

Identification and Evaluation of Land-Cover Classifications from Remotely Sensed Data Using Fuzzy-C-Means Algorithm

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Abstract

Remote sensing is an attractive source of data for land-cover mapping applications. This paper presents use and interpretation of satellite data to extract information about various land cover classifications using Fuzzy C-means algorithm. Mapping is achieved through the application of a conventional statistical classification, which allocates each pixel to a land use class. The conventional approaches are inappropriate for mixed pixels, which contain two or more land cover classes, so a fuzzy classification approach is required. Softening the output of a conventional 'hard' classification or using a fuzzy classification can derive the required type of representation. IRS-1D, LISS III Geocoded False Color Composite (FCC) data for Ganga river: Uttar Pradesh, true color image of Koyna site: Maharastra and black and white image of Patalganga river: Maharastra, India has been analyzed as a case study for basic three land cover classifications; water, forest and habitation. The results show the importance of recognizing and accommodating the fuzzyness for the land-cover on the ground. The results obtained are presented and compared with the Survey of India Topo-sheets and found to be promising.

Key Words: Land Cover, Clustering, Fuzzy-C-Means

1. Introduction

Information on the land-cover pattern and its spatial distribution is a pre-requisite, among the various parameters for the planning, utilization and formulation of policies and programmes for making any development plans. Although the importance of land cover is recognized, data on land cover are often out of date, of poor quality or inappropriate for a particular application. Furthermore, land-cover data is not easy to acquire for hilly areas and large areas if frequent up-dating is required.

In recent years, remote sensing has gained importance in natural resource management. Land use/land cover mapping with remotely sensed data is conducted at a single resolution by visual interpretation

and/or semi automated image classification algorithms and strategies, including supervised, unsupervised, and hybrid training approaches [1-2], artificial neural networks [3] and fuzzy sets [4]. Land-use/land-cover mapping is very much practiced to prepare dynamic maps of land use/cover classified for Kharif and Rabi seasons [5]. Remote sensing is gaining importance in natural resource management to analyze the information of lithology, tectonics, topography and drainage. It has been applied for 'Sung Valley' area affected by alkaline-ultramafic-carbonatite intrusion [6] and also to find status of soil erosion [7]. Satellite images have been used to evaluate water resources, to detect waterbody and delineation [8], estimation of run-off, assessment of groundwater [9], observations of water levels within

channels and ditches in wetlands [10]. Digital photogrammetry and image analysis techniques have also been used to obtain accurate high-resolution topographic information, such as slope gradients, drainage patterns for terrain analysis and hydrological modeling [11].

Clustering or segmentation is the first step in the image analysis process which divides the spectral domain into 'meaningful' parts or regions, on which the image is defined. These clusters are based on the partitioning of a collection of data points into a number of subgroups, where the objects inside a cluster or a subgroup show a certain degree of closeness or similarity. The focus of the paper is mainly on the analysis of the satellite image to extract useful information by interpretation of satellite image using Fuzzy-C-means algorithms [12-14].

2. Fuzzy-C-means Algorithm (FCM)

The Fuzzy C-Means (FCM) is an overlapping clustering algorithm, which allows one piece of data to belong to two or more clusters. This method (developed by Dunn in 1973 and improved by Bezdek in 1981) is frequently used in pattern recognition. This clustering algorithm may be used for either unsupervised or supervised classification. Fuzzy membership functions are calculated from which membership values indicate the relative strength of class membership of a pixel to each class. Each pixel in the image is allocated to the class with which it has the highest probability of the membership. The data are bound to each cluster by means of a membership function, which represents the fuzzy behavior of this algorithm.

The Fuzzy C-Means algorithm generalizes the hard C-Means algorithm to allow a point to partially belong to multiple clusters. To produce a constrained soft partition, the

objective function J , of hard C-Means has been extended in two ways [12]:

- i. The fuzzy membership degrees in clusters were incorporated into the formula, and
- ii. An additional parameter m was introduced as a weight exponent in the fuzzy membership

The extended objective function, denoted as J_m , is

$$J_m(P, V) = \sum_{i=1}^k \sum_{X_k \in X} (\mu_{ci}(X_k))^m \|X_k - V_i\|^2 \dots\dots Eq.1$$

where,

P is a fuzzy partition of the dataset X formed by C_1, C_2, \dots, C_k .

The parameter m is a weight that determines the degree to which partial member of a cluster affect the clustering result.

FCM tries to find a good partition by searching for prototypes v_i and also a membership functions c to minimize the objective function J_m . To accomplish these two objectives, a necessary condition for local minimum of J_m is derived from J_m .

Fuzzy C-Means Theorem states that, A constrained fuzzy partition $\{C_1, C_2, \dots, C_k\}$ can be a local minimum of the objective function J_m only if the following conditions are satisfied.

$$\mu_{ci}(x) = \frac{1}{\sum_{j=1}^k \left(\frac{\|x - v_i\|^2}{\|x - v_j\|^2} \right)^{\frac{1}{m-1}}} \dots\dots\dots 1 \leq i \leq k, x \in X \dots\dots Eq.2$$

V_i , is the i^{th} cluster center, which is described by m features and can be arranged in vector form $v_i = \{v_{i1}, v_{i2}, \dots, v_{im}\}$

$$V_i = \frac{\sum_{x \in X} (\mu_{ci}(x))^m \times x}{\sum_{x \in X} (\mu_{ci}(x))^m} \dots\dots\dots 1 \leq i \leq k \dots\dots\dots Eq.3$$

Based on this theorem, FCM updates the prototype and the membership function iteratively using equations (2) and (3) until a convergence criterion is reached.

$$\sum_{i=1}^c \|V_i^{\text{Previous}} - V_i\| \leq \epsilon$$

3. The Case Study:

The model validation has been done by analyzing the data for Ganga river: Uttar Pradesh, Koyna site: Maharashtra and Patalganga river: Maharashtra, India as a case study. The selected satellite images cover FCC image, True color image and Black & White image for land-cover classification. In table 1 details of the data used in the case study has been presented.

Table 1. SATELLITE DATA USED IN THE STUDY

Area	Satellite system	Path/ Row & Revisit (days)	Acquisition date	Spatial resolution (m) & No. of bands
Uttaranchal and Uttar Pradesh, India	IRS-1D, LISS-III, Multispectral	97,50 25	24 th January 2000	21.2-23.5 Three
Maharashtra	IRS-1D, LISS-III, Multispectral	96,59 25	July 1998	21.2-23.5 Three
Koyna site	www. Google earth.com			
SOI, Toposheets scale 1:50 000	Uttaranchal Pradesh (formerly in Uttar Pradesh) 53K/4, 53K/3, 53K/2, 53J/15, 53J/4, 53J/16			

Results obtained by the model and discussion have been presented in next paragraph.

4. Results and discussion

Since different objects or different parts of the object have different characteristics, feature values recorded at pixels belonging to various regions are different. Mapping the feature values at every pixel to a feature space, distinct clusters corresponding to types of the features and also features of the same object of regions in the image are formed. Various clusters are obtained for land cover classification.

In figure 1, 'A' represents the FCC satellite image for Ganga river which is fairly a plane

region and surrounding environment and 1-5 are the clusters obtained for the various land-cover classifications. In figure 2, 'A' represents the true color satellite image for Koyna site, Maharashtra and surrounding environment and 1-3 are the clusters obtained for the various land-cover classifications.

In figure 3, 'A' represents the Black & White satellite image for Koyna site, Maharashtra and 1-3 are the clusters obtained for the various land-cover classifications.

From figure 1, figure 2 and figure 3, it is seen that, though the images are for different

regions, different landscapes and different forms it is observed that, clustering is done based on the group of pixels belongs to a particular cluster.

Results of the figure 1 are compared with the ground data from survey of India topo sheets and then interpretation keys developed (for FCC) by various researchers based on the prior knowledge of the area, type of image and time when image is considered (Appendix-1). Cluster-1 belongs to a vegetation, cluster-2 belongs to the dense forest, cluster-3 belongs to a deep water, cluster-4 belongs to a sand bed or shallow water and cluster-5 belongs to

the habitation patterns. Similar comparisons can be made for figure 2 and figure 3.

It is also seen that, the FCM algorithm converges surely and the convergence of algorithm depends on the parameters 'm' (a weight that determines the degree of partial member of a cluster), ' μ_c ' (membership function) and initial prototype v_i .

The algorithm presented here provides a scientific methodology for land cover classification, assessment and generating updated maps which facilitate the use of remote sensing as a source of land cover data.

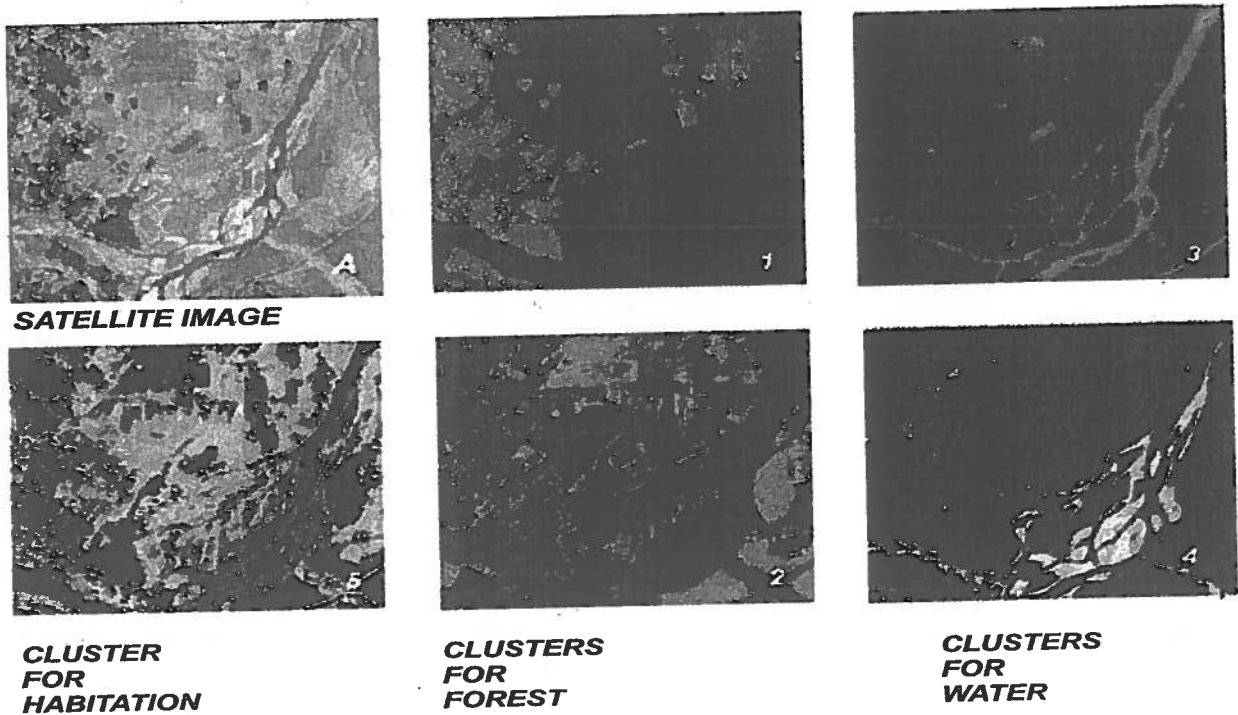
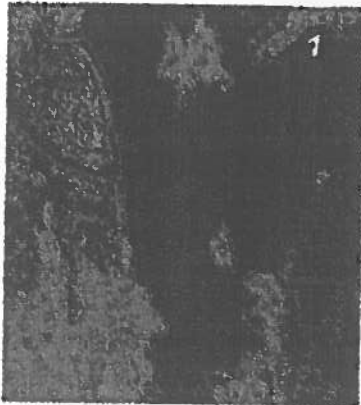


FIGURE 1 FCM CLUSTERS FOR LAND COVER CLASSIFICATION FOR FCC IMAGE



SATELLITE IMAGE (TRUE COLOR)



CLUSTER FOR FOREST



CLUSTER FOR WATER

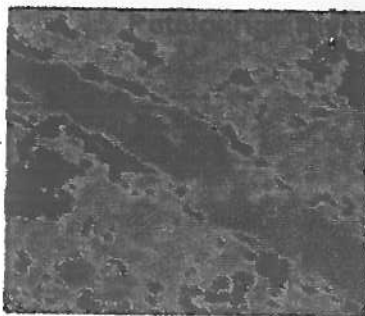


CLUSTER FOR HABITATION

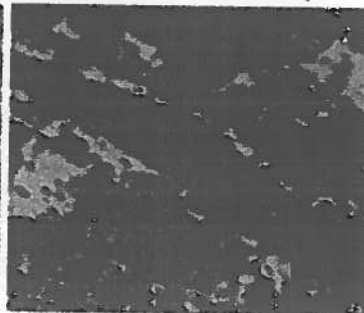
FIGURE 2: FCM CLUSTERES FOR LAND-USE PATTERNS FOR TRUE COLOR IMAGE



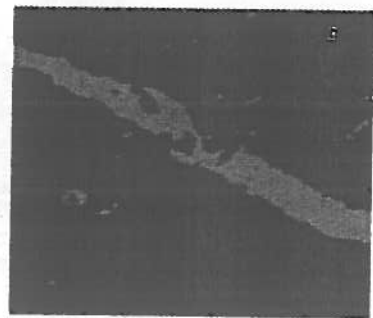
SATELLITE IMAGE



CLUSTER FOR FOREST



CLUSTER FOR HABITATION



CLUSTER FOR WATER

FIGURE 3: FCM CLUSTERS FOR BLACK & WHITE IMAGE

Appendix-1 FCC COLOR INTERPRETATION KEYS

Land use/ Land Cover	Tone	Texture	Location	Shape
Water Bodies				
River / Stream	Deep blue	Uniform	More than 3.0 m water depth	Elongate (sharp boundaries)
Canal	Light turquoise	Uniform	0.35-2.0 m water depth	--
Lake/ Reservoirs	Deep blue	Line segments	--	Sharp boundaries
Sandy area	White with blue tone	Non- uniform	Along the course of river	Irregular boundary
Forest				
Dense forests	Dark red	Pattern	--	Irregular boundary
Degraded Forests	Red with small brown or white patches	Non-uniform	--	Irregular boundary
Forest blank	Creamy patches	Non-uniform	--	Irregular patches
Forest plantation	Dark red to red	--	--	Particular pattern
Agricultural land with crops	Bright red to red	Uniform	Near habitation	Sharp boundaries
Settlements and habitation	Light gray with brownish maroon patches		Near agricultural land/ river bank etc.	Particular patterns for urban area. No particular patterns for rural area.
Snow	Bright white	Non Uniform	Hilly area	Irregular patches

Source: Thomas M.Lillesand & Ralph W. Kiefer, knowledge base from various sources.

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