Improving Land Use and Vegetation Cover Classification Accuracy using Fuzzy Logic - A Study in Pilibhit District, Uttar Pradesh, India

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Abstract

This study discusses a methodology for fuzzy classification and investigates the improvement of land use and vegetation cover classification accuracy of a fuzzy based classification over unsupervised classification in a test site of Pilibhit district, Uttar Pradesh, India. It also establishes a methodology of using higher resolution satellite data to gather reference points for classification accuracy assessment of outputs derived from low resolution images; apparently substituting ground validation. In this study the overall classification accuracy and overall kappa (K^) statistics of LUVC using fuzzy-based classification are 88.89% and 0.87 respectively, while the respective values are 82.22 and 0.79 of the unsupervised classification. This meets the requirement that K^ values >0.80 (i.e., >80%) represent strong agreement or accuracy between the classification map and the ground reference information, K^ values between 0.40 and 0.80 (i.e., 40 to 80%) represent moderate agreement, K^ values <0.40 (i.e., <40%) represent poor agreement (Landis and Koch, 1977 and Jensen, 2005). The study holds two promises i.e., (i) improved classification using fuzzy membership and (ii) utilization of higher spatial resolution data (merged data) to generate reference frame for evaluating classification accuracy.

1. Introduction

The challenges of feature extraction of land use and vegetation cover lie in accurate classification of remotely sensed imageries. Over the past years, many methods have been established for classifying images of remotely sensed data to improve the accuracy of land use/ cover classifications (Jensen, 1996). Different algorithms and strategies have been developed and tested for various feature extraction viz., supervised, unsupervised and hybrid classification (Richards, 1986); parametric and nonparametric classifiers; segmentation (Conner et al., 1984); artificial neural networks (Civco, 1993); fuzzy sets (Wang, 1990 and Foody, 1994) and knowledge-based systems (Kontoes and Rokos, 1996). Furthermore, since 1988 onwards the IRS (Indian Remote Sensing) series of satellites have been providing valuable data for studying land use and vegetation cover (LUVC) of the country. For instance, IRS P6 (Resourcesat) has been providing excellent data and has been widely used for wide range of applications in varied fields (Gupta and Jain, 2005 and Kandrika and Roy, 2008). Since unsupervised classification is a process wherein numerical operations are performed that search for natural groupings of the spectral properties of pixels, as examined in multi spectral feature space which does not require the user to specify any information about the features contained in the images (Banman, 2002). Many researchers have been using unsupervised classification technique to extract the features from the remotely sensed imagery, as it demonstrates the classification that can incorporate both the spectral and spatial features of the pixels in the image resulting in better defined categories in terms of its homogeneity (Fontaine et al., 1999, Idbraim et al., 2006 and Dubeni et al., 2008). However, it is difficult to classify in the areas with scenes having much heterogeneity, the mixed pixels may cause significant fuzziness in the training data, which is not only vital but needs to be classified and to overcome this type of situations fuzzy rule comes into play. So there can be improved not only the cluster labeling in unsupervised classification using fuzzy rules (Ji, 2003) also a significantly better classification with 5 to 10% higher accuracy can be performed (Forghani et al., 2007, Myint, et al., 2008 and Colditz et al., 2008). This paper discusses a detailed methodology for the fuzzy classification and investigates the improvement of land use and vegetation cover classification accuracy of a fuzzy based classification over unsupervised classification in a

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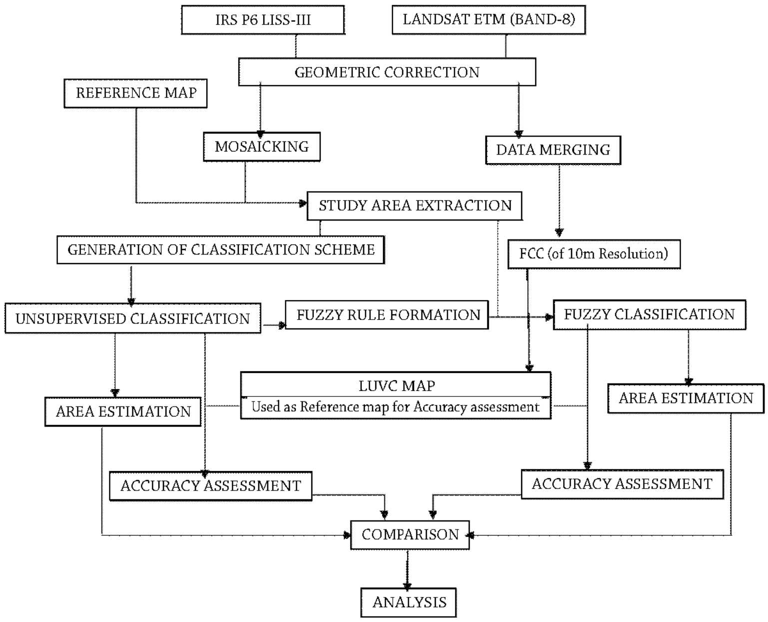

Figure 2: Methodology flowchart of the study

Table 1: Satellite data specifications

Satellite	Sensor	Path	Row	Date of pass	Spatial resolution
IRS P6	LISS III	98	51	18-Nov-05	23.5 m
IRS P6	LISS III	99	51	13-Oct-05	23.5 m
LANDSAT 7	ETM+PAN	144	40	9-Nov-99	10m
LANDSAT 7	ETM+PAN	145	44	15-Oct-99	10m

Table 2: Comparative classification accuracy assessment of land cover classes according to unsupervised classification and fuzzy-based classification

	Accuracy using unsupervised classification			Accuracy using fuzzy-based classification		
Class	Producers Accuracy (%)	Users Accuracy (%)	Kappa (K^)	Producers Accuracy (%)	Users Accuracy (%)	Kappa (K^)
Dense forest	93.33	87.50	0.85	100.00	100.00	1.00
Open forest and Scrubs	60.00	69.23	0.63	93.33	100.00	1.00
agricultural/fallow land	80.00	80.00	0.76	100.00	88.24	0.86
Moist land	93.33	70.00	0.64	93.33	63.64	0.56
Dry barren land	73.33	91.67	0.9	53.33	100.00	1.00
Water body	93.33	100.00	1	93.33	100.00	1.00
Overall Classification Accuracy		82.22%		88.89%		
Overall Kappa Statistics		0.79		0.87		

2.2.2 Geometric correction and study area extraction

Remotely sensed data cannot be used directly for resource information due to the inherent distortion in the image data. Some of the basic corrections like earth rotation, panoramic and some minimal radiometric corrections are generally carried out at data supply point using the standard parameters. However, precise corrections at scene-to-scene basis are required with respect to the topographic maps and transformation of a remotely sensed image provides scale and projection (Mather, 1987). The image data was geo-referenced *i.e.,* map co-ordinates were assigned to the image data and LCC projection system with WGS 84 datum was used. Each of the two scenes was geo-referenced separately. Further, proper band combination is needed for the identification of the required features in the image (Jensen, 1986). In this study, the band combination of NIR (red), R (green), G (blue) was used for LUVC classification and mapping (Figure 3).

test site of Pilibhit district, Uttar Pradesh, India. Fuzzy logic has been increasingly used in classification of remotely sensed data, where the classification works using a membership function, in which a pixel's value is determined by whether it is closer to one class than other including no definite boundaries, and each pixel can belong to several different classes because an element of fuzzy set can be assigned full or partial membership instead of just two values viz., 0 and 1 (Jensen, 1996). Fuzzy systems have the capability to represent classification decisions explicitly in the form of fuzzy 'if-then' rules that make use of vague, imprecise or uncertain information to generate simpler and more suitable models (Jindal et al., 2007). Many authors have performed better classifications with higher accuracy using fuzzy classifier (Nedeljkovic, 2004, Wang et al., 2004 and Colditz et al., 2008) as it is incorporated into existing fuzzy systems in order to make the benefits of fuzzy logic available to image classification (Qiu and Jensen, 2004). For accuracy assessment or validation of a classification output it is needed to tie up the result with the ground data. But if the ground data can be collected from any high resolution data, then the result can be validated using this high resolution data as a reference template. For example, Wang et al., (2005) had used 30m resolution ETM^{+} imagery and it was validated with 1m PAN sharpened IKONOS imagery. Since in the Landsat-TM images, the terrain features produces intricate patterns due to high spatial resolution for which it is difficult to identify the objects from the FCC image. In order to overcome this problem and to facilitate the generation of a thematic map of the terrain features, data merging techniques are used. Many researchers have been using data merging techniques to merge SPOT (10m pixels) and LANSAT (TM; 30m pixels) images for clear visualizing the objects (Parcharidis and Kazi-Tani, 2000 and Nasr and Ramadan, 2008).

2. Methodology

2.1 Study Area

The district of Pilibhit, lies between the parallels of $28^{0}06'$ N and $28^{0}53'$ N latitude and $79^{0}57'$ E and $80^{0}27'$ E longitude, is located in north-eastern part of Uttar Pradesh, which is situated in the sub Himalayan belt and its boundary with Udhamsingh Nagar district and the kingdom of Nepal lie on the north, Shahjahanpur district lies on the south, Bareilly district lies on the west (Figure 1). In its general appearance the district presents diverse features and topographically may be divided into several distinct tracts; a portion is enclosed by dense forest as well as open forest and scrubs; some regions is covered by dry barren lands and moist lands as well; in the upper part of the district the soil is sandy, while in the lower part it is clayey and produces finer crops. Sugar cane is the main crop in the district and many rivers as well as canals are in the district among which the Sharda canal is the main canal of the district, the others being its branches. The principal rivers are the Gogra, forming the northern boundary, and the Gumti, flowing through the middle of the district.

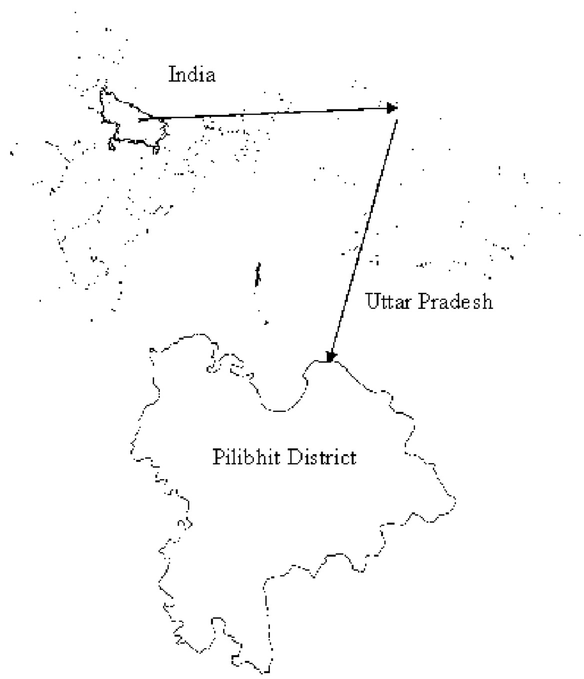

Figure 1: Location map of study area showing Pilibhit District, Uttar Pradesh, India

2.2 Methods

The detailed methodology includes feature extraction of six broad land use/vegetation cover classes; and classification accuracy assessment using higher resolution merged images (Figure 2).

2.2.1 Data used - satellite and ancillary data

Two Linear Imaging Self Scanning (LISS III) scenes of Indian Remote Sensing (IRS) satellite data were procured to accommodate the Pilibhit district (Table 2) which has four spectral bands i.e., 0.52-0.59, 0.62-0.68, 0.77-0.86 & 1.55-1.70µm. Two Enhanced Thematic Mapper (ETM^{+}) scenes of band 8 Landsat MX and PAN data were downloaded from ESDI to accommodate Pilibhit district (Table 1) which has 10m PAN data. Toposheets (1: 50000 scale) for reference purposes, socio-economic data and other ancillary data *i.e.* of past history were used.

negative impact on a human health. Before you dismiss this innovation because of its inherent difficulties of implementation, you might want to begin to look at some of the research that has been done over the past several decades that tells a very disturbing story about how human health and the environment intersect. You will discover information that could be extremely useful to help doctors help their patients, information that is not easily discoverable in form that it exists today. Thus the need for a more innovate approach to "just-in-time" data-linking and "smart" analysis. The public is desperately seeking not only better health, but more useful ways to incorporate everything that is known about a (health) problem into their unique situation.

How would this Actually Work in the Doctor's Office?

To have geographic intelligence at the fingertips of a physician at the time of a patient encounter could prove to be extremely valuable – if it arrives just-in-time. To have such a diagnostic aid means that it must be fast, accurate, insightful and referential. From a IT system perspective the place history data must be collected prior to the physician encounter either from an automated data collection device in the patient waiting area or from a pre-office eHistory collected in the comfort of the patients home and transmitted to the physician's office. Much like a title search on an automobile or real estate, the system would discover all known relevant facts prior to the transaction – the visit. Modern information technologies and advance web services can make this a reality quickly and efficiently, but not without acceptance of the medical community that geography matters – Until geography is viewed by the medical community and important context within which to understand, diagnosis and treat the human condition, we are probably not serving society as well as we could.

What is the Likelihood that "Geo-Medical" Intelligence will Improve People's Health?

Ultimately, the electronic health record must work for patients as much as for the medical research community and the "efficiency" experts working on lowering the cost of delivering healthcare. If health records are to be useful to patients directly, they must go beyond where there are today – just a complex array of information collected by imperfect systems, subjected to high levels of individual interpretations, and a lot of duplicative entries. Unless there is a more innovative analysis of the data housed inside a health record that can make information become "actionable" (meaning keeping people healthy, living longer, or protecting them from harm), we will likely have only satisfied a very limited set of stakeholders. I am suggesting that we begin to be more aggressive about our information innovations in health - especially when it comes to building and using the modern electronic health record. The incorporation of more accurate geographical references within any type of health or medical record that would allow the physician to gain greater insight into the contributions of a patients "environments'" to the health problem at hand, would seem to be a giant step forward in making the health record "useful" and efficient in making all the relevant information achieve its highest and best use.

What Could Future Health Record do for You?

Your personal health record stored on a portable electronic gadget, "sniffing" out compromised environmental conditions, comparing where you have been and where you're going, analyzing new medication consumption on the fly, informing and alerting you as well as the "right" medical people of immediate and long-term threats to your well-being – can be envisioned now. Perhaps it's time that the electronic health record community made an effort to become more inclusive in their deliberations about what makes a health record valuable to the very people that medicine is about – you!

Making Commitments to Innovation

Making our personal health data actually "do something" for us will take a community of geoscientists and health professionals focused around bringing two very critical rivers of information together - one caring data guided by medicine and healthcare administration, the other caring data created and guided by public health professionals and environmental researchers. The sheer flow of discrete data in these digital rivers is awesome and growing more quickly than our ability to analyze it and make it do something creatively for the benefit of individuals. It would seem imperative that these two critical "river communities" of medical and social information expertise recognize the enormous responsibility they have in helping more people enjoy greater health status. The author would enjoy receiving comments on the vision of this paper and encourage suggestions from any reader on either the merits of the ideas described or their assessment of the likelihood that medicine will begin to embrace the discussed benefits of adding more geographic intelligence into the complex equation of human health and the environment.

2.2.3 Data merging

The three multispectral bands *viz.* Red, Green and NIR were merged with the PAN band of the ETM^+ landsat data [IRS LISS-III(23.5m MSS) + Landsat ETM^+(10m PAN)] to make easy the boundary extent more visibility applying Intensity-Hue-Saturation (IHS) transformation technique. The IHS transformation is one of the most common methods used for data merging that offers the improvement that the separate channels outline certain color properties, namely intensity (I), hue (H), and saturation (S) where intensity describes the total color brightness and exhibits as the dominant component. This transformation consists of two basic steps. In the first step, RGB color values for three selected TM multispectral bands *viz.* Red, Green and NIR bands are converted to hue, saturation and intensity color components with the help of mathematical functions. The higher-spatial resolution image is constantly stretched in order to adjust the mean and variance to unit intensity. The second step is the substitution of the stretched panchromatic image for the intensity component of IHS and retransformation to RGB. The merged image was shown in the Figure 4.

2.3 Classification

The geometrically rectified FCC image was subjected to the process of classification using sequential steps by unsupervised and fuzzy technique. Then merged FCC was subjected to a reference template for the classification accuracy assessment. Initially, the image was classified by unsupervised method to separate the pixels of the image into different spectral clusters representing various land use and vegetation cover types.

2.3.1 Unsupervised classification

Here the numerical information in the spectral data classes were grouped first and further matched by the analyst to information classes. Clustering algorithms were used to determine the natural groupings or structures in the data where we specified the clusters to be looked for in the data, the parameters related to the separation distance among the clusters and the variation within each cluster. The iterative clustering process resulted in some clusters that were combined further to obtain meaningful classes.

2.3.2 Fuzzy-based classification

Since a certain data point that lied close to the center of a cluster will have a high degree of belonging or membership to that cluster and another data point that lied far away from the center of a cluster will have a low degree of belonging or membership to that cluster. It had been started with an initial guess for the cluster centers, which are intended to mark the mean location of each cluster where the guess is most likely incorrect. By iteratively updating the cluster centers and the membership grades for each data point, it moved the cluster centers to the right location within a data set. This iteration were based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point's membership grade. Classification was conducted by the ERDAS Imagine and Matlab. Matlab's Fuzzy logic toolbox needs two parameters for the valid membership function definition viz., mean and standard deviation value which were obtained from the unsupervised classification. The following two equations (Equation 1 and Equation 2) describe the fuzzy parameters of the training data:

$$\mu_c^* = \frac{f_c(x_i)x_i}{\sum_{i=1}^{n} f_c(x_i)}$$

Equation 1

$$\sum\nolimits_c^* = \frac{\sum_{i=1}^{n} f_c(x_i)(x_i-\mu_c^*)(x_i-\mu_c^*)^T}{\sum_{i=1}^{n} f_c(x_i)}$$

Equation 2

Where, μ_c^* is the fuzzy mean of training class c; $\sum_c^*$ is the fuzzy covariance of training class c; x_i is the vector value of pixel *I;* $f_c(x_i)$ is the membership of pixel x_i to training class c; n is the total number of pixels of the training data; T is the Transpose of the Matrix. In order to find the fuzzy mean (Equation 1) and fuzzy covariance (Equation 2) of every training class, it must know the membership of pixel x_i, to training class c first. In this study, the membership function is defined based on the conventional maximum likelihood classification algorithm with fuzzy mean and fuzzy covariance (Maximum likelihood Classification is a statistical decision criterion to assist in the classification of overlapping signatures and pixels are assigned to the class of highest probability).

$$f_c(x_i) = \frac{P_c^*(x_i)}{\sum_{i=1}^{m} P_c^*(x_i)}$$

Equation 3

Where, $P_c^*(x_i) = (2\pi)^{-N/2}\left|\sum\nolimits_c^*\right|^{-1/2} e^{-1/2(x_i-\mu_c^*)^T \sum_c^{*-1}(x_i-\mu_c^*)}$.

Where, $f_c(x_i)$ is the membership of pixel x_i, to class c; $P_c^*(x_i)$ is the maximum likelihood

Figure 3: Image showing False Color Composite of the Pilibhit district

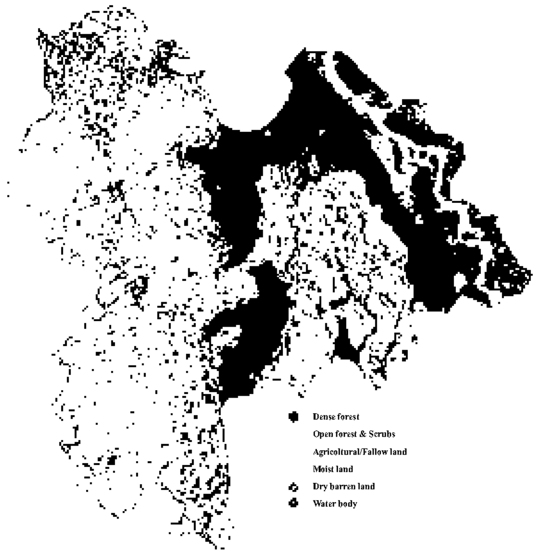

Figure 4: Image showing the Merged Imagery ETM (10m) + IRS (23.5) PAN + MSS with Random sample points overlaid on it used for classification accuracy assessment of LUVC maps derived following unsupervised and fuzzy-based classification

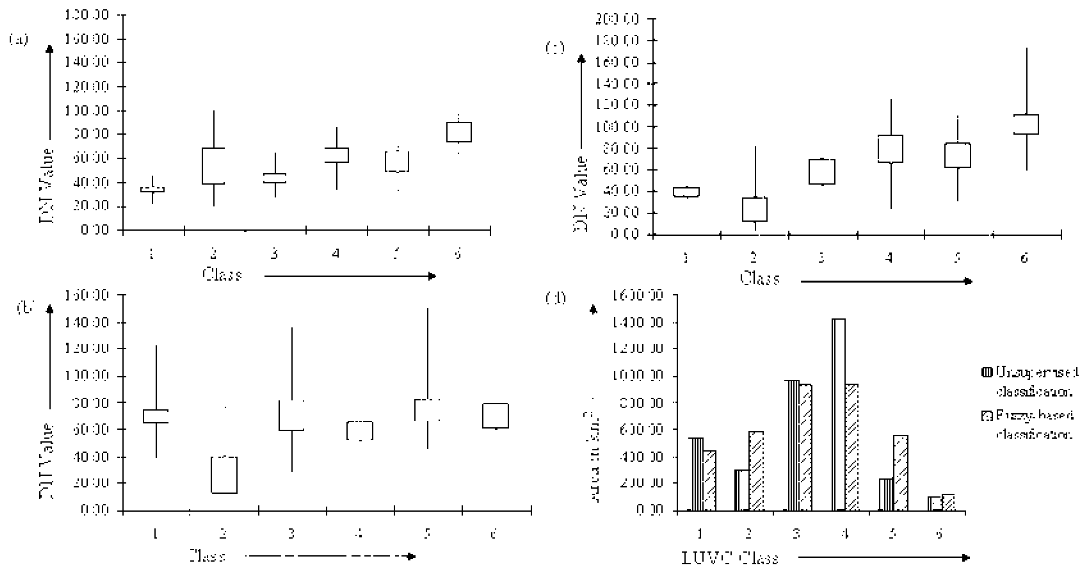

Figure 5: Showing the distribution of mean, standard deviation, minimum, and maximum DN values with respect to different classes for (a) Red band; (b) Green band; (c) NIR band. (d) Histogram showing comparison of area statistics of various LUVC classes 1, 2, 3, 4, 5 and 6 as dense forest, open forest & scrubs, agricultural/fallow land, moist land, dry barren land and water body respectively following unsupervised and fuzzy-based classification.

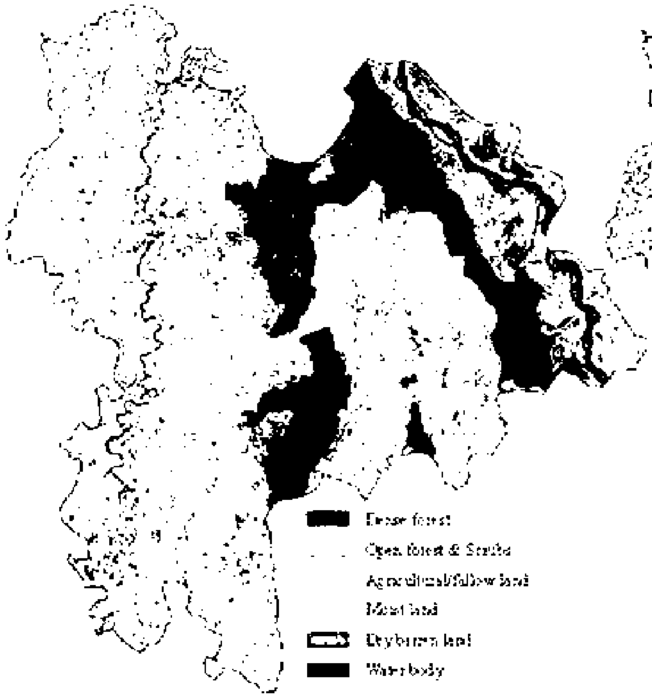

Figure 6: LUVC map using Unsupervised Classification

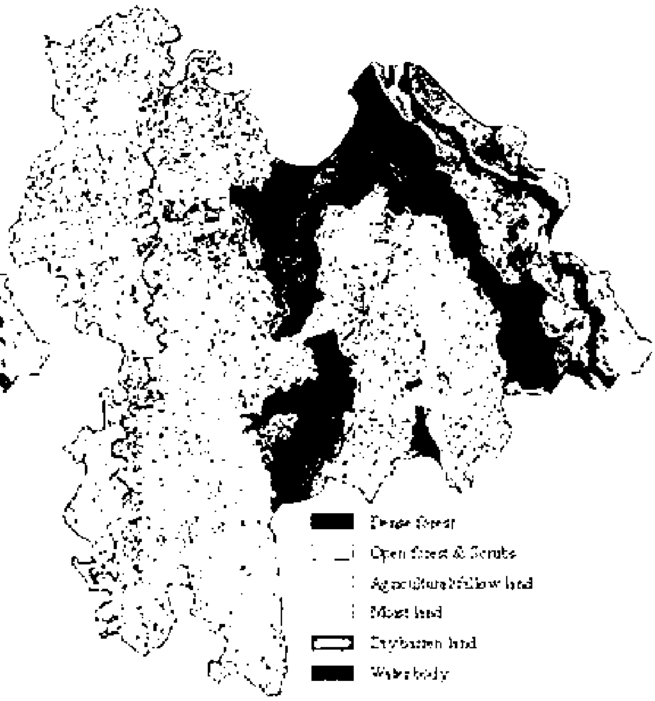

Figure 7: LUVC map using fuzzy-based Classification

3.1 Area Comparison of both Unsupervised Classification and Fuzzy-based Classification

The comparative area estimates is given in Table 3 which shows a lot of variations in all land use vegetation cover classes following both classifications (Figure 5d). Due to minimum distance character in case of unsupervised classification, there might be fuzziness in classifying the boundary pixels as well as the mixed pixels which results some pixels of other classes to dense forest class have been treated as dense forest and some pixels of the open forest and scrubs might have been classified as agricultural/fallow land or moist land. On the other hand, due to assignment of the membership functions for each class in fuzzy-based classification, no other pixels have been treated as the dense forest and each pixel in the open forest, scrubs and agricultural fallow land were better classified (Table 4). As a result of which, each pixels are divided into different parts through the membership grades so that there is a minimum chance that a mixed pixel be classified as one class solely. In unsupervised classification, the open forest and scrubs occupied 8.41% of the whole area, whereas in the fuzzy-based classification, the area increased by 7.99% (Table 3). Similarly, in case of unsupervised classification, the dry barren land was 6.68% of the whole area, whereas in the fuzzy-based classification, it increased by 9.07% (Table 3).

Hence, improvements in class-wise separation were noticed and the moist land, in case of unsupervised classification, was 39.83% of the whole area while in the fuzzy classification it reduced by 13.7%. Similarly, in case of unsupervised classification, dense forest was 15.09% of whole area, whereas in the fuzzy-based classification, it was reduced by 2.72%. Hence it is an improvement of the result that each pixel in the moist land has been classified to different classes. The accuracy assessment shows that the fuzzy-based classification provides better classification accuracy as compared to the unsupervised classification (Table 2). The data merging technique here helps to provide a reference template for which we could check the classification accuracy assessment for both the classification technique. Due to the similarity in the properties of color, tone, texture of moist land and dry barren land, in unsupervised classification, all these three classes are showing a great disorder of classification where the pixels that were remained as unclassified. On the other hand, due to the membership function each pixel has been classified in appropriate manner in case of fuzzy-based classification. All these details addressed by the matrix analysis (Table 4) that gives the distribution of areas in km^2 to different classes for both the classifications which were discussed as follows;

3.1.1 Dense forest

416.3 km^2 areas of dense forest class were constant in both the classifications as revealed in Table 4. An over estimation area of dense forest was seen in case of unsupervised classification due to spectral mixing of open forest and scrubs (111.66 km^2) and agricultural/fallow land (9.77 km^2) classes which was rightly taken care in fuzzy classification. It was also seen that there is an intermixing between vegetation classes *i.e.,* open forest and scrubs and the fuzzy membership functions has accepted an extra area of 27.67 km^2 which was otherwise classified by the unsupervised classification (Table 4).

3.1.2 Open forest and scrubs

243.42 km^2 areas of open forest and scrubs class were common to both the classifications as exposed in Table 4. An over estimation area of open forest and scrubs was seen in case of unsupervised classification due to spectral mixing of agricultural/fallow land (29.86 km^2) class which was precisely taken care in fuzzy classification. It was also seen that there is an intermixing between vegetation classes *i.e.,* agricultural/fallow land (120.49 km^2) and moist land (112.59 km^2) and the fuzzy membership functions has accepted these additional areas which was otherwise classified by the unsupervised classification (Table 4).

3.1.3 Agricultural / fallow land

670.91 km^2 areas of agricultural/fallow land class were general to both the classifications as showing in Table 4. An over estimation area of agricultural/fallow land was seen in case of unsupervised classification due to spectral mixing of open forest and scrubs (120.49 km^2), moist land (133.87 km^2) and dry barren land (42.56 km^2) classes which was precisely taken care in fuzzy classification. It was also seen that there is an intermixing between vegetation classes i.e., open forest and scrubs (29.86 km^2) and moist land (217.77 km^2) and the fuzzy membership functions has accepted these additional areas which was otherwise classified by the unsupervised classification (Table 4).

3.1.4 Moist land

769.34 km^2 areas of moist land class were constant to both the classifications as viewing in Table 4. An over estimation area of moist land was seen in case of unsupervised classification due to spectral mixing of open forest and scrubs (112.59 km^2), agricultural fallow land (217.66 km^2), dry barren land (310.52 km^2) and water body (18.59 km^2) classes which was rightly taken care in fuzzy classification. It was also seen that there is an intermixing between vegetation classes *i.e.,* agricultural/fallow land (133.87 km^2) and dry barren land (27.21 km^2) and the fuzzy membership functions has accepted these additional areas which was otherwise classified by the unsupervised classification (Table 4).

3.1.5 Dry barren land

205.4 km^2 areas of dry barren land class were general to both the classifications as revealed in Table 4. An over estimation area of dry barren land was seen in case of unsupervised classification due to spectral mixing of moist land (27.21 km^2) and water body (6.45 km^2) classes which was rightly taken care in fuzzy classification. It was also seen that there is an intermixing between vegetation classes *i.e.,* agricultural/fallow land (42.56 km^2), moist land (310.52 km^2) and water body (5.55 km^2) and the fuzzy membership functions has accepted these additional areas which was otherwise classified by the unsupervised classification (Table 4).

3.1.6 Water body

95.56 km^2 areas of water body class were constant to both the classifications as exposed in Table 4. An over estimation area of water body was seen in case of unsupervised classification due to spectral mixing of moist dry barren band (5.55 km^2) class which was rightly taken care in fuzzy classification. It was also seen that there is an intermixing between vegetation classes *i.e.,* moist land (18.59 km^2) and dry barren land (6.45 km^2) and the fuzzy membership functions has accepted these additional areas which was otherwise classified by the unsupervised classification (Table 4).

Table 3: Comparative Area estimation of land cover classes following fuzzy and unsupervised classification. % of area is shown in parenthesis

Class names	Area (in km^2) using unsupervised classification	Area (in km^2) using fuzzy-based classification	Difference (in %)
Dense forest	541.54(15.09)	443.97(12.38)	-2.72
Open forest and Scrubs	301.82(8.41)	588.30(16.40)	7.99
agricultural/fallow land	968.2(26.99)	931.37(25.96)	-1.03
Moist land	1428.8(39.83)	937.28(26.13)	-13.70
Dry barren land	239.52(6.68)	565.01(15.75)	9.07
Water body	107.68(3.00)	121.63(3.39)	0.39

Table 4: Matrix representation of classified of areas of unsupervised classification with respect to fuzzy-based classification

Classes	Dense forest	Open forest & Scrubs	agricultural/ fallow land	Moist land	Dry barren land	Water body	Unsupervised classification
Dense forest		111.66	9.77	2.25	0.92	0.64	541.54
Open forest & Scrubs	27.67		29.86	0.78	0.06	0.02	301.82
agricultural/fallow land	0.00	120.49		133.87	42.56	0.37	968.20
Moist land	0.00	112.59	217.77		310.52	18.59	1428.81
Dry barren land	0.00	0.02	0.45	27.21		6.45	239.52
Water body	0.00	0.12	2.62	3.83	5.55		107.68
Fuzzy-based classification	443.97	588.30	931.37	937.28	565.01	121.63	3587.57

Fuzzy membership function has rightly recognized the spectral intermixing between vegetation classes and classified to their true classes. The range of standard deviation and mean used formulating the membership functions. Membership function therefore has an advantage over unsupervised classification, where in the clustering and distribution often does not separate clearly between the similar classes. In other hand, fuzzy based classification is a time bound approach and therefore offers higher classification accuracy.

4. Conclusions

This study utilizes fuzzy-based classification approach, which performs better as compared to the unsupervised classification approach. The approach in terms of fuzzy-set procedures proved to be effective in implementing a simple fuzzy procedure (rules) to classify the heterogeneity areas. The approach is found to be computationally much simpler than the conventional approaches that are currently used for classification. It can incorporate collateral data easily so that some similar land covers can be classified well and it provides membership values in the classification results. In this paper, the data merging of MSS and PAN data provided the better imagery for digitization. This provided better visibility for finding out the reference template to check the accuracy assessment. This study establishes a methodology of using higher resolution satellite data to gather reference points for classification accuracy assessment of outputs derived from low resolution images, apparently substituting ground validation.

Acknowledgement

IRS Satellite data supplied by National Remote Sensing Centre (NRSC), Hyderabad for 'Biodiversity Characterization at Landscape level in UP state' Project was utilized in the study. The authors thank Dr. PS Roy, Project Director and Deputy Director, Remote Sensing and GIS Applications Area, NRSC for kindly permitting to utilize the data for the study. The Landsat ETM+ data were gathered from Global Land Cover Facility (GLCF), www.landcover.org for utilization in the work is thankfully acknowledged.

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