistic algorithm for estimating vegetation canopy leaf area index and fraction of absorbed photosynthetically active radiation from MODIS and MISR data. *J. Geophys. Res.*, 1998, **103**, 32257–32274.
31. Myneni, R. B., Hall, F. G., Sellers, P. J. and Marshak, A. L., The interpretation of spectral vegetation indexes. *IEEE Trans. Geosci. Remote Sensing*, 1995, **33**, 481–486.
32. Agrawal, S., Joshi, P. K., Shukla, Y. and Roy, P. S., SPOT-VEGETATION multi temporal data for classifying vegetation in south central Asia. *Curr. Sci.*, 2003, **84**, 1440–1448.
33. Shabanov, N. V., Huang, D., Yang, W., Tan, B., Knyazikhin, Y. and Myneni, R. B., Optimization of the MODIS LAI and FPAR algorithm performance over broadleaf forests. *IEEE Trans. Geosci. Remote Sensing*, 2005, **43**, 1855–1865.
34. Land use and crop region map. Survey of India, 1978.
35. Wang, R. Y., An approach to tree-classifier design based on hierarchical clustering. *Int. J. Remote Sensing*, 1986, **7**, 75–88.
36. Zade, M., Panigrahy, S. and Parihar, J. S., Estimation of curve number for major basins of India using remote sensing. *Hydrol. J.*, 2006, **29**, 97–105.
37. Soil texture map, Survey of India, 1978.
38. Dhruvanarayan, V. V., Soil and water conservation research in India. ICAR Krishi Anusandhan Bhavan, New Delhi, 1993.
39. Zade, M. R., Ray, S. S., Dutta, S. and Panigrahy, S., Analysis of runoff pattern for all major basins of India derived using remote sensing data. *Curr. Sci*., 2005, **88**, 1301–1305.
40. Vendersypen, D. R., Bali, J. S. and Yadav, Y. P., *Handbook of Hydrology*, Soil Conservation Division, Ministry of Agriculture, Government of India, 1972.
41. Chow, V. T., Maidment, D. R. and Mays, L. W., *Applied Hydrology*, Series on Water Resources and Environment Engineering, McGraw Hill, 1988, p. 147.
42. Panigrahy, S., Manjunath, K. R. and Ray, S. S., Deriving cropping system performance indices using remote sensing and GIS. *Int. J. Remote Sensing*, 2005, **26**, 2595–2606.
43. Papa, F., Prigent, C., Durand, F. and Rossow, W. B., Wetland dynamics using a suite of satellite observations: A case study of application and evaluation for the Indian Subcontinent. *Geophys. Res. Lett.*, 2006, **33**, 1–4.
44. Chattopadhyay, A. and Dutta, S., Mapping monsoonal wetness regions from multi-temporal VEGETATION dataset. *Int. J. Remote Sensing*, 2006, **27**, 4693–4700.
45. Chaudhari, K. N., Sarkar, C., Patel, N. K. and Parihar, J. S., An inter-comparison of satellite based NOAA CPC rainfall estimates and gauge observations. In ISPRS Symposium on 'Geospatial Databases for Sustainable Development', Goa, 27–30 September 2006.

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