RESEARCH ARTICLE OPEN ACCESS

Investigating ISODATA Misclassification in Semi-urban Area

A. L. Choodarathnakara[1], Dr. Jayanth J[2], Dr. Shivaprakash Koliwad[3], Dr. C. G. Patil[4] and Srikrishnashastri C[5]

1(Assistant Professor, Dept. of Electronics & Communication Engineering, Government Engineering College, Kushalnagar)
2 (Associate Professor, Dept. of E&C Engineering, GSSSIETW, Mysore.)
3 (Emeritus Professor, Dept. of Electronics & Communication Engineering, Malnad College of Engineering, Hassan)
4 (Director (R), Dept. of Space (ISRO), Master Control Facility (MCF), Hassan)
5 (Assistant Professor, Dept. of Electronics & Communication Engineering, VCET, Puttur)

Abstract:

Semi-urban area forms its own 'landscape' with low density, apparently random, scattered or fragmented and leap fogging forms of urban land use. 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 data are of LISS-IV (Linear Imaging and Self Scanning) sensor of IRS-P6 (Indian Remote Sensing Satellite) and Panchromatic image of IRS-P5 satellites launched and maintained by the Indian Space Research Organization (ISRO). The images are characterized by many noises such as, clouds, haze, roofs and roads covered by rainwater, which cause confusion between urban class, water body and wetland. Hard classification was applied with ISODATA unsupervised classification technique and result is a proof of good choice of the study area characterized with mixed classes. Hard classification is a good tool for homogeneous area where no mixed pixels exist. ISODATA hard classifier failed to classify heterogeneous nature of Arasikere Semi-urban area.

Keywords — **Remote Sensing, Semi-urban Area, Mixed Pixels, Hard Classification.**

I. INTRODUCTION

Image classification is one of the most commonly undertaken analysis of remotely sensed data. The objective of classification is to replace visual analysis of the image data with quantitative techniques for automating the identification of features in a scene. In a multi-spectral remote sensed image with 'n' bands, each pixel of the image is described by an n-dimensional vector called the pixel's spectral signature. In image classification, one considers 'k' distinct classes and looks for the best assignment of each pixel to one and only one class. Formally, an assignment of pixels is a function y such that $y_i^c = 1$ if pixel i is assigned to class c, and is 0 otherwise. In other words, pixel i belongs to class c if $y_i^c = 1$. Supervised classification techniques typically look for a partition $R_1, \ldots\ldots, R_k \subset R^n$ of the space of spectral signatures such that the best decision rule given by $y_i^c = 1$ if and only if $x^{(i)} \in R_c$ and $x^{(i)}$is the spectral signature of pixel i. If d is an approximate distance between the pixels signatures and classes, this is equivalent to minimizing the global function $D=\sum_{i,c} d_i^c y_i^c$, where, d_i^c is the distance from pixel i to class $c$and the classifiers differ in the choice of function d.

The ISODATA clustering is employed to find out the most homogenous areas and to delineate spectrally dissimilar areas in an image when nothing is known about the classes. In the migrating means (or ISODATA, or nearest mean) algorithm, the value of the function to be minimized is the average Euclidean distance between each sample point and the corresponding cluster mean. Intuitively, this is equivalent to generating spherical clusters with small variances or scatter. There is no analytical method for generating clusters that minimize the value of this function. There are a number of different forms of this algorithm, but in all of them at least two parameters must be specified by the user: the number of clusters and the maximum number of iterations. The latter parameter ensures that the method will terminate if convergence is not achieved. Moreover, unsupervised classified images may serve as an input to the succeeding stages of classification like segmentation or creating signatures for advanced classifiers.

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 hard classification was 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 ISODATA hard classifier failed to classify semi-urban area with mixed pixels.

II. SATELLITE DATA & METHODOLOGY

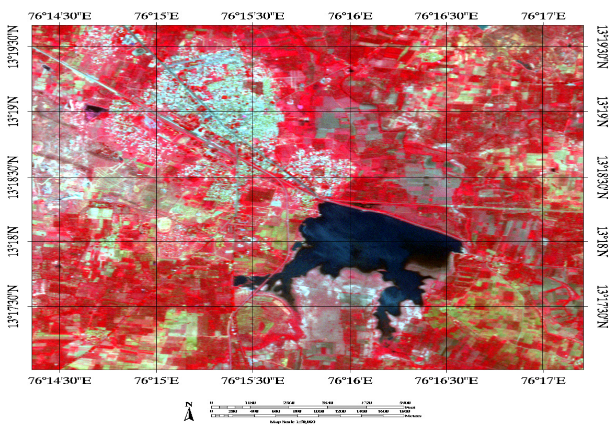


Fig. 1 IRS-P6 LISS-IV Multi-spectral Satellite Image of the Arasikere Semi-urban Area

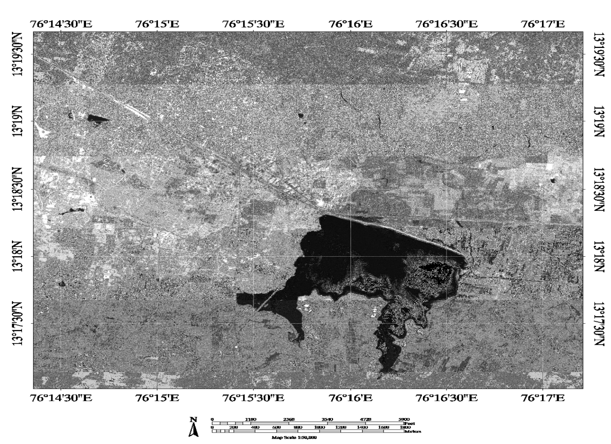


Fig. 2 IRS-P5 Panchromatic Satellite Image of the Arasikere Semi-urban Area

The area under investigation was the Arasikere City, located at 44km North of Hassan District in Karnataka State, India (Fig. 1 and Fig. 2). This semi-urban study area is spread over a land between13° 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 of man-made structures and natural land cover features.

A. *Satellite Data*

The Table I provide 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 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 one band recorded at 0.55-0.85µm are used in this study.

TABLE I
CHARACTERISTICS OF THE DATA PRODUCTS IRS-P5 PAN AND IRS P6 LISS-IVMS 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			

TABLE II
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

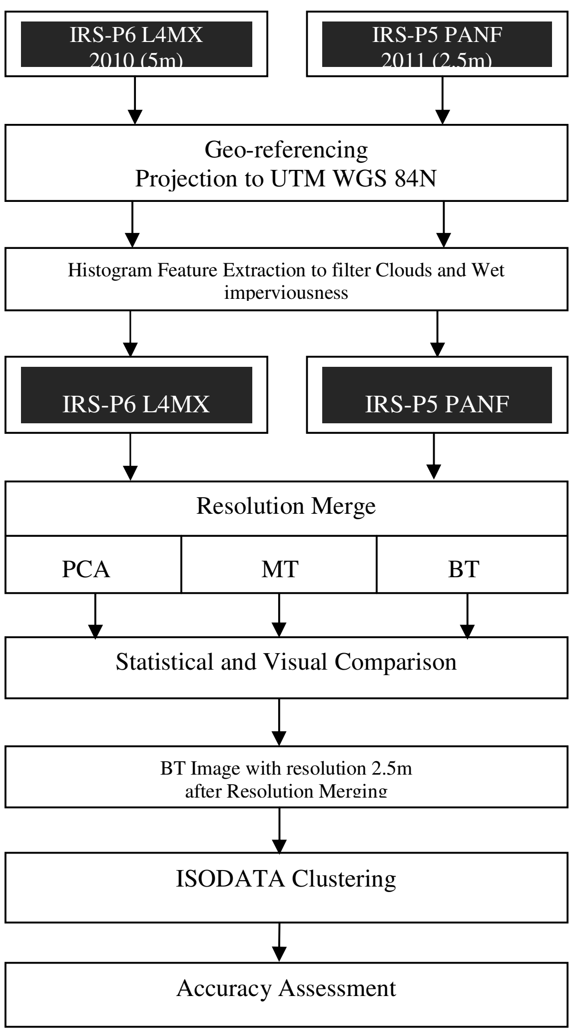


Fig. 3 Flowchart developed to study filtering, resolution merging and ISODATA mis-classification in semi-urban area

The IRS images of PAN and MS were geo-referenced 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 the Table II.

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 higher spatial resolution, so one had 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 BT. Based on histogram statistics of the bands of the merged image, BT was found to be the best result with the lowest standard deviation. Further, filtered, noise free, BT image is used to perform ISODATA unsupervised hard classification.

III. IMPLEMENTATION AND RESULTS

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. Fig. 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.

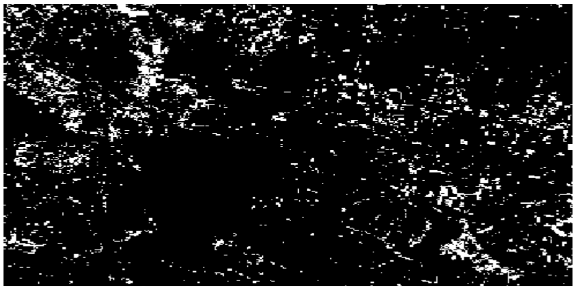


Fig. 4 Clouds extracted using the histogram; the result shows the study area is noised by clouds

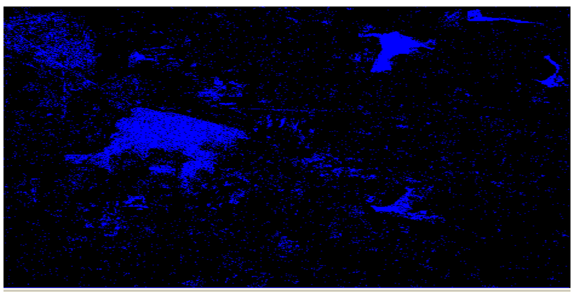


Fig. 5 Rains are covering built-up area causing confusion between Water body, Wetland and Built-up area

The Fig. 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 bodies.

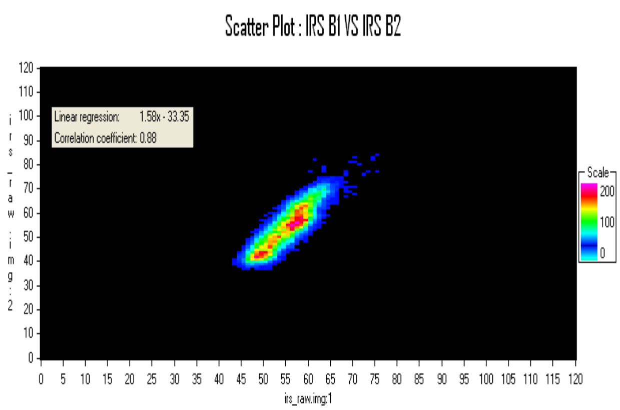


Fig. 6 Scatter Plot: IRS B1 VS IRS B2

The Fig. 6 and Fig. 7 shows 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.,

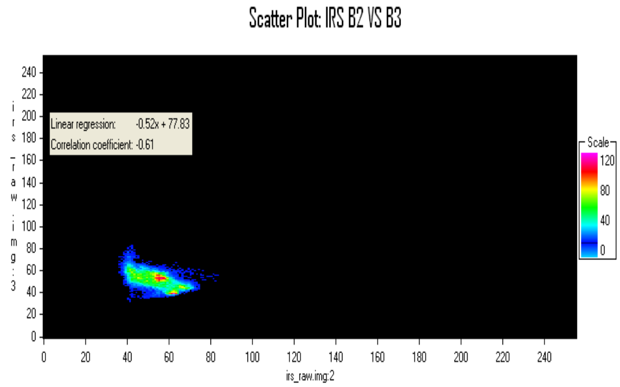


Fig 7 Scatter Plot: IRS B2 VS B3

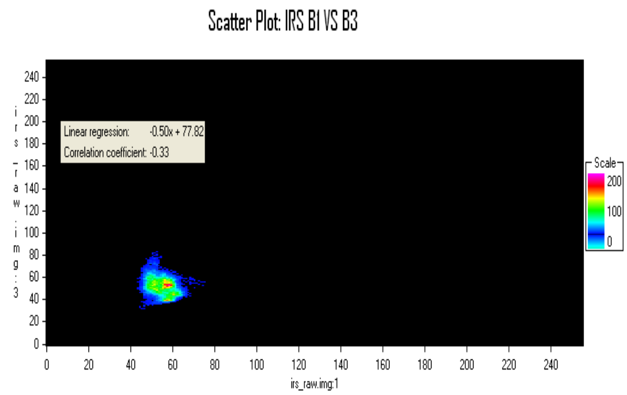


Fig. 8 Scatter Plot: IRS B1 VS B3

The Fig. 8 shows no correlation between B1 and B3, this means band ratios between B1 and B3 will produce beneficial results.

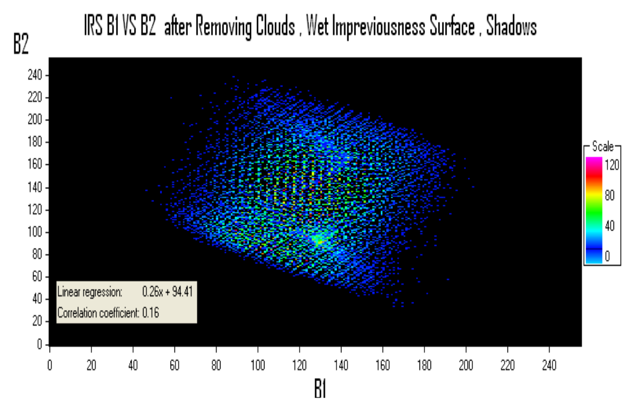


Fig. 9 IRS B1 VS B2 after removing Clouds, Wet imperviousness surface, Shadows

The Fig. 9 and 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.

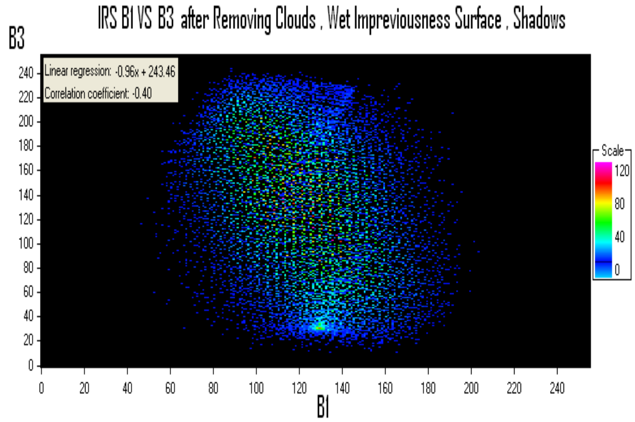
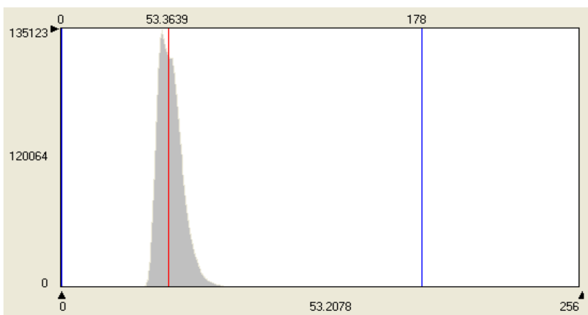
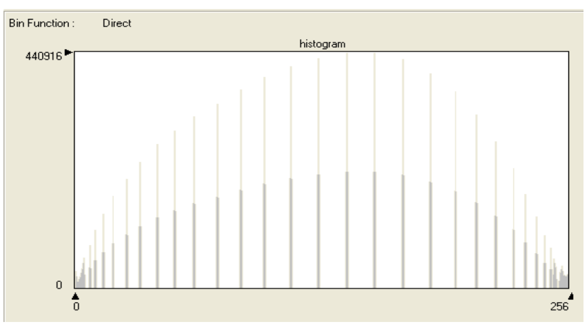


Fig. 10 IRS B1 VS B3 after removing Clouds, Wet imperviousness surface, Shadows

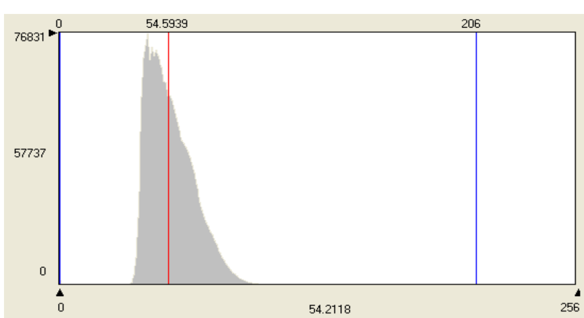


(a)

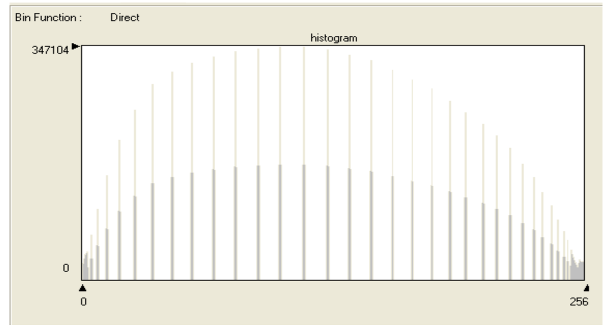


(b)

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

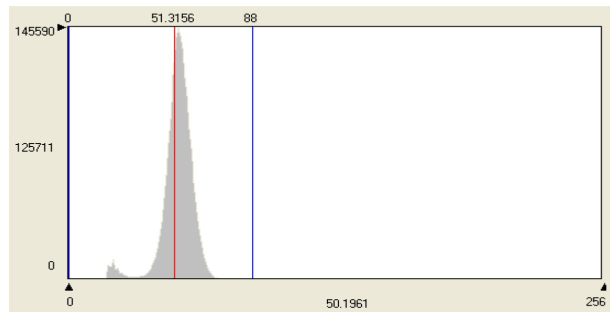


(a)

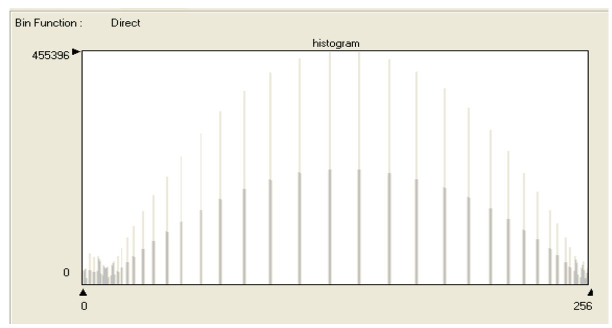


(b)

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



(a)



(b)

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

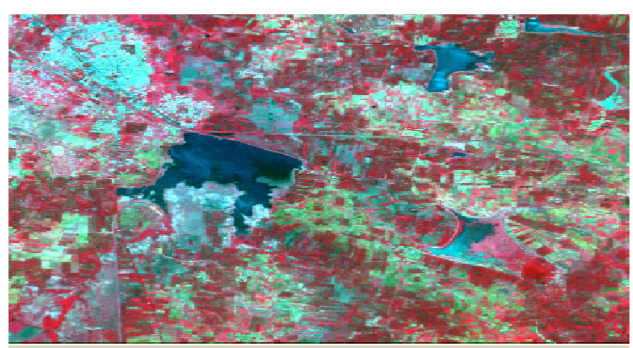


Fig. 14 Raw IRS Image, full of noise

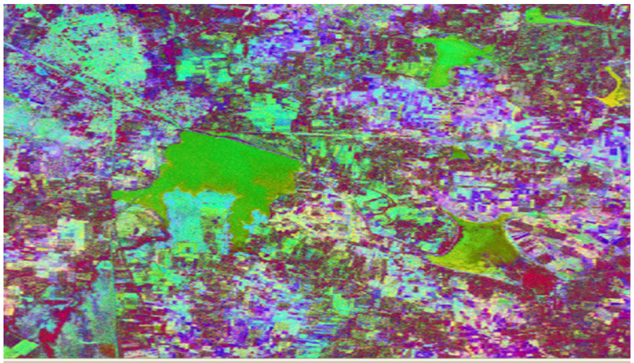


Fig. 15 The final filtered image, Noise free

The Fig. 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 Fig. 11 (b), 12 (b) and 13 (b) indicate 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. Also, from visual check as seen in Fig. 15 compared with Fig. 14, it was found that the data was free from clouds and other obscures and exhibit excellent spectral fidelity.

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 Fig. 16 shows filtered, Brovey Transformed image.

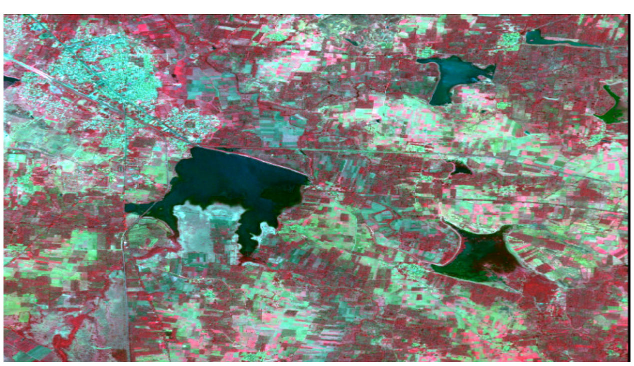
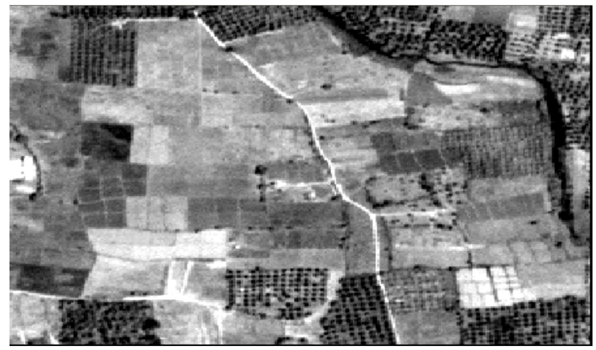


Fig. 16 Filtered, Noise free, Brovey Transformed Image

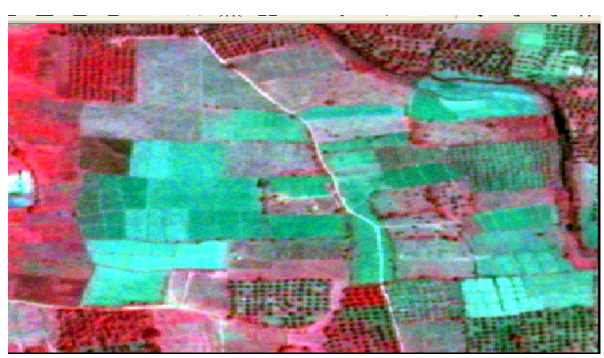
TABLE III
HISTOGRAM STATISTICS (STD. DEV.) OF THE BANDS OF THE MULTISPECTRAL, PANCHROMATIC AND MERGED IMAGES

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	



(a)

(b)



(c)

Fig. 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 Fig. 17 (a), (b) and (c) show, more details of semi-urban area after resolution merging using Brovey transformation. 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 Fig. 18 shows that 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 Fig. 18.

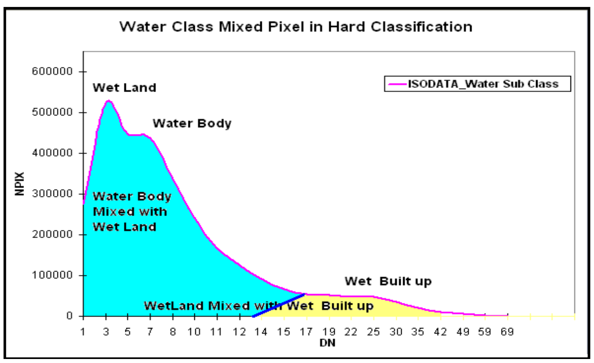


Fig. 18 Histogram of water class in ISODATA

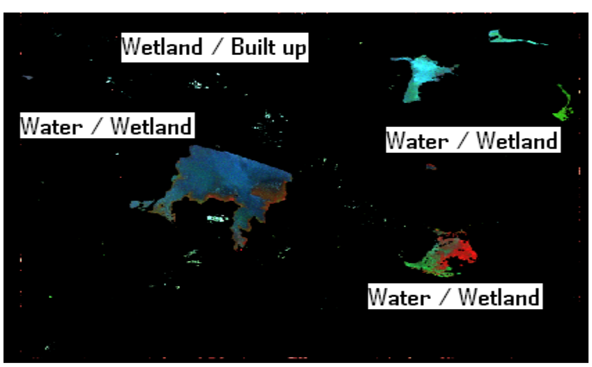


Fig. 19 Confused water class in ISODATA

The Fig. 19 shows the confused water class in ISODATA and Fig. 20 shows the result of ISODATA unsupervised classified image with 10 classes. 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 posed by mixed pixels.

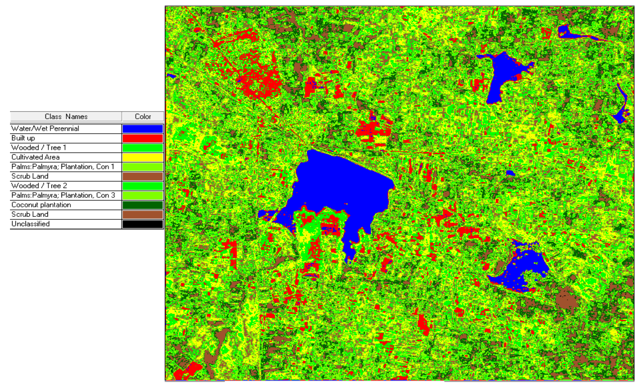


Fig. 20 ISODATA unsupervised classified image

TABLE IV
CLASSWISE PRODUCER'S ACCURACY OF ISODATA AT VARIOUS VALIDATION SETS

Class Name	**Producer's Accuracy (%)**							
	VP = 100	**VP = 200**	**VP = 300**	**VP = 400**	**VP = 500**	**VP = 600**	**VP = 700**	**VP = 800**
Water	75.00	50.00	55.56	55.26	59.57	61.22	66.10	67.21
Built up	45.45	45.00	43.48	37.93	38.71	40.48	46.43	48.39
Wooded / Tree 1	71.43	76.92	82.35	80.95	78.26	79.13	76.32	76.19
Cultivated Area	28.57	23.53	24.68	26.36	28.97	28.14	28.81	28.43
Palms: Palmyra; Plantation, Con 1	60.00	72.73	84.21	87.10	83.33	84.44	77.36	72.46
Scrub Land	100	90.00	93.33	90.48	88.00	87.50	82.22	81.03
Wooded / Tree 2	100	100	95.24	95.83	96.67	82.61	76.79	77.61
Palms: Palmyra; Plantation, Con 3	75.00	92.31	85.00	84.62	87.18	86.36	81.63	82.14
Coconut plantation	42.86	38.46	41.94	43.42	41.05	39.82	39.37	40.74
Scrub Land	100	100	100	100	100	100	80.00	66.67
Unclassified	---	---	---	---	---	---	---	---
OCA (%)	**51.00**	**51.00**	**51.67**	**52.25**	**52.40**	**52.50**	**52.57**	**53.13**

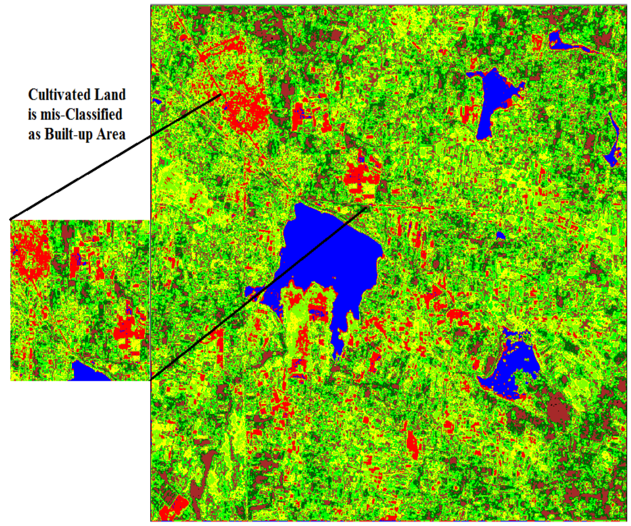
TABLE V
CLASSWISE USER'S ACCURACY OF ISODATA AT VARIOUS VALIDATION SETS

Class Name	User's Accuracy (%)							
	VP = 100	**VP = 200**	**VP = 300**	**VP = 400**	**VP = 500**	**VP = 600**	**VP = 700**	**VP = 800**
Water	100	100	100	100	100	100	100	100
Built up	62.50	52.94	38.46	34.38	32.43	38.64	47.27	48.39
Wooded / Tree 1	33.33	38.46	37.84	37.78	33.33	36.51	38.67	37.65
Cultivated Area	66.67	57.14	59.38	63.04	66.67	64.38	60.71	59.18
Palms: Palmyra; Plantation, Con 1	23.08	32.00	41.03	50.00	47.62	48.72	47.13	48.54
Scrub Land	38.46	34.62	37.84	38.78	37.29	36.84	43.02	47.00
Wooded / Tree 2	61.54	57.69	54.05	45.10	43.94	46.34	45.26	48.60
Palms: Palmyra; Plantation, Con 3	37.50	50.00	48.57	47.83	53.97	53.52	49.38	51.11
Coconut plantation	81.82	75.00	78.79	80.49	78.00	76.27	72.46	66.27
Scrub Land	50.00	57.14	44.44	46.67	47.06	45.83	41.38	45.16
Unclassified	---	---	---	---	---	---	---	---
OCA (%)	**51.00**	**51.00**	**51.67**	**52.25**	**52.40**	**52.50**	**52.57**	**53.13**

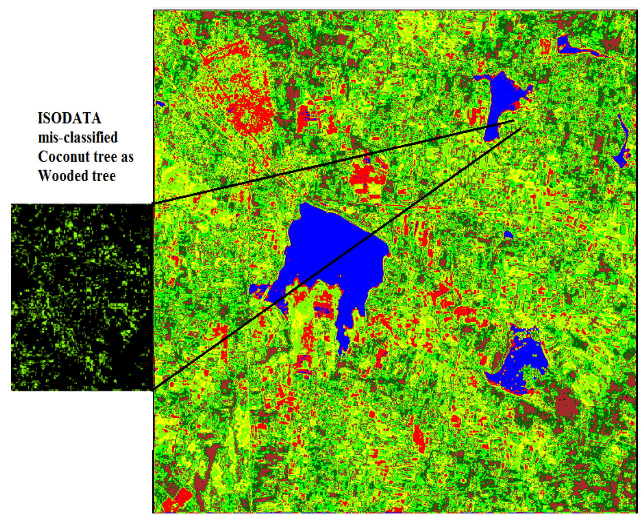
TABLE VI
CLASSWISE KAPPA STATISTICS OF ISODATA AT VARIOUS VALIDATION SETS

Class Name	Kappa Statistics							
	VP = 100	**VP = 200**	**VP = 300**	**VP = 400**	**VP = 500**	**VP = 600**	**VP = 700**	**VP = 800**
Water	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Built up	0.579	0.477	0.334	0.293	0.280	0.340	0.427	0.441
Wooded / Tree 1	0.283	0.342	0.341	0.343	0.301	0.333	0.352	0.342
Cultivated Area	0.537	0.425	0.454	0.490	0.531	0.507	0.474	0.452
Palms: Palmyra; Plantation, Con 1	0.190	0.280	0.370	0.458	0.436	0.446	0.428	0.437
Scrub Land	0.352	0.312	0.346	0.354	0.340	0.333	0.391	0.429
Wooded / Tree 2	0.582	0.543	0.506	0.416	0.404	0.419	0.405	0.439
Palms: Palmyra; Plantation, Con 3	0.349	0.465	0.449	0.442	0.501	0.498	0.456	0.474
Coconut plantation	0.770	0.689	0.733	0.759	0.728	0.708	0.664	0.594
Scrub Land	0.490	0.563	0.437	0.457	0.462	0.448	0.401	0.437
Unclassified	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
OKS	**0.453**	**0.457**	**0.463**	**0.469**	**0.469**	**0.470**	**0.476**	**0.477**

The unsupervised ISODATA classification accuracy assessment report is presented in Table IV. The Table IV reports that ISODATA failed to classify cultivated area, built-up area, and coconut plantation. The Tables V and VI show class wise user accuracy and kappa statistics for unsupervised ISODATA classification. The Table V shows that wooded tree, palm, scrubland failed to classify because overlapped area in semi-urban area due to mixed pixel.



(a)



(b)

Fig 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 Fig. 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 Fig. 21 (b).

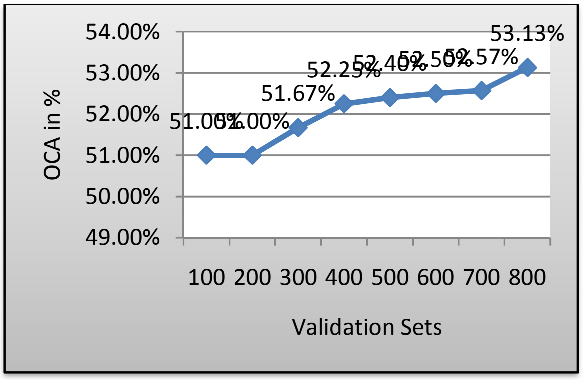


Fig. 22 Plot of OCA of ISODATA at various validation sets

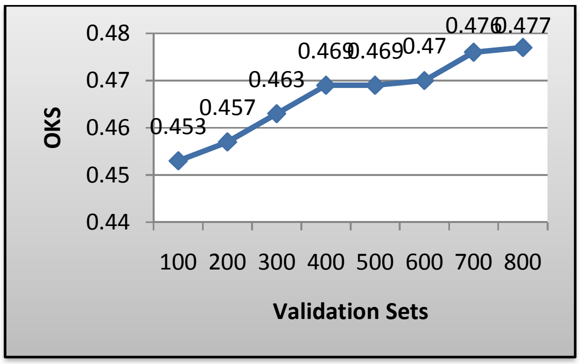


Fig. 23 Plot of OKS of ISODATA at various validation sets

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

TABLE VII

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 Area	1481.61	9.38%
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%**

The Table VII show around 30% of the study area is wet land which is an exaggerated value due to the following reasons:

- Most of the study region is cultivated land.
- The image was taken on a rainy day 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. It causes confusion between wet roads and wet roofs with wet agricultural land.

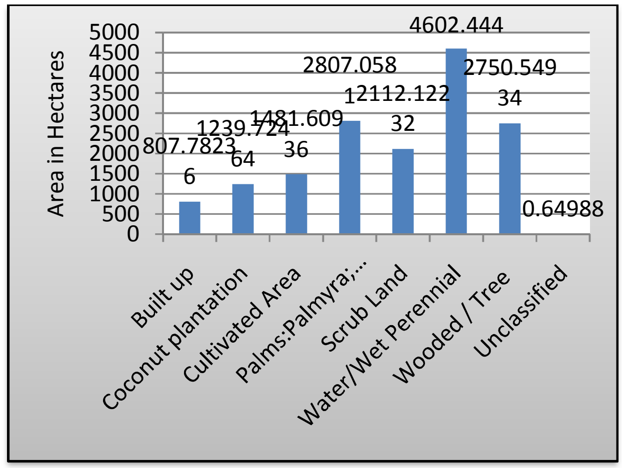


Fig. 24 Plot of Area_Ha in ISODATA interpretation

Built-up area is under estimated because of the wet roofs and wet roads that are 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.

V. Conclusions

The result shows that unsupervised ISODATA hard classification technique failed to discriminate between water/ wetland and wetland/ flooded built-up area. ISODATA also shows the confusion between built-up area and cultivated land wherever mixed pixels are there. It is finally, concluded that ISODATA hard classification failed to classify heterogeneous areas where mixed pixels exist.

ACKNOWLEDGMENTS

The authors would like to graciously thank National Remote Sensing Centre (NRSC), Hyderabad, INDIA for providing the data products for the study. Thanks are also 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.

REFERENCES

1. *Ashok Kumar T, Advanced Image Processing Techniques and Algorithms For Classification of Semi-Urban Land Use/Land Cover Features Using High Resolution Satellite Data, Ph.D. Thesis, Visvesvaraya Technological University, 2010.*
2. *Asmala Ahmad and Suliadifirdaussufahani, Analysis of LANDSAT 5TM Data of Malaysian Land Covers using ISODATA Clustering Technique, IEEE, 2012, pp. 92-97.*
3. *Bahador Khaleghi, Alaa Khamis, Fakhreddine O. Karray and Saiedeh N. Razavi, Multisensor Data Fusion: A Review of the State-of-the-Art, Elsevier, 2012, pp 2-6.*
4. *Barbara Zitova and Jan Flusser, Image Registration Methods: A Survey, Image and Vision Computing, Elsevier Publications, Vol. 21, 2003, pp. 977–1000.*
5. *Bin Wang, Atsuo Ono, KanakoMuramatsu and Nonboru Fujiwara, Automated Detection and Removal of Clouds and their Shadows from Landsat-TM Images, IEICE Transactions on Information and System, Vol. E82-D, No. 2, February 1999, pp. 453-460.*
6. *C. Pohl and J. L. Van Genderen, Multisensor Image Fusion in Remote Sensing: Concepts, Methods and Applications, International Journal of Remote Sensing, Vol. 19, No. 5, 1998, pp. 823-854.*
7. *Dengsheng Lu and QihaoWeng, Use of Impervious Surface in Urban Land-Use Classification, Remote Sensing of Envi., Elsevier, Vol. 102, 2006, pp. 146-160.*
8. *D. Lu and Q. Weng, A Survey of Image Classification Methods and Techniques for Improving Classification Performance, International Journal of Remote Sensing, Taylor & Francis, Vol. 28, No. 5, 2007, pp. 823–870.*
9. *ERDAS IMAGINE Tour Guide, ERDAS Incorporation, Atlanta, Georgia, USA, 2001.*
10. *ERDAS Field Guide, ERDAS Incorporation, Atlanta, Georgia, USA, 5th Edition, 1999.*
11. *Flavio R Dias Velasco, Thresholding using the ISODATA Clustering Algorithm, IEEE Trans. on Systems, Man & Cybernetics, Vol. SMC-10, No. 11, Nov. 1980, pp. 771-774.*
12. *Giles M. Foody, Status of Land Cover Classification Accuracy Assessment, Remote Sensing of Environment, Elsevier Publications, Vol. 80, 2002, pp. 185– 201.*
13. *Konstantinos G. Nikolakopoulos, Comparison of Nine Fusion Techniques for Very High Resolution Data, Photogrammetric Engineering & Remote Sensing, Vol. 74, No. 5, May 2008, pp. 647-659.*
14. *Luis Angel Garcia-Escudero, Alfonso Gordaliza, Carlos Matran and Agustin Mayo-Iscar, A Review of Robust Clustering Methods, Springer-Verilog, 2010, pp. 89-109.*
15. *Mahesh Pal, Factors Influencing the Accuracy of Remote Sensing Classifications: A Comparative Study, Ph. D. Thesis, University of Nottingham, May 2002.*
16. *Manfred Ehlers, Sascha Klonus, Par Johan Astrand and Pablo Rosso, Multi-Sensor Image Fusion for Pansharpening in Remote Sensing, International Journal of Image and Data Fusion, Taylor & Francis, Vol. 1, No. 1, March 2010, pp. 25–45.*
17. *Md. Khalid Imam Rahmani, Naina Pal and Kamiya Arora, Clustering of Image Data using K-means and Fuzzy K-means, International Journal of Advanced Computer Science and Applications, Vol. 5, No. 7, 2014, pp. 160-163.*
18. *Michael J Sabin, Convergence and Consistency of Fuzzy C-Means/ ISODATA Algorithms, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. Pami-9, No. 5, September 1987, pp. 661-668.*
19. *O. Duran and M. Petrou, Mixed pixel classification in Remote Sensing-Literature Survey, Technical Report VSSP-TR 1/2004, School of Electronics & Physical Sciences, University of Survey Guildford, GU27XH, United Kingdom, February 2004, pp. 1-37.*
20. *Official Website of Hassan District, www.hassan.nic.in, maintained by Hassan District Administration & Designed by National Informatics Centre, Hassan District Centre, 1st Floor, Zilla Panchayat, Hassan – 573201.*
21. *P. L. Brito and J. A. Quintanilha, A Literature Review, 2001-2008, of Classification Methods and Inner Urban Characteristics Identified in Multispectral Remote Sensing Images, Proc. 4th GEOBIA, 2012, Brazil, pp. 586-591.*
22. *P. S. Roy and A. Giriraj, Land Use and Land Cover Analysis in Indian Context, Journal of Applied Sciences 8 (8), 2008, pp. 1346-1353.*
23. *QihaoWeng, Remote Sensing of Impervious Surfaces in the Urban Areas: Requirements, Methods and Trends, Elsevier Publications, Vol. 117, 2012, pp. 34-49.*
24. *Safaa M. Bedawi and Mohamed S. Kamel, A Comparative Study of Clustering Methods for Urban Areas Segmentation from High Resolution Remote Sensing Image, IEEE, 2009, pp. 169-174.*
25. Steven J. Meeus, Semi-Urban Areas in Landscape Research: A Review, Living Rev. Landscape Res., 2, 2008, Vol. 3, pp. 1-45.
26. TanjaDuda, Morton Canty and Dieter Klaus, Unsupervised Land-Use Classification of Multispectral Satellite Images: A Comparison of Conventional and Fuzzy-Logic Based Clustering Algorithms, IEEE, 1999, pp. 1256-1258.
27. Zhijun Wang, Djemel Ziou, Costas Armenakis, Deren Li and Qingquan Li, A Comparative Analysis of Image Fusion Methods, IEEE Transactions on Geoscience and Remote Sensing, Vol. 43, *No. 6, 2005, pp. 1391-1402.*