Crop Identification by Fuzzy C-Mean in Ravi Season Using Multi-Spectral Temporal Images

Sananda Kundu, Deepak Khare, Arun Mondal and P. K. Mishra

Abstract Information regarding spatial distribution of different crops in a region of multi-cropping system is required for management and planning. In the present study, multi dated LISS-III and AWiFS data were used for crop identification. The cultivable land area extracted from the landuse classification of LISS-III image was used to generate spectral-temporal profile of crops according to their growth stages with Normalised Difference Vegetation Index (NDVI) method. The reflectance from the crops on 9 different dates identified separate spectral behavior. This combined NDVI image was then classified by Fuzzy C-Mean (FCM) method again to get 5 crop types for around 12,000 km^2 area on Narmada river basin of Madhya Pradesh. The accuracy assessment of the classification showed overall accuracy of 88 % and overall Kappa of 0.83. The crop identification was done for one entire Ravi season from 23 October 2011 to 10 March 2012.

Keywords Crop identification · NDVI · Fuzzy C-Mean · Narmada river basin

S. Kundu (✉) · D. Khare · A. Mondal
Department of Water Resources Development and Management, Indian Institute of Technology, Roorkee, India
e-mail: sanandakundu@gmail.com

D. Khare
e-mail: kharefwt@gmail.com

A. Mondal
e-mail: arun.iirs@gmail.com

P. K. Mishra
Water Resources Systems Division National Institute of Hydrology, Roorkee, India
e-mail: erprabhash@gmail.com

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1 Introduction

In Indian climatic condition, various types of crops are grown in a place. Monoculture of crops is done only in few places and so most of the time spectral signatures of different crops overlap each other in a same date. Thus it is important to identify these crops and from a single date image it is quite difficult to do crop mapping [1, 2]. To identify the crops, high resolution data of different time series were used to create NDVI and classify the landuse into different vegetation classes [3]. The use of spectral-temporal profile from satellite images to identify crops was initiated in 1980s [4] when a crop profile was presented by using vegetation indicator which measures the reflectance [5]. Many studies were done with the Normalized Difference Vegetation Index (NDVI) by generating profiles from temporal images [6, 7]. NDVI is considered as the most commonly used index for application in agricultural field or for crop identification [8]. Wardlow et al. [1] used MODIS EVI and NDVI (Normalised Difference Vegetation Index) for 12 months data series from the agricultural fields. It is possible to separate the crops during the growth stages at some point from one another. Crop identification from the temporal data series for 8 dates was performed by Doriaswamy et al. [9] with NDVI from MODIS and similar work with MODIS data was done by Ying et al. [10] with 4 images to demarcate wheat crop from others. Based on the crop calendar and growing season of the crops, AWiFS data was used for classification of crops [11].

One of the necessary things is to know the optimum number of dates or images to be used in the crop classification purpose or to have maximum separability. The highest separability with various combinations of dates was found by Murthy et al. [12] to study overlap of spectral signatures among various crops. Similar other works were conducted by Niel et al. [13] and Zurita-Milla et al. [14]. Proper identification of crops is again related to the landuse classifications and problems of mixed pixels. Different techniques used to solve this problem are Fuzzy classifications, Neural Networks, etc. The fuzzy classification is a model where an individual pixel can have partial membership which corresponds to several landuse classes [15]. Wang [16] explained that fuzzy method of classification, due to its multiple membership helps in achieving better accuracy. This method was used by various researchers to improve the identification of crop classes which improves the accuracy of the classification and helps to predict further production [17, 18]. For mapping of vegetation, Vegetation Index was used by combination of two or more spectral bands [19]. Xie et al. [20] also reviewed that NDVI is an important technique for mapping vegetation cover. Kappa coefficient is a discrete multivariate technique used for accuracy assessment [21].

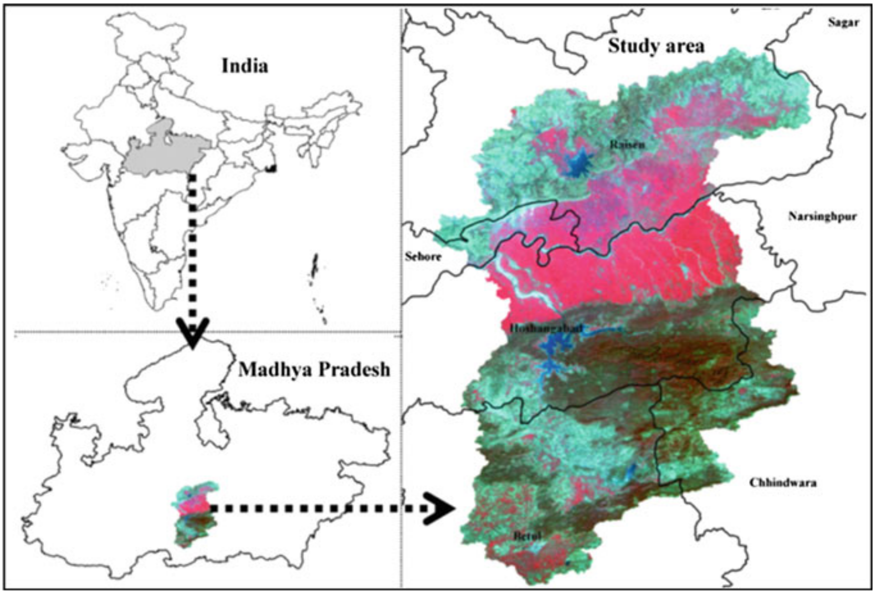

Fig. 1 Study area

2 Study Area

The study area is a part of Narmada River basin in Madhya Pradesh. The area extends from 21°47′24″ to 23°25′49″N latitude and from 77°35′04″ to 78°44′E longitude with total area of 12,678 km^2. It covers five districts of Raisen, Hoshangabad, Sehore, Betur and Chhindwara. The region experiences subtropical type of climate with hot dry summer and a cool dry winter. The average rainfall is about 1,370 mm which decreases from east to west (Fig. 1). The present research involves the landuse classification with the Fuzzy C-Mean algorithm and identification of croplands using 9 temporal satellite images of AWiFS and LISS-III data from October, 2011 to March, 2012.

3 Data and Methodology

AWiFS and LISS-III data sets were taken for the study. All the images were projected with UTM zone 43 projection and WGS 84 datum. The images were registered by first order polynomial model and with the Root Mean Square Error (RMSE) of 0.5 pixel. Then the radiometric normalization was done. The corrected LISS-III images were classified with good accuracy and the agricultural land was extracted from the classified images. The NDVI method was applied on the 9

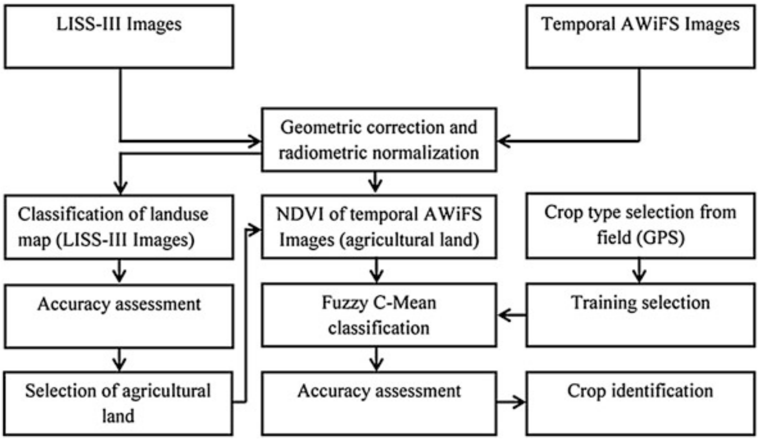

Fig. 2 Methodology

Table 1 Data list

AWiFS				
Sl No.	Date	Band	Wavelength (μm)	Resolution (m)
1	23-Oct-11	2	0.52–0.59 (green)	60
2	11-Nov-11	3	0.62–0.68 (red)	60
3	21-Nov-11	4	0.77–0.86 (near-IR)	60
4	10-Dec-11	5	1.55–1.70 (SWIR)	60
5	24-Dec-11			
6	12-Jan-12			
7	5-Feb-12			
8	20-Feb-12			
9	10-Mar-12			

images of AWiFS data on agricultural land to get the spectral difference of various crops at different growing stages. These images were then stacked to obtain a single image which was classified with Fuzzy C-Mean (FCM) and accuracy assessment with Kappa statistic was done (Fig. 2). The data used are given in Table 1.

3.1 NDVI Method

The temporal AWiFS data of 9 dates give the difference in spectral signature. The NDVI images were generated from the LISS-III and AWiFS images which give unique spectral response of each crop and demarcate them from the non-vegetation classes. These NDVI images were stacked chronologically according to the dates to get the growth profile of the crops. These profiles were then used for FCM classification with the training data set from the images and samples collected from the field.

In NDVI, absorption of chlorophyll or green pigments in the red spectrum and very high reflectivity in the near infra-red spectrum helps in identifying and differentiating vegetation types. It also indicates the health of the vegetation and hence is important in identifying crops. It is calculated as:

$$NDVI = \frac{\rho nir - \rho red}{\rho nir + \rho red} \tag{1}$$

where, ρnir is the near infra-red band and ρred is the red band of the sensor.

3.2 Fuzzy C-Mean Classification

In this study, Fuzzy C-Mean (FCM) algorithm was applied for the classification. It is based on the minimization of the objective function through iteration:

$$J_m(U, v) = \sum_{i=1}^{C} \sum_{k=1}^{N} u_{ik}^m \|y_k - v_i\|_A^2 \tag{2}$$

where,

Y is $\{Y1,\ Y2 \ldots YN\} \subset \mathrm{Rn} =$ the data,
c is number of clusters in Y; $2 \leq c \leq n$,
m is weighting exponent; $1 \leq m < \infty$,
U is fuzzy c-partition of Y; $U \in \mathrm{Mfc}$,
v is (v1, v2 … vc) = vectors of centers,
vi is (vi1, vi2, …, vin) = center of cluster i,
$\|\|_A$ is induced A-norm on R'', and
A is positive-definite (n × n) weight matrix.

The following three constraints are satisfied by the membership values:

$$0 \leq u_{ik} \leq 1; \text{ where } i \in \{1, \ldots C\}; \quad k \in \{1, \ldots N\} \tag{3}$$

$$\sum_{i=1}^{C} u_{ik} = 1; \quad k \in \{1, \ldots, N\} \tag{4}$$

$$\sum_{k=1}^{N} u_{ik} > 0; \quad i \in \{1, \ldots, C\} \tag{5}$$

The objective function is represented as the sum of the square of the Euclidean distances between each input sample and its corresponding cluster centre, and the distances are weighted by the fuzzy memberships. This is an iterative algorithm and uses the following equations:

Table 2 Area covered by different classes

Sl No.	Crop type	Area (km^2)	Area (%)
1	Settlement	281.00	2.20
2	Grassland	2,942.60	23.06
3	Forest	918.94	7.20
4	Open/Degraded forest	1,485.06	11.64
5	Double crop land	2,608.29	20.44
6	Ravi crop (wheat)	1,689.17	13.23
7	Water body	520.72	4.08
8	Kharif crop (paddy)	2,272.75	17.81
9	River bank	44.85	0.35
	Total	12,763.37	100

$$\hat{v}_i = \left[\sum_{k=1}^{N} u_{ik}^m y_k\right] \Big/ \sum_{k=1}^{N} u_{ik}^m \tag{6}$$

$$\hat{u}_{ik} = 1 \Big/ \sum_{j=1}^{C} \left[\|y_k - v_i\| / \|y_k - v_j\|\right]^{2/(m-1)} \tag{7}$$

All input samples are considered and the contributions of the samples are weighted by the membership values for calculating cluster centre. The membership value in each class of a sample depends on its distance to the corresponding cluster centre. The weight factor m decreases the impact of small membership values. Greater the value of m, smaller will be the influence of samples with small membership values [22].

4 Results and Analysis

4.1 Landuse Classification and Accuracy Assessment

The LISS-III image was classified into 9 landuse classes, viz., settlement, grassland, forest, open/degraded forest, double crop land, ravi crop (wheat), water body, kharif crop (paddy) and river bank. The area covered by different classes is given in Table 2. The classified landuse is given in Fig. 3.

4.2 Crop Identification

The landuse classified from LISS-III image was used to extract cultivable area or agricultural land to develop NDVI profile. The NDVI values from 9 images were stacked to form one image. Difference in the spectral-temporal curves is observed in Fig. 4 where spectral reflectance in NDVI of each crop is different from the other.

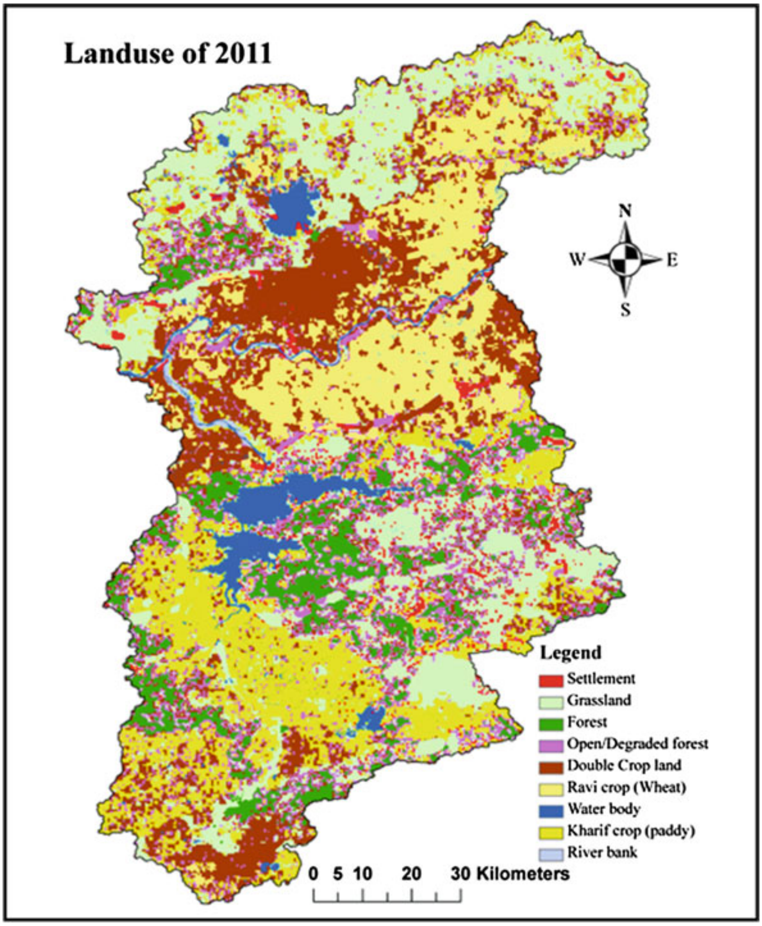

Fig. 3 Landuse classification of 2011

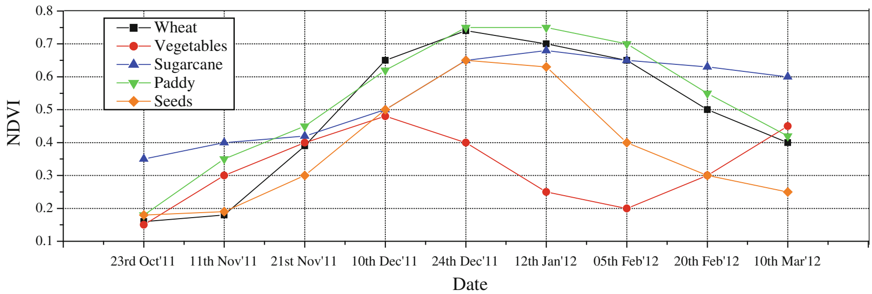

Fig. 4 Spectral curves of different landuse classes

Table 3 Area occupied by different crops

Sl No.	Crop type	Area (km^2)	Area (%)
1	Wheat	1,930.00	44.91
2	Vegetables	577.88	13.45
3	Seeds	1,212.49	28.21
4	Paddy	277.22	6.45
5	Sugarcane	299.86	6.98
	Total	4,297.45	100

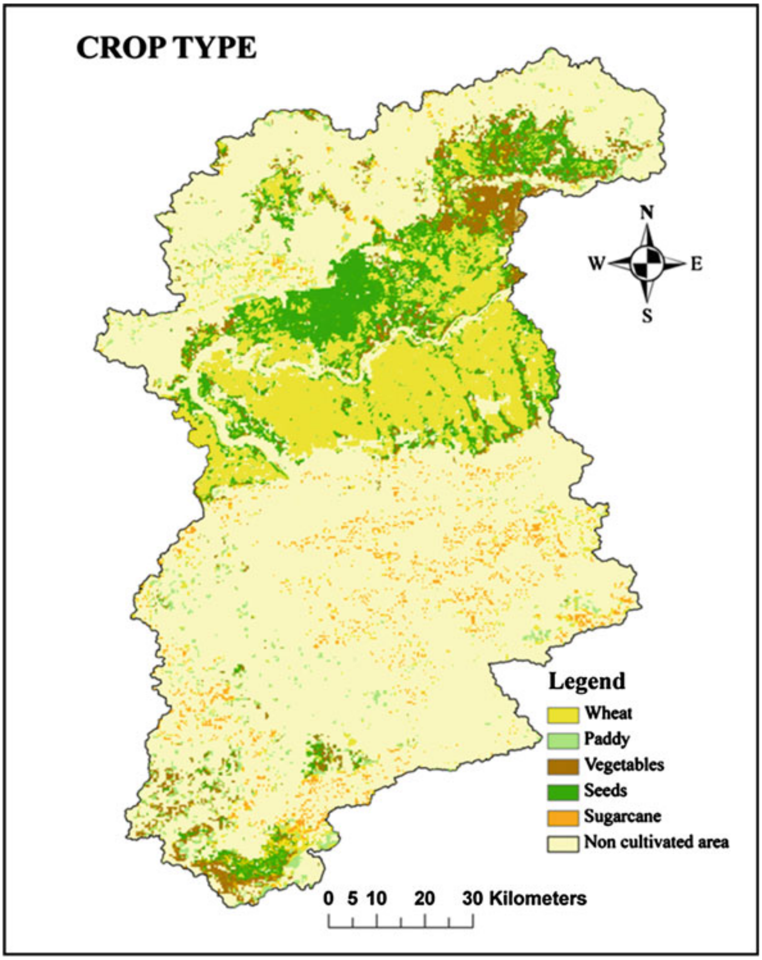

Fig. 5 Crop identification by Fuzzy C-Mean

Table 4 Accuracy assessment of the crops

Rabi crops					
Class name	Reference totals	Classified totals	Number of correct points	Producers accuracy (%)	Users accuracy (%)
Wheat	51	52	46	90.20	88.46
Paddy	10	10	8	80.00	80.00
Vegetables	18	18	16	88.89	88.89
Sugarcane	11	11	9	81.82	81.82
Seeds	35	34	31	88.57	91.18
Total	125	125	110	…	…

The stacked NDVI image was then classified by Fuzzy C-Mean into different croplands namely wheat, sugarcane, seeds, vegetables, paddy and non-cultivable areas. Among all the crops, wheat is found to have highest proportion of area with around 45 % of the total area followed by seeds (28.21 %), vegetables, sugarcane and paddy. This difference is reflected in the NDVI values of growth stage from the temporal images. Table 3 signifies the area occupied by different crop types.

Various crops identified by FCM are given in Fig. 5. The crops were identified with the help of crop profiles of NDVI. Total of 125 samples were collected from the field for 5 crops classified in the image. The Producer's and User's accuracy achieved for 5 different crops were 80 % and above (Table 4). The overall accuracy was 88 % and the overall Kappa was 0.83.

5 Conclusions

The availability of temporal images is necessary for obtaining crop profile. The identification of crops and its spatial distribution is required to understand the agriculture of a region and for further planning and management. The given study involves identification of crop profiles through NDVI from 9 temporal AWiFS data for the entire Ravi season from 2011 October to 2012 March. The agricultural land was extracted from the classified landuse of LISS-III image and NDVI profiles were drawn only for this portion of landuse. The profiles indicated different spectral signatures at the growing stages for different crops which helped in identifying the mixed crops of the area which are grown side by side. Further, the Fuzzy C-Mean classification was done with the stacked NDVI image to provide definite crop types of the area and their distribution in Ravi season with accuracy assessment. Thus this method provides spatially distributed crop data within a region.

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