International Journal of Scientific Research in Computer Science, Engineering and Information Technology

© 2018 IJSRCSEIT | Volume 3 | Issue 3 | ISSN : 2456-3307

Investigating Misclassification of Semi-urban LU/ LC Features on IRS Data based on Fuzzy K-mean

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ABSTRACT

Semi-urban area is a dynamic functioning of land use as 'divide' between city and countryside (the urban fringe theory). The area under investigation is the Arasikere Semi-urban Area, located at 44km North of Hassan District, Karnataka State, INDIA with an elevation of approximately 806 m (2,644 ft) Above Mean Sea Level and is known for its coconut production. The satellite data are of multispectral image of IRS-P6 and panchromatic image of IRS-P5 satellites launched and maintained by the Indian Space Research Organization. Since all the three bands of IRS image are correlated, all bands must be filtered carefully until no correlation is present. Hard classification techniques were applied with ISODATA followed by Fuzzy K-mean unsupervised classifiers on Arasikere semi-urban area and found that hard classifiers failed to classify semi-urban area since the study area is characterized with mixed classes. Semi-urban area is difficult to be classified when "Hard Classification" is used but is good tool for homogeneous area where no mixed pixels exist.

Keywords: Remote Sensing, Semi-urban Area, Mixed Pixels, ISODATA, Fuzzy K-Mean.

I. INTRODUCTION

Image classification has become an important part in the field of Remote Sensing, Image Analysis, and Pattern Recognition. In some instances, the classification itself may form the object of the analysis. The overall objective of image classification procedures is to automatically categorize all pixels in an image into land cover classes or themes. A pixel is characterized by its spectral signature, which is determined by the relative reflectance in different wavelength bands. Multi-spectral classification is an information extraction process that analyses these spectral signatures and assigns the pixels to classes based on similar signatures [5], [3]. The classification process is based on the following assumptions: Patterns of their DN usually in multichannel data (Spectral Classification); Spatial Relationship with neighbouring pixels; Relationships between the data acquired on different dates.

In general, the classification of RS image can be seen as an iterative process in which each of its pixels is automatically assigned to one of the several predefined LU/ LC classes of interest or themes to be mapped. This is accomplished by dividing the feature space into a set of non-overlapping regions, one for each class. The themes or classes are represented by colour codes in the legend. In other words, a classifier can be defined as a function $d(x)$ defined on X such that for every x in X, $d(x) = j$ if and only if x has class j.

A classifier partitions X into disjoint subsets where members of each subset have the same class. Usually, a subset T of X is used to train the classifier, and the aim is to determine the class of a new object. Conventionally, the classification is based on a unique relationship between the LU/ LC class and its reflected radiation at certain wavelength (reflectance) contained in a spectral band of an image; in other words, it is called a one-pixel–one-class relationship. The hard classification is based on one-pixel-one-class approach and is commonly categorized into unsupervised and supervised classification methods [2]. A "hard" classification of a given pixel may fail because the spectral signature of a land cover (e.g., forest) may be too general to describe properly all the pixels considered to be a part of it (e.g., different tree species with different age, health and water content). The spectral signature is a statistical description of the reflectance of a land cover type in every spectral band considered (minimum, maximum, mean, variance, and co-variances with the other bands).

Fuzzy classification algorithms, commonly known as "soft" classifiers, have been developed and it is important to emphasize that their applicability is of even greater relevance when an image has a large proportion of mixed pixels. Compared with the conventional methods, this method improves remote sensing image classification in the aspects of: representation of geographical information, partitioning of spectral space and in the estimate of classification parameters.

The clustering algorithms can be classified into two categories namely, hard clustering and soft (fuzzy) clustering. In hard clustering, the data are divided into distinct clusters, where each datum element belongs to exactly one cluster. But in soft clustering, data elements belong to more than one cluster, and associated with each element is a set of membership levels. Fuzzy K-Means clustering algorithm subdivides a data set into k-clusters or classes. It begins by randomly assigning pixels to classes and iteratively moves the pixels to other classes with the aim of minimizing the generalized least-squared error. The Fuzzy k-means algorithm is particularly useful in circumstances where it is not reasonable to make assumptions about the statistical distributions of sample data. For each pixel a fractional value is obtained for each class in the form of a real number between 0 and 1, and will generally sum up to 1.0 across all candidate classes. To implement the fuzzy k-means algorithm, additional parameters are required to guide the partitioning process. These parameters are: selection of a distance measure and choosing a weighting exponent. The weighting exponent controls the 'hardness' or 'fuzziness' of the classification. The Fuzzy k-means classifier performed best where pure pixels are small, locating and quantifying inclusions in mixed pixels [17], [15], [13], [7].

The study area considered is Semi-urban area with its own 'landscape' with low density, apparently random, scattered or fragmented and leap fogging forms of urban land use. The satellite data are of IRS MS data with 5m and PAN data with 2.5m. The ISODATA followed by Fuzzy K-Mean hard classifiers were applied to investigate misclassification in semi-urban area. The result is a proof of good choice of study area which is characterized by mixed pixels and hence, ISODATA, Fuzzy K-Mean hard classifiers failed to classify semi-urban area with mixed pixels.

II. SATELLITE DATA METHODOLOGY

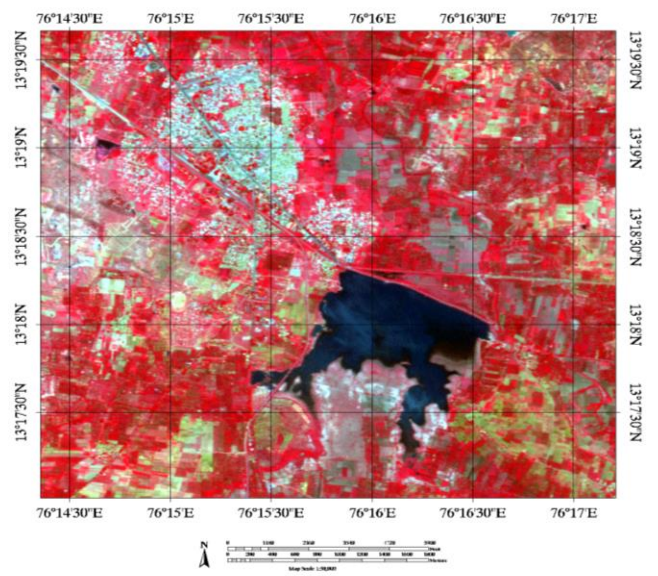


Figure 1. IRS-P6 LISS-IV Multi-spectral Satellite Image of the Arasikere Semi-urban Area.

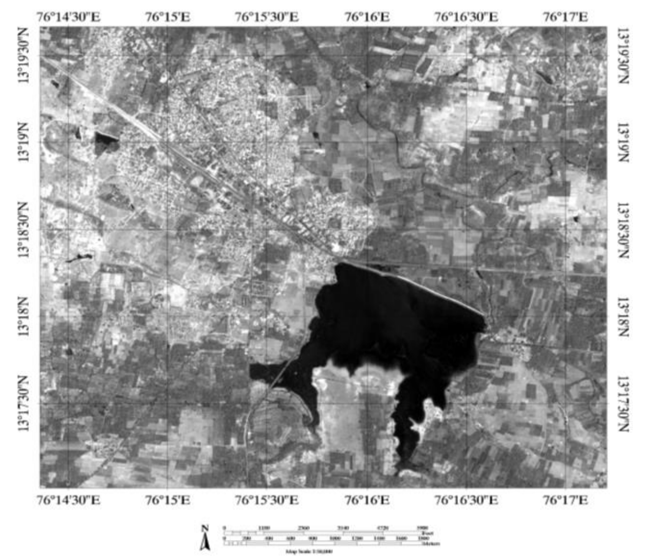


Figure 2. IRS-P5 Panchromatic Satellite Image of the Arasikere Semi-urban Area

The area under investigation was the Arasikere City, located at 44km North of Hassan District in Karnataka State, India (Figure 1 and Figure 2). This semi-urban study area is spread over a land between 13° 16′ 01.99"N - 13° 19′ 38.54′′N latitude and 76° 14′ 36.14′′E - 76° 18′ 38.67′′E longitude with an height of nearly 806 m (2,644 ft) Above Mean Sea Level (AMSL). This study area has a good mixture of spectrally overlapping classes comprising man-made structures and natural land cover features.

A. Satellite Data

The Table I provides the specification of satellite data being utilized in this study. The data products are of LISS-IV sensor multi-spectral RS image of IRS-P6 Resourcesat-I and Panchromatic RS image of IRS-P5 Cartosat-I satellites which are launched and further supervised by ISRO. These satellite data were procured from the NRSC, Hyderabad, India. IRS-P6 LISS-IV satellite data was captured on 1st June 2010 (path: 102, row: 112; 5.0 m spatial resolution) consisting of three multispectral (MS) bands recorded at Green (0.52-0.59μm), Red (0.62-0.68μm) and Infrared (0.77-0.86μm) wavelengths and IRS-P5 PANF satellite data was captured on 4th April 2011 (path: 538, row: 334; 2.5 m spatial resolution) consisting of one band recorded at 0.55-0.85μm are used in this study.

TABLE 1. CHARACTERISTICS OF THE DATA PRODUCTS IRS-P5 PAN AND IRS-P6 LISS-IV SATELLITE IMAGERY FOR SEMI-URBAN (LU/LC) STUDY SITES

Sl. No	Satellite Sensor	Date of Acquisition	Spectral Resolution	Spatial Resolution	Orbit Path/ Row
1.	IRS-P6 L4MX	01/06/2010	G: 0.52-0.59 μm R: 0.62-0.68 μm IR: 0.77-0.86 μm	5.0 m	102/112
2.	IRS-P5 PANF	04/04/2011	0.55-0.85 μm	2.5 m	538/334
3.	Topograhic Maps (Survey of India)	D43Q3 D43Q7	Scale: 1:50000	Datum: WGS84	Projection: UTM
4.	Field Data on LU/LC	2014-2016			

and projected on to UTM (zone-43) coordinate system with datum WGS 85 North projection with reference to the GPS readings taken as GCPs. To correct the images from topographic displacement, real world GCP was acquired with GPS and utilized for geo-referencing with Tie Points which are well distributed within the image. In this work, GCPs are used along with around 100 tie points for geo-referencing all the images and the registration was done with RMSE of less than a pixel. The spread of the various semi-urban LU/ LC classes with their hierarchy levels I, II and III of study area with attribute codes are shown in Table II.

TABLE 2. DETAILS OF LU/ LC CLASS HIERARCHY LEVELS I, II AND III WITH ATTRIBUTE CODES FOR THE ARASIKERE SEMI-URBAN STUDY AREA

LU/LC Code	Level-I	Level-II	Level-III
01-00-00-00-00	1. Built-up		
02-00-00-00-00	2. Agriculture		
02-01-00-00-00		2.1 Cultivated	
02-03-00-00-00		2.2 Plantations	
02-03-26-00-00			2.2.1 Coconut
02-03-27-00-00			2.2.2 Wooded
02-03-28-00-00			2.2.3 Palms
04-00-00-00-00	3.Wastelands		
04-03-00-00-00		3.1 Scrubland	
05-00-00-00-00	4. Water bodies		

(Source: Standards for Bio-geo Database-version 1, NRDMS, DST, India)

B. Proposed Methodology

The original satellite images of this semi-urban study area are full of noise especially atmospheric noise; clouds and haze, air vapour, land flooded by rains. These clouds were extracted using histogram feature extraction method. The study was intended to be carried out on a higher spatial resolution, so one has to rely on data merging. The sole intention of image fusion is to merge IRS images with the PAN image to derive increased spatial resolution from 5 m to 2.5 m and spectral information from the fused data than the single data alone. Once the images are filtered and co-registered they are ready for fusion. The resolution merging is employed with three conventional resolution merging techniques namely, Principal Component Analysis, Multiplicative Technique and Brovey Transformation. Based on the histogram statistics of the bands of the merged image, Brovey Transform was found to be the best result with the lowest standard deviation. Further, this filtered, noise free, Brovey Transformed image is used to perform ISODATA and Fuzzy K-mean unsupervised classification. The methodology developed to study filtering, resolution merging; ISODATA and Fuzzy K-mean mis-classification in semi-urban area is shown in Figure 3.

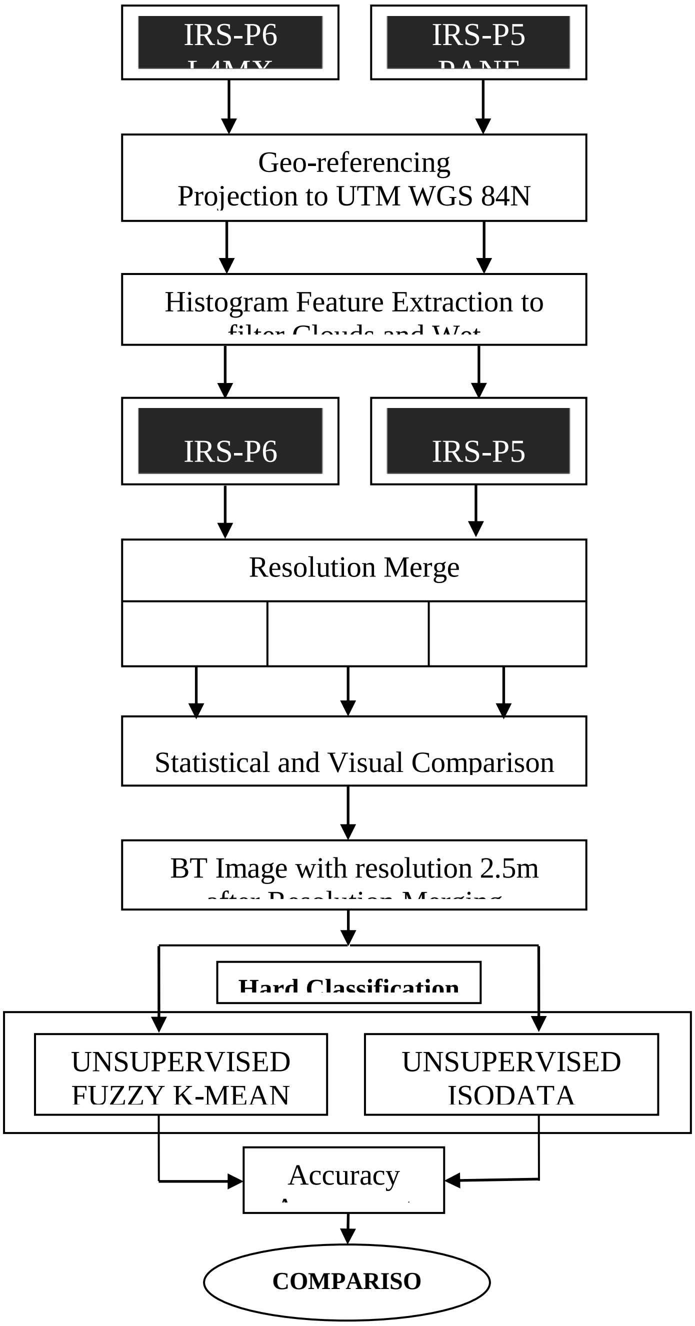


Figure 3. Flowchart developed to study filtering, resolution merging, ISODATA and Fuzzy K-mean mis-classification in semi-urban area

III. IMPLEMENTATION AND RESUTLS

A. Filtering: Cloud

The original IRS images are full of noise especially atmospheric noise; clouds and haze. These clouds were removed by applying histogram feature extraction. Figure 4 shows clouds extracted using histogram and the result shows the study area is noised by clouds. This part of the histogram must be removed. Another, confusion present in the study area is air vapour and land flooded by rains.

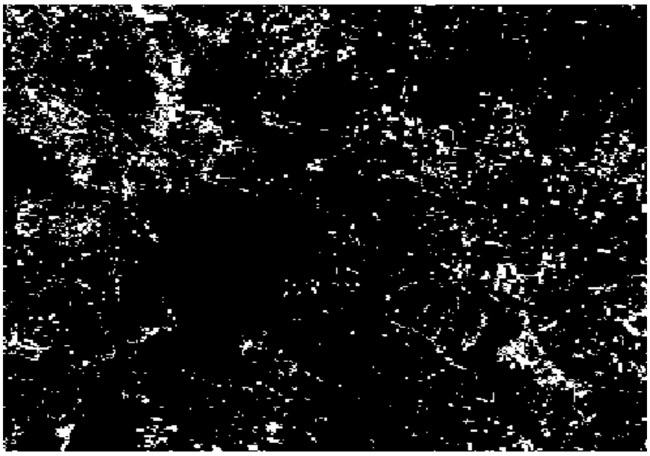


Figure 4. Clouds were extracted using the histogram; the result shows the study area is noised by clouds

The Figure 5 is the evidence for impact of the rains on built-up area causing confusion between water body, wetland and built-up area. These flooded areas are difficult to be discriminated from water body.

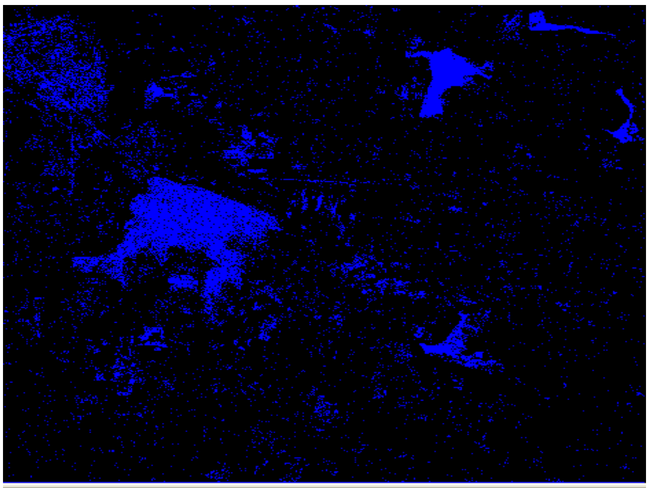


Figure 5. Rains are covering built-up area causing confusion between Water body, Wetland and Built-up area

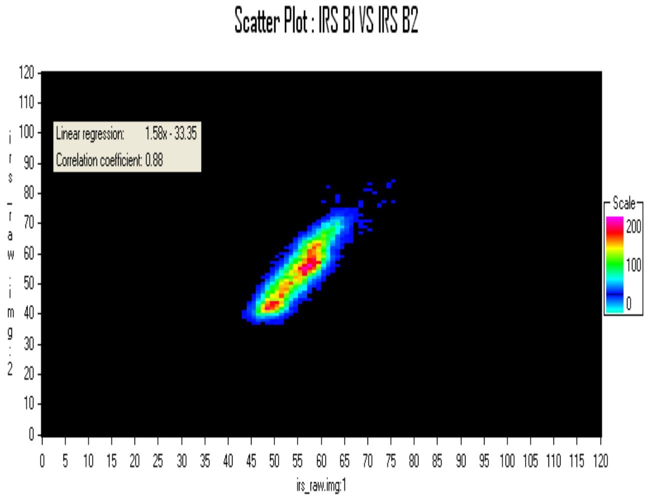


Figure 6. Scatter Plot: IRS B1 VS IRS B2

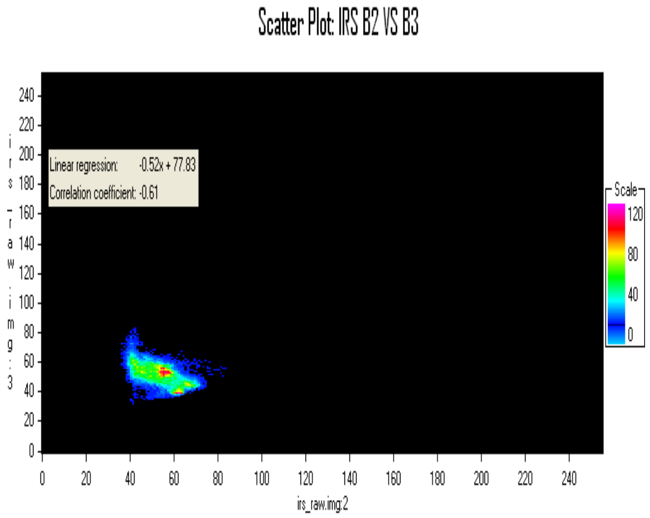


Figure 7. Scatter Plot: IRS B2 VS B3

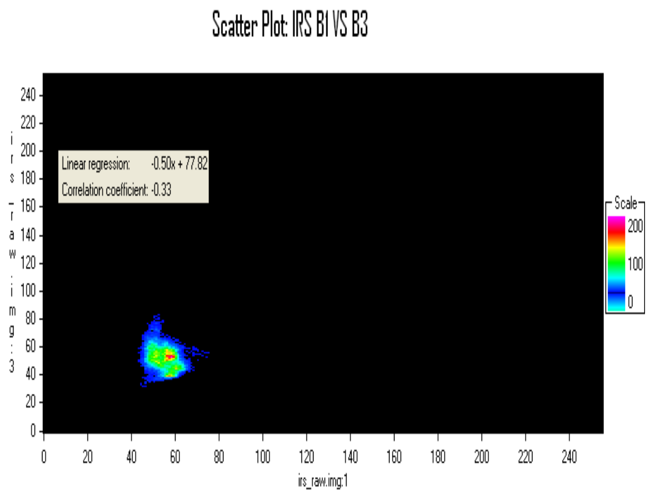


Figure 8. Scatter Plot: IRS B1 VS B3

The Figure 6 and Figure 7 reveal high correlation between B1 with B2 and between B2 with B3 bands respectively. This high correlation between different bands proves that the images are noisy. That is, there is a need for removing all suspected regions of correlation such as clouds, haze, wet areas, etc., The Figure 8 shows no correlation between B1 and B3, this means band ratios between B1 and B3 will produce beneficial results.

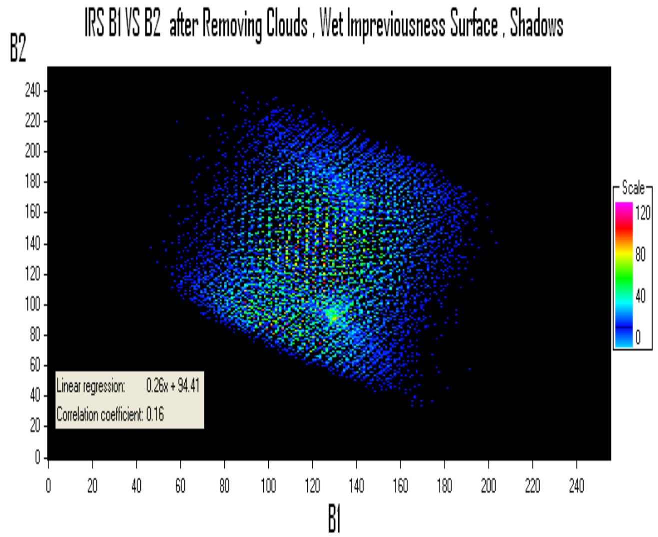


Figure 9. IRS B1 VS B2 after removing Clouds, Wet imperviousness surface, Shadows

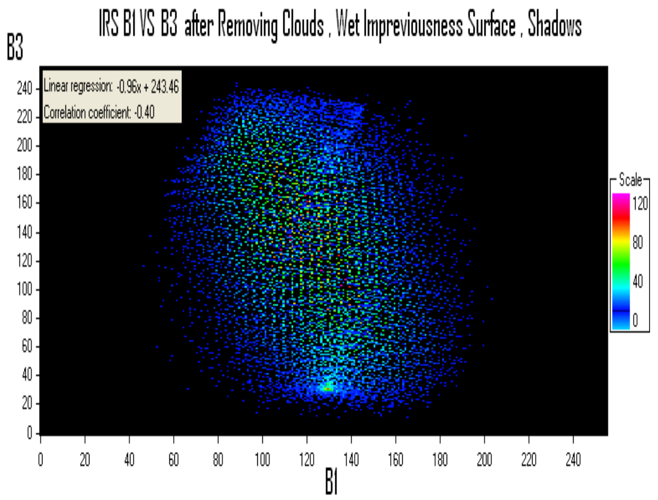
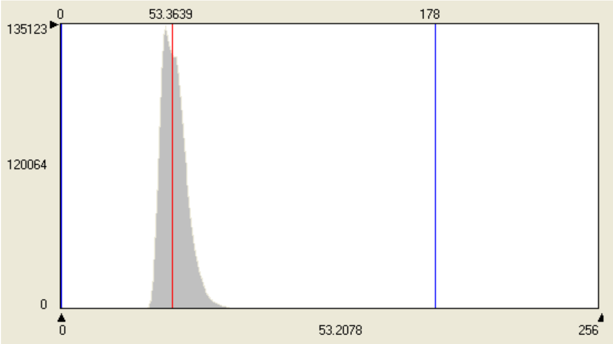
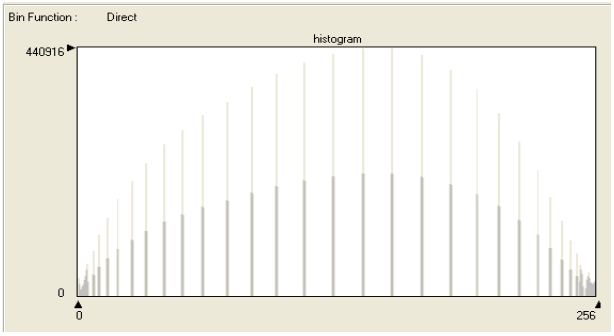


Figure 10 . IRS B1 VS B3 after removing Clouds, Wet imperviousness surface, Shadows

The Figure 9 and Figure 10 shows no correlation between B1 with B2 bands and between B1 with B3 bands respectively. This means removing all suspected regions of correlation was successful.

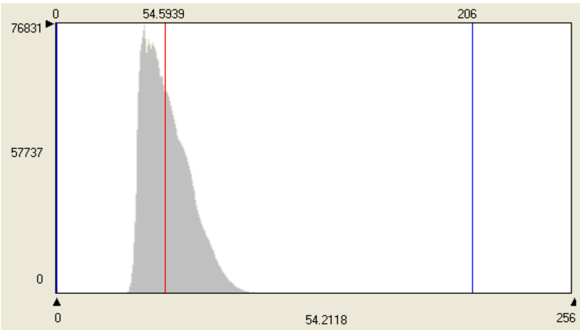


(a)

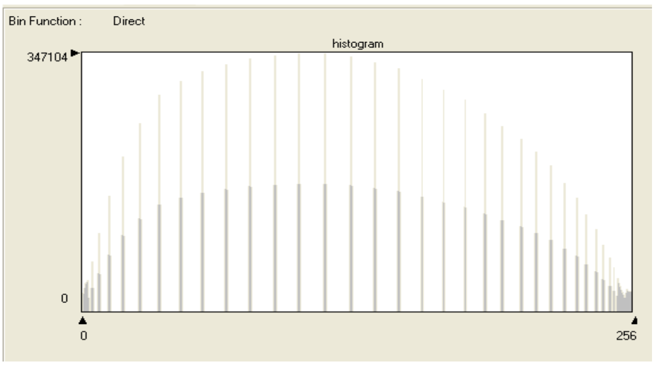


(b)

Figure 11. (a) Histogram of IRS B1 image 5m (b) Histogram of IRS B1 after filtering Clouds, Wet imperviousness surface & Shadows

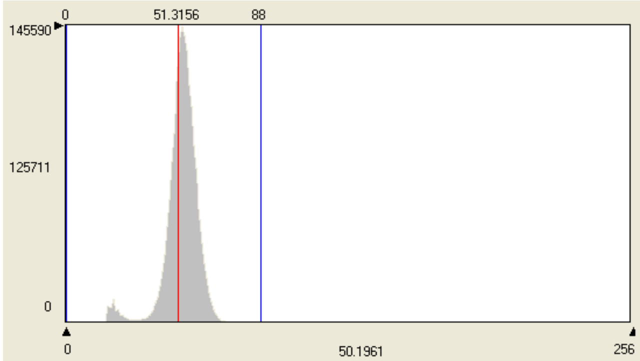


(a)

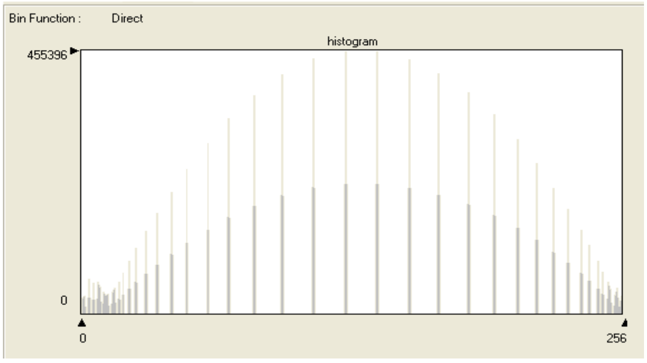


(b)

Figure 12. (a) Histogram of IRS B2 image 5m (b) Histogram of IRS B2 after filtering Clouds, Wet imperviousness surface & Shadows



(a)



(b)

Figure 13. (a) Histogram of IRS B3 image 5m (b) Histogram of IRS B3 after filtering Clouds, Wet imperviousness surface & Shadows

The Figures 11 (a), 12 (a) and 13 (a) reveal that all bands of IRS image have noises in the form of clouds and wet imperviousness surface. These clouds were detected and removed using Histogram Based Analysis Algorithm using ERDAS Modeler. The Figures 11 (b), 12 (b) and 13 (b) indicates that all bands are ready for classification since it is error free, where no correlation between different bands is existing after removing clouds and wet imperviousness surface. Further, from visual check as seen in Figure 15 compared with Figure 14, it was found that the data was free from clouds and other obscures and exhibit excellent spectral fidelity.

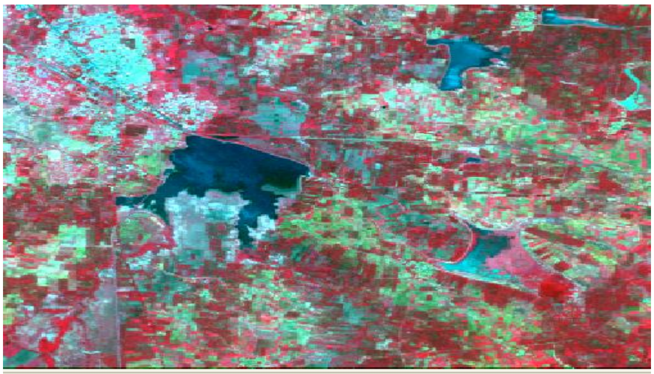


Figure 14. Raw IRS Image, full of noise

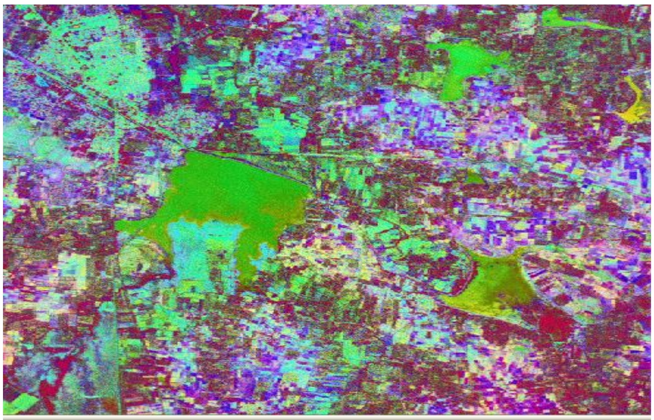


Figure 15. The final filtered image, Noise free

B. Resolution Merging

Image merging is used to merge IRS images with the PAN image to change the resolution from 5 m to 2.5 m. The resolution merging is considered with three conventional resolution merging techniques i.e., Principal Component Analysis, Multiplicative Technique and Brovey Transformation. The Table III indicates that BT exhibits the best result with the lowest standard deviation and Figure 16 shows filtered, Brovey Transformed image.

TABLE 3. HISTOGRAM STATISTICS (STD. DEV.) OF THE BANDS OF THE MULTISPECTRAL, PANCHROMATIC AND MERGED IMAGES

Bands	MS	PCA	MT	BT	PAN
Band 1	6.487	5.841	7.450	5.489	21.962
Band 2	11.727	5.785	8.477	7.219	
Band 3	8.163	21.609	8.049	6.630	

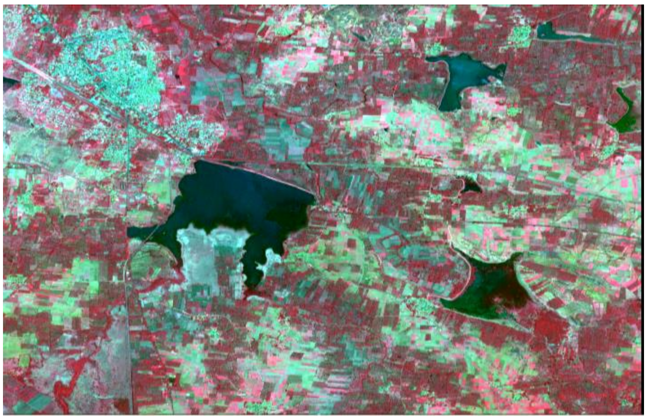
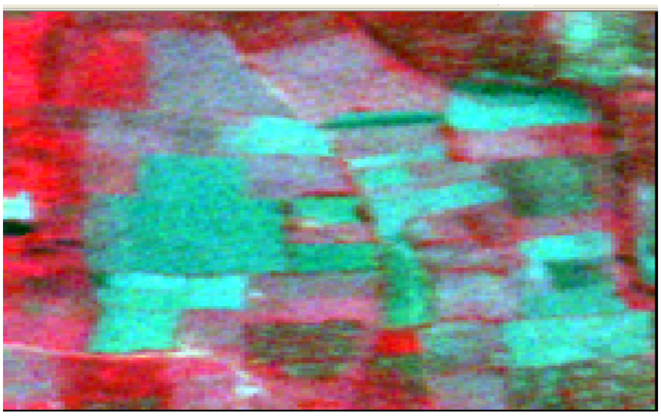


Figure 16. Filtered, Noise free, Brovey Transformed Image

(a)



(b)

(c)

Figure 17. Subset of semi-urban area (a) PAN with resolution 2.5m (b) IRS with resolution 5m (c) Brovey with resolution 2.5m after merging with PAN

The Figure 17 (a), (b) and (c) reveal, more details of semi-urban area after resolution merging using Brovey transformation. It is finally concluded that Brovey transformed image exhibits the best result with the lowest standard deviation and is used to investigate the performance of ISODATA hard classification technique.

IV. UNSUPERVISED ISODATA CLASSIFICATION

The Figure 18 shows three peaks are overlapping; Water body Peak Overlapped by Wetland Peak causing confusion (MIXED PIXELS) between water body and wetland. Wetland Peak Overlapped by Wet built-up causing confusion (MIXED PIXELS) between wetland and built-up land. It is clear that ISODATA unable to discriminate between Water / Wetland and Wetland / flooded built up area as shown in Figure 18.

The Figure 19 shows the confused water class in ISODATA. The Figure 20 shows the result of ISODATA unsupervised classified image with 10 classes. The ISODATA failed to classify cultivated area, built-up area, and coconut plantation. The ISODATA failed to discriminate between built-up area and cultivated land wherever mixed pixels are there. Further, ISODATA failed to differentiate between the overlapped classes. There is need to apply another technique to solve the problem of mixed pixels.

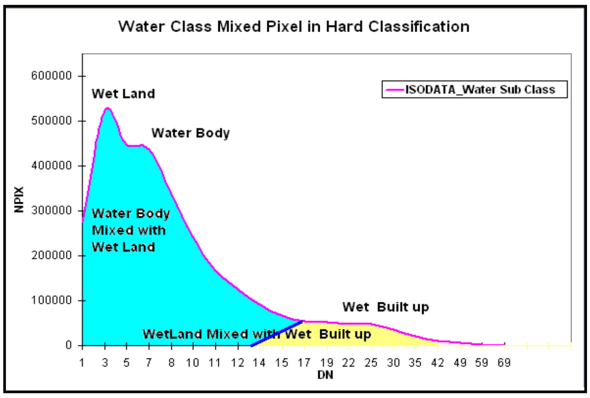


Figure 18. Histogram of water class in ISODATA

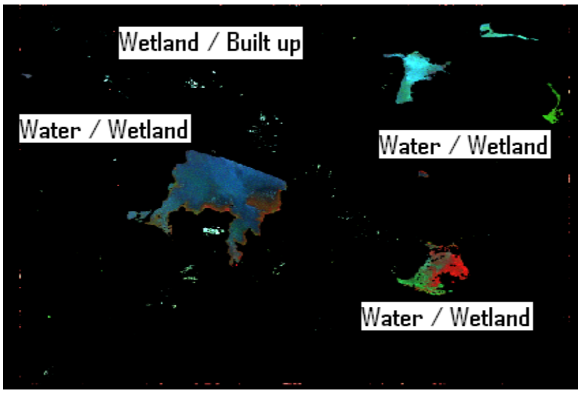


Figure 19. Confused water class in ISODATA

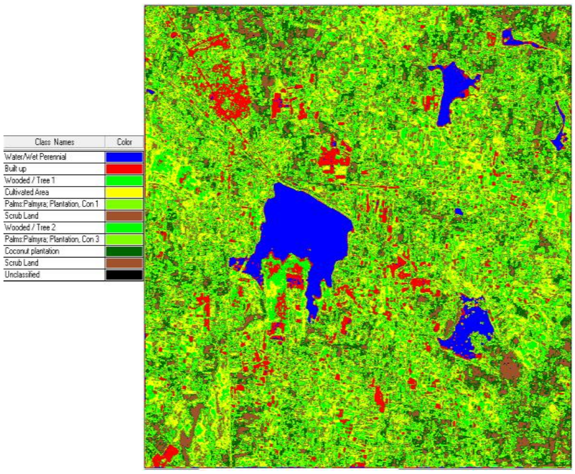
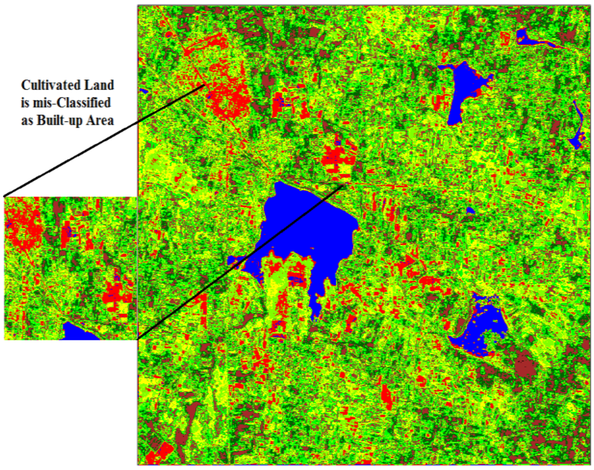
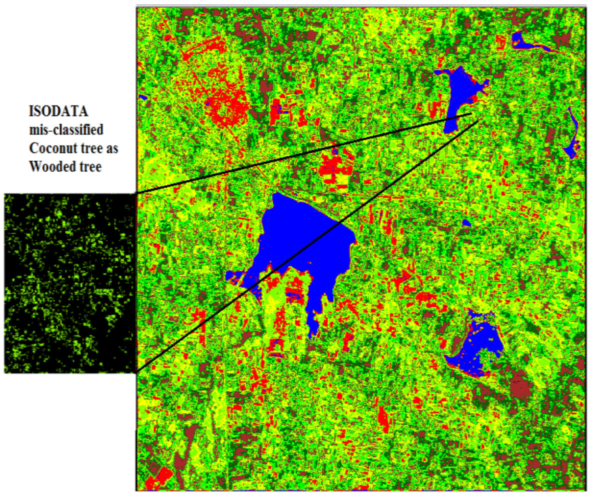


Figure 20. ISODATA Unsupervised Classified Image



(a)



(b)

Figure 21. ISODATA Misclassified (a) Cultivated Land as built-up area (b) Coconut Trees as Wooded Trees

It is clear that the cultivated area above the largest perennial closer to built-up area in the north west of the study area is misclassified and is as shown in Figure 21 (a). Also, it is clear that ISODATA failed to classify Palms with accuracy 37.5 %. Further, wooded tree was classified with low accuracy 33.33%. The reason is the confusion between coconut trees and wooded trees as shown in Figure 21 (b).

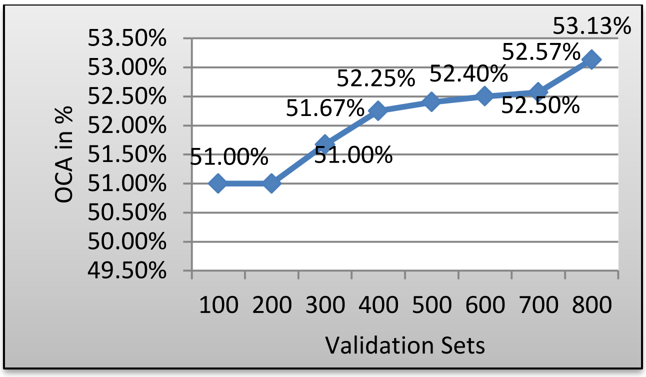


Figure 22. Plot of OCA of ISODATA at various validation sets

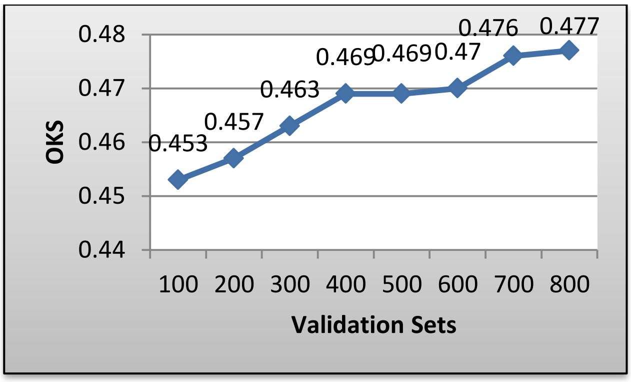


Figure 23. Plot of OKS of ISODATA at various validation sets

The Figures 22 and Figure 23 reveal that with increase of number of validation points, the ability of unsupervised ISODATA classifier is increasing.

The Table IV shows that around 30% of the study area is wet land which is an exaggerated value due to the following reasons: (1) Most of the study region is cultivated land (2) The image was taken on a rainy season where most of the impervious surface like tar roads and concrete roofs are wet with rain water. This causes confusion between wet agricultural land and water body. Also, it causes confusion between wet roads and wet roofs with wet agricultural land

TABLE 4. PERCENTAGE OF AREA IN ISODATA CLASSIFICATION

Class Name	Area_ ISODATA_Ha	Area (%)
Built up	807.78	5.11%
Coconut plantation	1239.72	7.85%
Cultivated	1481.61	9.38%

Area		
Palms: Palmyra; Plantation, Con	2807.06	17.76%
Scrub Land	2112.12	13.37%
Water/Wet Perennial	4602.44	29.12%
Wooded / Tree	2750.55	17.41%
Unclassified	0.65	0.00%
Total Area_Ha	**15801.94**	**100.00%**

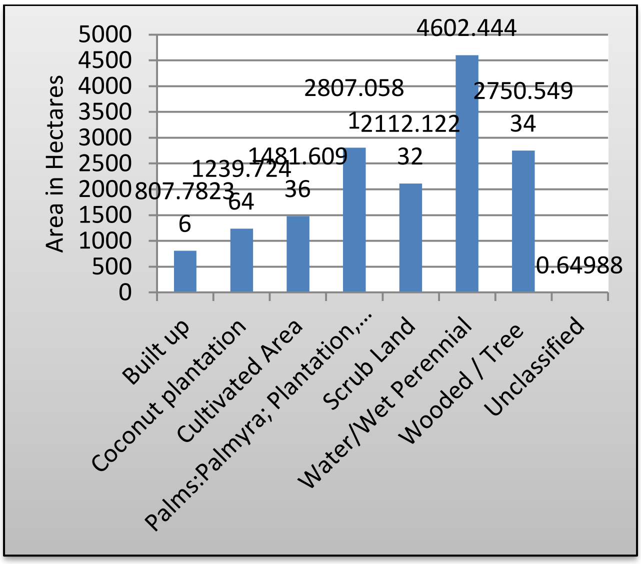


Figure 24. Plot of Area_Ha in ISODATA Interpretation

Built-up area is under estimated because of the wet roofs and wet roads that is mis-classified as wet agricultural field. The area of wooded tree is under-estimated too because of the confusion with the coconut trees. ISODATA failed to differentiate between the overlapped classes. Hence, there is a need for another technique to overcome this previous drawback and Fuzzy K-Mean classification is proposed as second level of unsupervised classification.

V. UNSUPERVISED FUZZY K-MEAN CLASSIFICATION

The Figure 25 shows the result of Fuzzy K-mean unsupervised classified image with 21 classes. Fuzzy K-mean failed to discriminate between cultivated land and built-up area as uncovered in Figure 26. The unsupervised Fuzzy K-mean classification accuracy reports that Fuzzy K-mean failed to classify Palms: Palmyra; Plantation, Con 2, Palms: Palmyra; Plantation, Con 4, Palms: Palmyra; Plantation, Con 6, cultivated area 2, coconut plantation 3 and cultivated area 3.

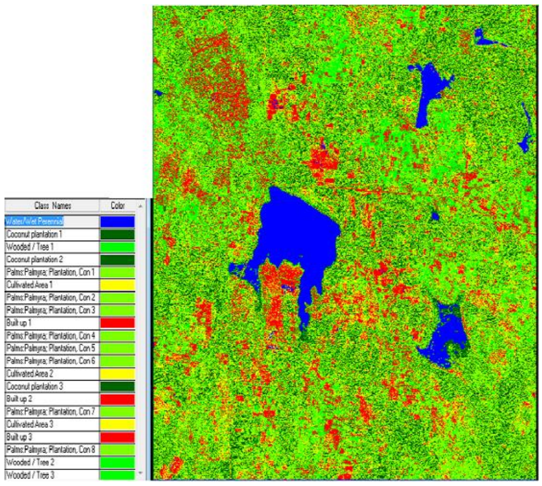


Figure 25. Cultivated Land misclassified as Built-up Area

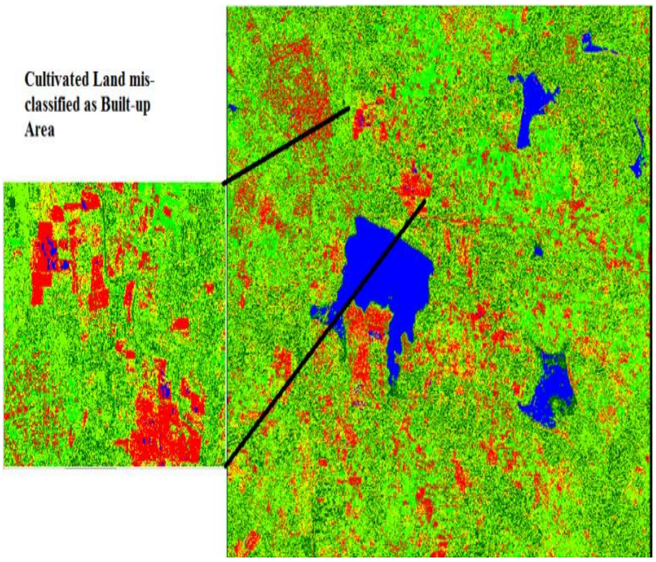


Figure 26. Fuzzy K-Mean Classified Image

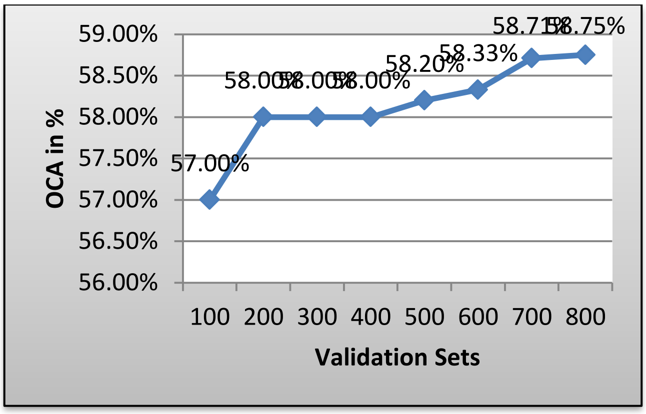


Figure 27. Plot of OCA of Fuzzy K-mean at various validation sets

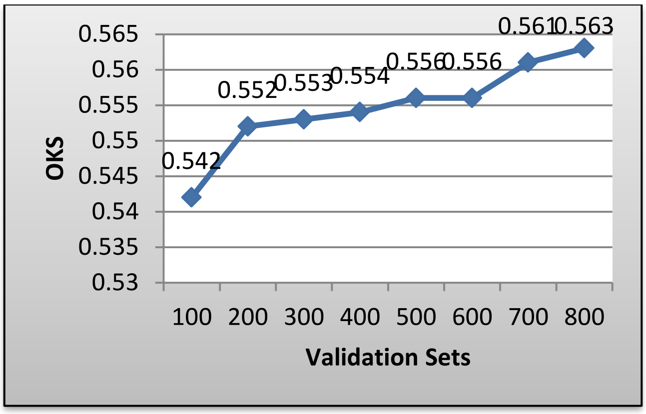


Figure 28. Plot of OKS of Fuzzy K-mean at various validation sets

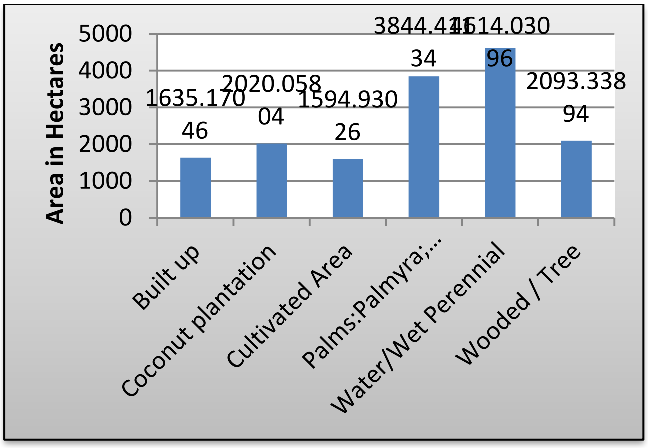


Figure 29. Plot of Area_Ha in Fuzzy K-mean Classification

The Figure 27 and Figure 28 shows that with increase of number of validation points, the ability of unsupervised Fuzzy K-mean classifier is increasing.

VI. PERFORMANCE COMPARISON OF ISODATA VERSUS FUZZY K-MEAN

The Figure 30 indicates many overlapping classifications (coconut overlapped with wooded tree), misclassifications (scrub land), as well as area of class exaggeration (wooded tree) have been done by ISODATA technique. Fuzzy K-Mean has successfully circumvented those fetal errors.

TABLE 5. PERCENTAGE OF AREA IN ISODATA V/S FUZZY K-MEAN CLASSIFICATION

Class Name	Area ISODATA_Ha	Area Fuzzy K-mean_Ha	ISODATA Area (%)	Fuzzy K-Mean Area (%)
Built up	807.78	1635.17	5.11%	10.35%
Coconut plantation	1239.72	2020.06	7.85%	12.78%
Cultivated Area	1481.61	1594.93	9.38%	10.09%
Palms: Palmyra; Plantation, Con	2807.06	3844.41	17.76%	24.33%
Scrub Land	2112.12		13.37%	
Water/ Wet Perennial	4602.44	4614.03	29.12%	29.20%
Wooded / Tree	2750.55	2093.34	17.41%	13.25%
Unclassified	0.65		0.00%	
Total Area_Ha	**15801.9**	**15801.94**	**100.00%**	**100.00%**

Figure 30. Plot of Area_Ha in ISODATA v/s Fuzzy K-mean Classification

TABLE 6. CROSS TABLE BETWEEN ISODATA CLASSES V/S FUZZY K-MEAN CLASSES

Area_ ISODATA	Area_Fuzzy_K-Mean					
	Built up	Coconut plantation	Cultivated Area	Palms: Plantation, Con	Water/ Wet Perennial	Wooded / Tree
Built up	202.42%					
Coconut plantation		162.94%				
Cultivated Area			107.64%			
Palms: Palmyra; Plantation, Con				136.95%		
Water/ Wet Perennial					100.25%	
Wooded / Tree						76.10%

From the Table VI, we observe that the built-up area estimated by Fuzzy K-mean was two times of the estimated built-up area by ISODATA. Coconut plantation estimated by Fuzzy K-mean was 1.6 times the estimated coconut plantation by ISODATA. Cultivated area estimated by Fuzzy K-mean was 1.1 times the estimated cultivated area by ISODATA. Palm trees estimated by Fuzzy K-mean were 1.4 times the estimated palm trees by ISODATA. Wet perennial/wet land estimated by Fuzzy K-mean was similar to the estimated Wet perennial/wet land by ISODATA. Wooded trees estimated by Fuzzy K-mean were three forth the estimated wooded trees by ISODATA.

VII. CONCLUSIONS

The result revealed that unsupervised ISODATA hard classification failed to discriminate between water/ wetland and wetland/ flooded built-up area. Besides the ISODATA shows the confusion between built-up area and cultivated land wherever mixed pixels exist. Further, Fuzzy K-mean unsupervised classification failed to discriminate between cultivated land and built-up area. But, many overlapping classifications (coconut overlapped with wooded tree), misclassifications (scrub land), as well as area of class exaggeration (wooded tree) have been created by ISODATA technique which were successfully circumvented by Fuzzy K-mean. It is finally, concluded that Fuzzy K-mean unsupervised classification failed to classify complete semi-urban area and succeeded only in solving those fetal errors created by ISODATA.

VIII. ACKNOWLEDGMENTS

The authors would like to graciously thank the National Remote Sensing Centre (NRSC), Hyderabad, INDIA for providing the data products for the study. Thanks also are due to the Survey of India (SOI), Bangalore, INDIA for providing the Topographic Maps for this study and Karnataka State Remote Sensing Application Centre (KSRSAC), Bangalore. The authors would finally like to thank Mr. Nasser

Mustafa Saleh Abdin, for suggestions, guidance and other contributions to this study.

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