Estimating Spatial Curve Number for Hydrologic Response analysis of a small Watershed

Subashisa Dutta[1], Ashok Mishra[3], S Kar[3] and Sushma Panigrahy[2]

Abstract

An approach to estimate the curve number (CN) at each pixel unit of a satellite imagery, which is a key parameter in the widely used Soil Conservation Service Curve Number (SCS-CN) hydrologic model, is proposed. Instead of mapping land use and its temporal dynamics from satellite imageries, this approach linearly unmixes the multi-spectral radiances into three fractional layers which primarily control the degree of saturation within a watershed occurring due to a 25 cm-depth storm event, i.e., physically interpreted as the CN. The fraction layers used are water, sand and pure vegetation. In order to obtain a relationship between the fractional statistics and CN, a multi-correlationship analysis of known combinations of land use, hydrologic condition and hydrologic soil group is carried out in an agricultural watershed. The obtained relationship is applied onto the fractional layers to compute the spatial distribution of CN. The performance of the SCS-CN model with the spatial CN is found to be 14% more accurate than that of the model results with only land use information from satellite imageries. The spatial difference of two CN layers in which the one represents the condition of the watershed before soil and water conservation measures was taken up and the other for the post conservation period indicates change in the hydrologic response of the watershed spatially.

Key words: Curve Number; Satellite Imagery; Watershed modeling; GIS.

Introduction

Estimation of direct surface runoff in a watershed is necessary for planning, designing, operation and environmental impact analysis of water resources projects. The characteristics of the hydrologic processes governing direct surface runoff vary both in space and time scales. One of the critical components, land use and land cover (LULC) is generally changed by soil and water conservation measures. In order to analyze change in the hydrologic response, the SCS-CN model is the most appropriate hydrologic model (Wurbs and James 2002, Mishra and Singh 2002). This model is defined by a single parameter, namely the curve number that is an integer value varying between 0 and 100. From empirical analyzes of rainfall-runoff data on small watersheds and hillslope areas, the National Resource Conservation Service (NRCS) proposed a table of CN values with four defining parameters: LULC, hydrologic condition, hydrologic soil group and Antecedent Moisture Conditions (AMC) (NRCS, 1985). For a watershed of complex combinations of land use and hydrological soil group, an effective CN of the watershed is computed by linear combination of the CN of all combinations, weighted by their respective area (Beven 1999).

Satellite imageries that offer multi-spectral, temporal and spatial information about the earth features are commonly used to map LULC and its temporal dynamics in water resources studies (Schultz and Engman 2000). Some earlier studies used visual interpretation analysis of single date imagery to obtain the accurate map of land use and land cover (Chatterjee *et*

[1]*Department of Civil Engineering, Indian Institute of Technology, Guwahati, India*
[2]*Agro-ecology Management Division (ARG), Space Applications Centre (ISRO), Ahmedabad 380015, India.* [3]*Agriculture and Food Engineering Department, Indian Institute of Technology, Kharagpur, India*

al. 2001). Sharma *et al.* 2001 digitally analyzed multi-date satellite imageries for improving more accuracy in mapping LULC in a multi-crop cultivated watershed. Use of a Geographic Information System (GIS) helps to spatially integrate all the parameters of the model (Gangodagamage *et al*. 2001). In summary, all the previous studies focused on the mapping of land use and its spatial integration with other parameters in a GIS for improving the performance of the model.

Recent studies on the SCS-CN Model (Svodda 1991, Mishra and Singh 1999, Yu *et al.* 1997, Mishra and Singh 2002, Mishra *et al.* 2003) define that CN is the percent degree of saturation of a watershed resulting by a 25-cm depth storm event. The critical parameters, which control the degree of saturation, are focused in this paper and are mapped from multi-spectral satellite imageries. Linear Mixing Method (LMM) is applied onto the imageries to map the parameters. Many previous studies demonstrated the use of LMM on satellite imageries in different application studies: forest cover (Hlavka and Spanner 1995), crop area (Quarmby *et al.* 1992) and lake area (Hope *et al.* 1999). The objective of this paper is to   compute the spatial distribution of CN across a watershed by spectral unmixing of satellite imagery. The performance of the SCS-CN model with the spatial CN is evaluated and a hydrologic response study for soil and water conservation measures is also addressed.

Study Area and Data used

Banha watershed, in Damodar Valley Command (DVC) area of Jharkhand state, India was considered as the study area. It lies between longitudes 85^0 13′ 50″E to 85^0 16′ 00″E and latitudes 24^0 13′ 30″N to 24^0 17′ 00″ N. The average annual rainfall is 1200 mm of which more than 90% occurs during monsoon months (June to October). Indian Remote Sensing (IRS) Linear Imagining Self Scanner (LISS)-III sensor imageries acquired during October 1996 and December 2000 were used. The sensor has four spectral bands (green, red, Near Infrared (NIR), Short wave Infrared) with average spatial resolution of 23.5 meters in the first three bands (Pandya *et al.* 2000), but 70 meters resolution in the last band. In this watershed, soil and water conservation measures like construction of small check-dams, tree plantation, etc, were taken up from year 1997 onwards. Therefore, the 1996 year image represents the hydrologic condition before the conservation measures whereas the 2000 year image for the post period. Soil and topographic survey maps of 1:10,000 scale from the concerned watershed authority were collected and prepared as a basic hydrologic database in a GIS. Based on topography, the watershed was divided into 9 subwatersheds (Fig.1). The database was made with the projection of Universal Transverse Mercator (UTM). Some of the model parameters like land slope, subwatershed area, watershed area, hydrologic soil group, etc, were obtained by analyzing the topography and soil dataset. In addition to this, ground information about land use, land cover, vegetation condition, topsoil condition, etc were collected in and around the area. The daily observed runoff of the gauged outlet and daily rainfall from a weather station for year 1996 were also collected from the watershed authority. As mentioned earlier, the hydrologic response analysis needs an overlay analysis between two spatial layers. Note that an overlay analysis requires sub-pixel accuracy in geometric between the layers. Therefore, both satellite imageries were geometrically rectified using 22 known and identifiable locations throughout the study area. The root mean square error of all the locations was found to be about 12 m (near to the sub-pixel size).
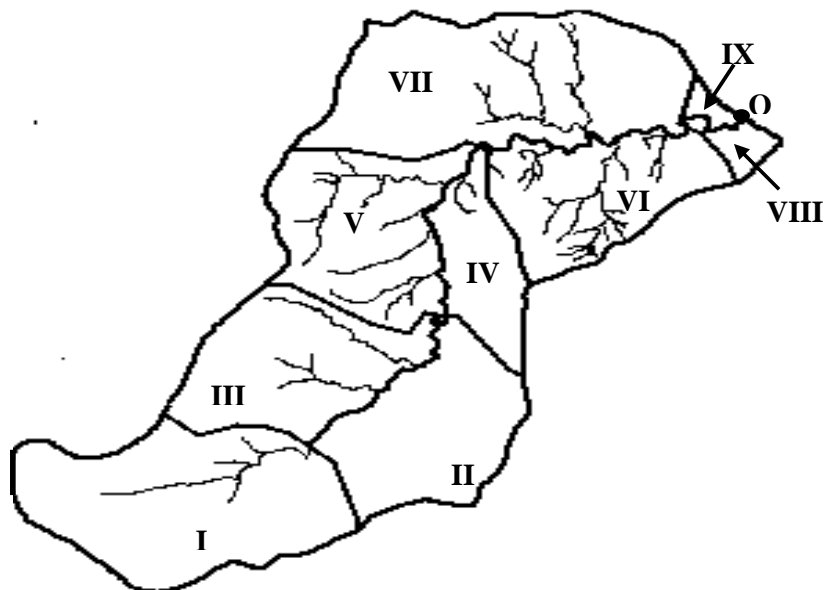
Fig.1 Banha Watershed in India with boundary of 9 subwatersheds, Outlet(O) and Drainages(Scale: 1: 50,000).(Greek numbers represent subwatershed number)

Methodology
The methodology used is divided into two parts: effective CN computation and spatial CN computation.

Traditional Land Use and cover Method (LUM)
In order to cluster land use and land cover classes, maximum likelihood classifier was used with some known training locations in the watershed. Seven LULC classes were dense forest, open forest, wasteland with minor natural vegetation, barren wasteland, rice agriculture, rice agriculture fields after harvesting and water body. The same training locations were used in clustering both images so that uniform classes can be obtained. After getting LULC classes and their spatial extent, the soil database was clustered into a number of hydrologic soil groups. In a GIS system, an overlay analysis between the two polygon layers was performed. The appropriate CN of each polygon was assigned and aggregated to each subwatershed.

Linear Mixing Model (LMM) Method
Rationale of the present approach
As mentioned earlier, the objective of the present approach is to compute the controlling parameters of the degree of saturation within the watershed from satellite imagery. The degree of saturation is primarily controlled by degree of vegetation, sand fraction in the topsoil and moisture-holding capacity of the topsoil. Physically, increasing degree of vegetation reflects higher degree of saturation, *i.e.,* decreasing CN.

The controlling parameters can easily be located in a satellite image as dense forest, sandy area and water body. Using the LMM, multi-spectral satellite imagery can be unmixed into three fractional layers of the parameters. The fast convergence of the LMM with least residual error needs a condition that the chosen classes should be located in the three extreme

vertices of red and NIR scatter plot (Schowengendt 1993). Interestingly, this condition is satisfied for the chosen classes. A multi-correlationship analysis between the fractional statistics and CN of known combinations of land use, hydrologic condition and soil hydrologic group is to be carried out to define the relationship which is further implemented onto the prepared image database to obtain the spatial distribution of CN at each pixel of the satellite imagery.

Basic concept of LMM

Linear Mixing Model is based on principle that observed radiance in a satellite observation unit (pixel) can be modeled as the sum of the radiometric interactions of individual pure signature classes (called the endmember) weighted by their relative fraction (Graetz 1990, Schowengendt 1993). The model is described mathematically as a linear vector-matrix equation in which K and L are number of chosen spectral bands and endmember, respectively. It can be given as follows

$$DN_{ij} = Ef_{ij} + \varepsilon_{ij} \qquad (1)$$

Where E is the K x L endmember signature matrix, DN_{ij} is the K-dimensional spectral vector at pixel *ij*, and f_{ij} is the L x 1 vector of endmember fractions. The added term ε_{ij} represents the residual error in the fitting of a given pixel's spectral vector by the sum of L endmember spectra and unknown noise. The constraints used are:

$$0 \le f_{ij} \le 1 \qquad \sum_{j=1}^{L} f_{ij} = 1 \qquad (2)$$

This constraint produces two restrictions: i) endmember fractions must be range in between 0 and 1, ii) and sum of the fractions should equal to 1. The constraint keeps the physical realistic of the endmember fractions.

Computation of spatial CN

As discussed in the rationale section, water, dense forest and sand were considered as endmembers for LMM approach. The pure sites representing the endmembers were located in and around the study area. Although, no ground information is required for the identification of the sites since these are spectrally distinct classes. To compute fractional layers (f_{ij}), three selected spectral bands (B2: 0.52-0.59μm, B3: 0.62-0.68 μm and B4: 0.77-0.86 μm in IRS LISS-III sensor) were used in Eqs(1-2) with computed E matrix from the statistics of chosen endmembers. The fractional layers were rescaled into a range of 0 to 100 by multiplying with 100. Within each hydrological soil class, known locations of different combination of LULC and hydrologic condition were identified over the image to generate their fractional statistics. A multiple correlationship analysis between the average of fractional layers and CN value of the combinations at AMC-I were carried out. Since there was no rainfall in the last 5 days from the image acquisition, both satellite imageries belong to the watershed at AMC-I state. It was found in the correlation analysis that inclusion of water class (the highest CN value (100)) with other combinations decreased the coefficient of determination of the relationship. It was therefore decided to exclude water bodies in the correlationship analysis. So, water bodies were easily obtained by scaled fraction layer of water (the fraction > 75) and assigned separately to its CN. A statistically significant correlation was obtained and applied over the whole fractional layers to get spatial CN. The results obtained by this method are referred as LMM in further sections.

SCS-CN model

The SCS-CN model with appropriate initial abstraction for Indian conditions given in Gurmel *et al.* 1996 gives a relationship between the direct runoff (Q_c) and total rainfall (P), both in cm:

$$Q_c = \frac{(P - 0.3S)^2}{(P + 0.7S)}$$ (3)

Where S is the potential maximum storage, in cm, and can be expressed in terms of CN as follows

$$S = \frac{254}{CN} - 25.4$$ (4)

Results and Discussion

The study area is a small watershed of about 1751 hectares. Topographic analysis showed that the slope of area varies from 1% to 18% with an average slope of 2%. Forest and rice (paddy) agriculture were the major land cover and land use, respectively. Rice was the single dominant agriculture crop in rainy season (July-November). As soil type of the study area belongs to a single type, *i.e.* laterite, hydrologic soil group B was considered in runoff estimation (Dhruvanarayana 1993).

Analysis of Obtained CN by traditional approach

Since both images used belong to post-monsoon period, agricultural fields in the watershed were covered with fully matured rice (paddy) at crop stage in the October image or just being harvested in the December image. In image classification, separability analysis and overall accuracy are conducted to know the accuracy of the clustering. After classification of the imageries, the resulting overall classification accuracy for all the classes was found to be about 83.73 and 88.28 percent in the October and December imagery, respectively. The separability analysis of the training classes by Bhattacharya distance (Jensen 1996) showed that both rice agriculture classes had a spectral overlap with other classes such as wasteland with minor natural vegetation, barren wasteland (minimum separability found to be less than 1.0) for both the dates. The obtained CN maps for AMC-I are shown in Fig.2 (b&e) for both dates. Note that the multi-spectral variations observed in the standard False Color Composite (FCC) of B2, B3 and B4 bands of IRS LISS III images are also shown in Fig.2(a&d).

Analysis of Obtained CN by the proposed approach

The training sites of pure classes (Water body, dense forest and sandy area) required in LMM approach were kept same for both images. Signature statistics of these sites are enumerated in Table 1. It can be observed that signature statistics of the water body, sand and dense forest in both dates were different as it is expected in any non-atmospheric corrected image data. The fractional layers were obtained by LMM approach and available ground information about 14 LULC classes with hydrologic conditions (poor and good) was used to find out their fractional statistics. A multi-correlation analysis between the fractional statistics and its respective CN value for AMC-I was separately conducted for each image date (Table-2). As given in Table.2, statistically significant relationships (calculated F > F significant and high coefficient of determination R^2) were obtained. However, coefficients of these relationships remain fairly same order in both dates. This trend has proved that selection of controlling parameters is appropriate in defining the degree of saturation. Another characteristic shown in the relationship is that fraction of vegetation cover primarily controls the degree of saturation and so is a critical factor for CN computation. The resulted CN maps are depicted in Fig.2(c,f).
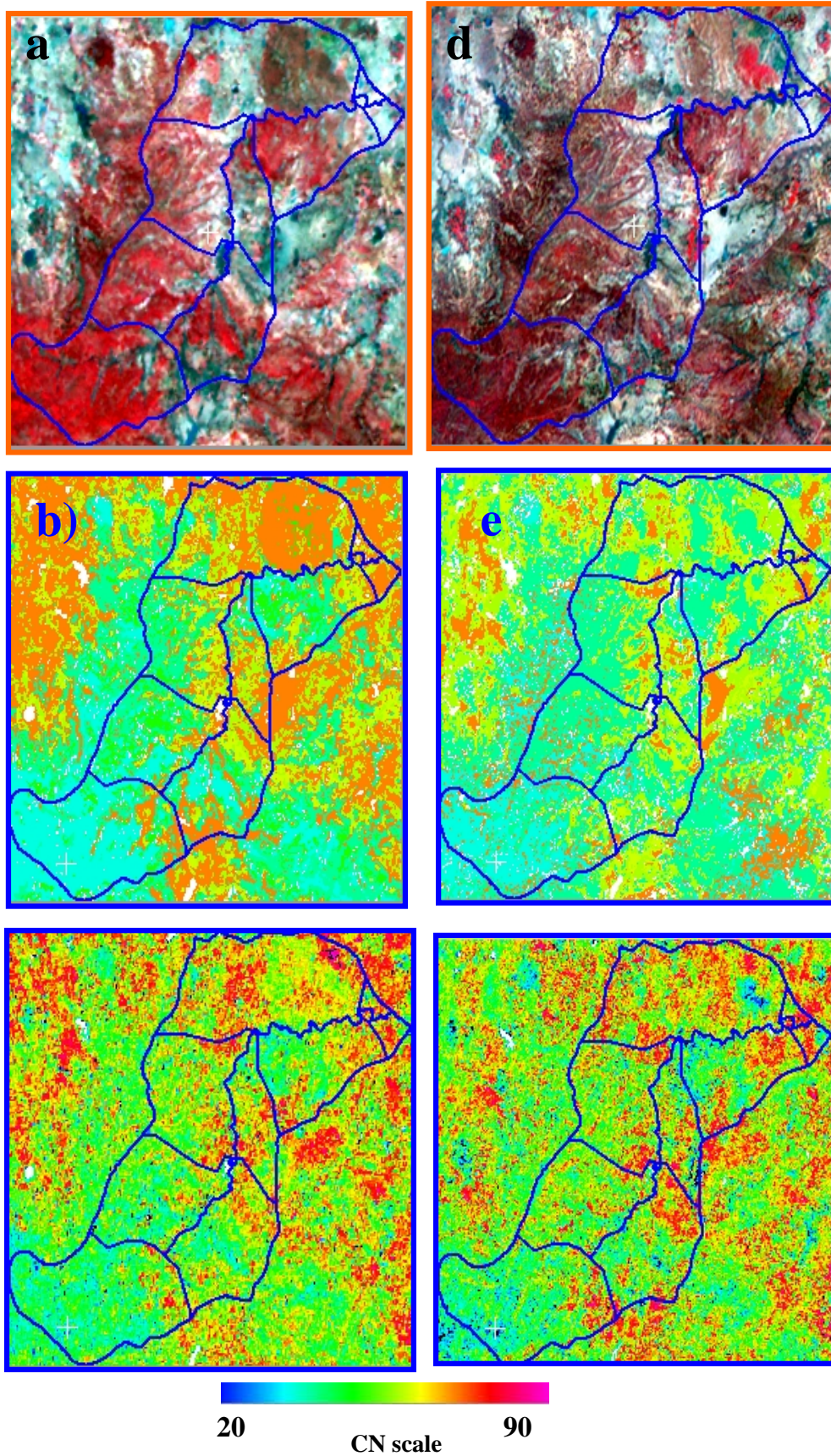
Fig. 2 a) FCC, b) CN map by LUM, c) CN map by LMM for year 1996 d) FCC e) CN map by LUM and f) CN map by LMM for year 2000

Table 1: Spectral Statistics of Endmembers

Image year	Endmember	Statistics of Endmember		
		Average Digital Number (standard deviation)		
		B2: Green	B3: Red	B4:NIR
1996	Water bodies	64.78 (1.03)	30.38 (0.52)	17.08 (0.27)
	Sandy area	147.92 (3.21)	127.71 (4.78)	112.71 (2.01)
	Dense forest	72.70 (0.86)	36.14 (0.51)	115.92 (1.28)
2000	Water bodies	66.93 (0.94)	42.77(0.51)	26.08 (0.90)
	Sandy area	109.92(2.40)	102.91(4.30)	98.71 (02.50)
	Dense forest	63.50(1.02)	43.14 (1.26)	95.91 (1.58)

A comparison study of computed average CN values between LUM and LMM approaches at subwatershed level was conducted. In Fig.3 (a), a plot between them along with variance ratio and the line of perfect is shown for October, 1999 and similar plot for December, 2000 in Fig.3(b). The variance ratio is a ratio between the variance obtained by LMM and LUM approaches in a subwatershed. In most of subwatersheds, variance ratios of more than 1.0 indicate that spatial CN approach accounts of more spatial variation than traditional LUM. A good agreement between the average CN values for all subwatersheds was found for year 1996. The absolute deviation of CN between the two dates remained within ±10 (Fig.4). In 2000 year, similar agreements were found except in III, V and VII subwatersheds. These disagreements might be attributed for the presence of spectral overlap classes in the subwatersheds. In short, spatial CN approach gives fairly same trend as of LUM approach in a single class dominated subwatershed, but differs in a subwatershed of many LULC classes.

Table 2: Relationship equations for spatial CN computation

Image year	N	Relationship equation	R^2	SE	F_{cal} (F_{sig})
1996	14	$CN = 112.62 – 0.13*X_w-0.45*X_s-1.01X_f$	0.84	11.39	13.16(0.015)
2000	14	$CN = 108.51–0.11*X_w-0.33*X_{hs}-0.935X_f$	0.78	9.36	9.36(0.028)

(Fraction symbols: X_w for water bodies, X_s for sandy area and X_f for dense forest, SE: Standard Error, F_{cal}: Calculated F, F_{sig}: Significant F, N: No of the combinations)

Direct Runoff Computation

This section gives a comparison between the estimated storm runoff by both approaches and observed runoff. Three storm events occurred in year 1996 were considered. Average CN values for the whole study area for both approaches were computed for two AMC conditions (I and II). By substituting the average CN in EQs.(3-4), direct runoff depth of these events were estimated. The estimated runoff depths are summarized against the observed runoff depth (Table.3). The runoff volume deviation (D_v) in %, one of the evaluation criteria in the rainfall-runoff model, was computed. It can be found in Table.3 that D_v values obtained by the present approach is less than that obtained by LUS approach expect storm event II. Increasing D_v of LUM in storm event II is not much significant and this deviation may have resulted due to the effects of initial abstraction on a less rainfall depth storm event. By considering all the storm events, accuracy in direct surface runoff estimation by the proposed approach is found to be 14% more accurate than LUS approach.
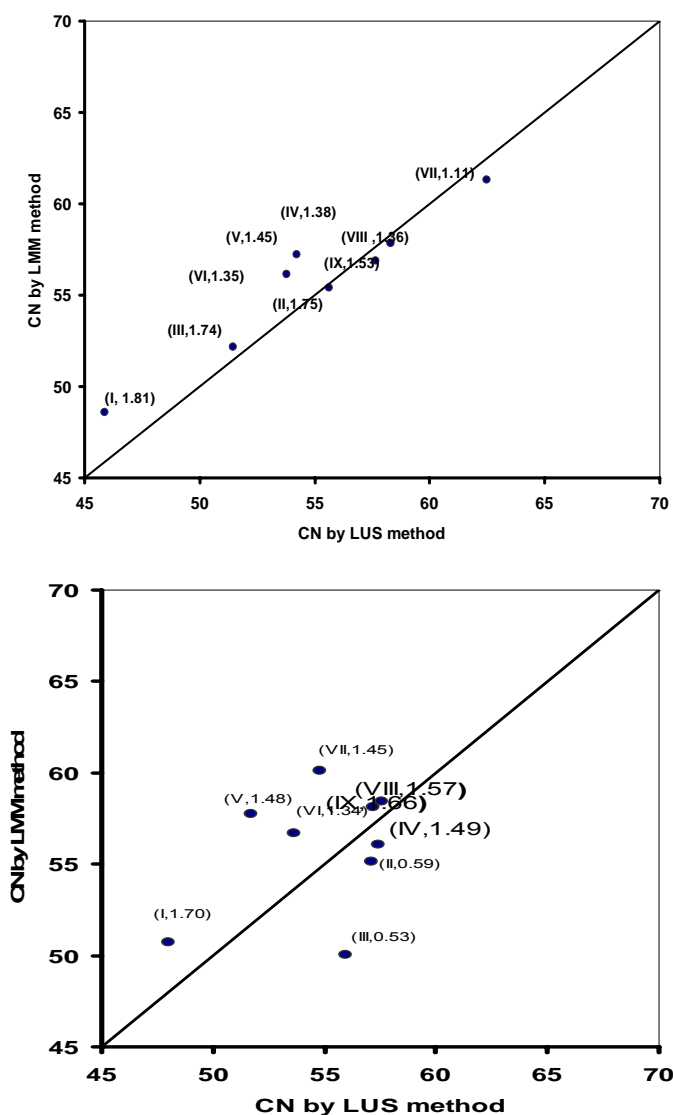
Fig. 3 Scatterplots of estimated CN by LUS and LMM for a) year, 1996 and b) year, 2000 with the line of perfect (1:1) (Inside contents of the brackets showing watershed number and variance ratio)

Table 3: Performance of the SCS-CN model with spatial CN

Storm Sr. no	Storm period	P cm	AMC	Estimated Q_c, cm		Observed Q_m, cm	Deviation D_v (%)	
				LMM	LUM		LMM	LUM
I	20 −28 ,June	21.98	I	7.31	5.69	9.01	18.84	36.84
II	18 −26, July	12.33	II	5.31	4.16	4.71	14.48	11.64
III	1 −11, Aug	30.82	II	22.00	19.75	22.1	0.45	10.21

AMC: Antecedent Moisture Content, P: Total precipitation, Q_c: Total runoff, LUM: the model with only land use and land cover and LMM : the model with spatial CN
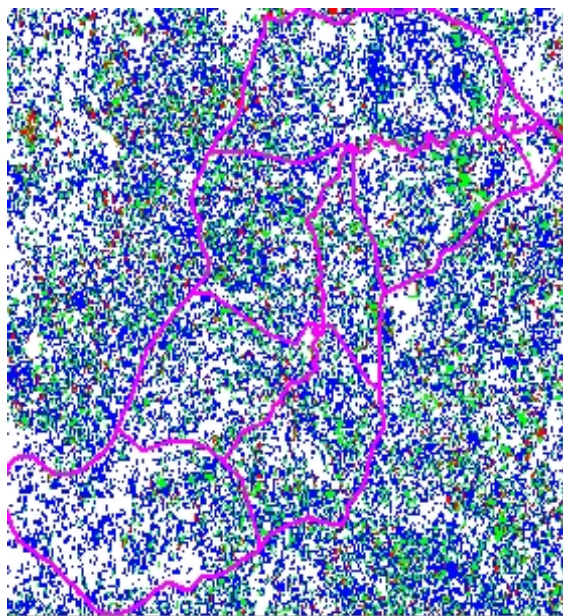
Fig.4 Absolute difference CN between LUS and LMM methods for year 1996
(white (< 5), blue (5 – 10), green (10-20) and Red (> 20))

Hydrologic Response study

Change in the hydrologic response of the watershed due to soil and water conservation measures was studied by differencing spatial CN maps of year 1996 and 2000. During that period, small water harvesting structures were constructed and tree plantations were made (clearly visible in Fig.1b FCC image, 2000) as soil and water conservation measures. The difference CN map by LMM method is shown in Fig.5. The map shows well cluster regions of decreasing CN value at the downstream subwatersheds where the measures were taken up. However, scattered clusters of increasing CN value were found in the upstream subwatersheds. Change in the hydrologic response of the watershed was quantified by computing the difference between average CN of year 1996 and 2000 for AMC-I condition. The difference was found to be 0.87 and indicates that the average hydrological response remains same for both the years. This might be attributed to a fact that the presence of the measures (afforestation) at the downstream and forest degradation at the upstream nullify each other in improving the total soil moisture retention capacity. Because of spatial CN approach, hydrologic response study at small watershed scale can be feasible.

Conclusions

The proposed approach has demonstrated that estimation of spatial CN in an agricultural watershed becomes feasible by spectral unmixing of satellite imagery. Direct surface runoff computation using the SCS-CN model with spatial CN is more accurate than that of the model results of only land use from satellite imagery. In any hydrologic response study, spatial CN is more relevant because it helps to compute the change spatially. In this study, only three controlling parameters for the degree of saturation were used and enabled to describe about 80 percent variation of the CN range. Use of the additional controlling parameters with high-resolution satellite imagery can be feasible in future. It is necessary to evaluate the performance of the approach in different land use dominated watersheds.
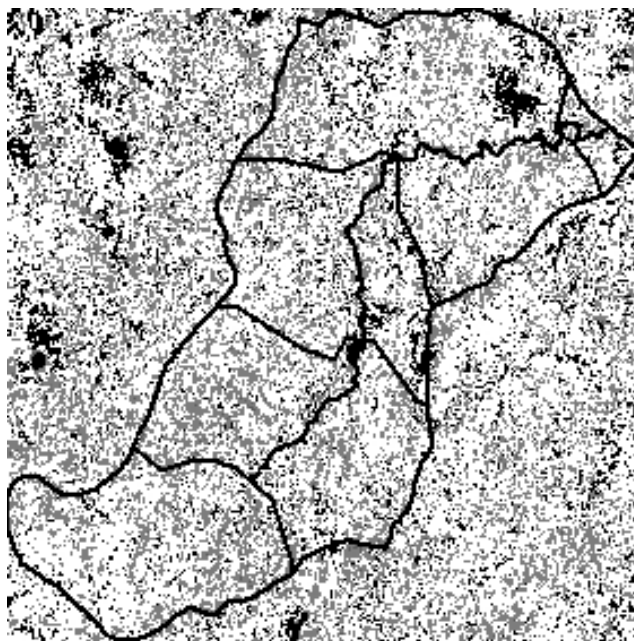
Fig.5 Absolute difference CN between year 1996 and 2000 using LMM method.
(white: < ± 5,   shade: < -5,black : > +5)

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