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PER-FIELD CLASSIFICATION OF INDIAN URBAN ENVIRONMENT USING IRS-1C SATELLITE DATA

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ABSTRACT
The paper presents investigations to determine the suitability of conventional per-pixel approach and results of per-field (segment) classification for classifying Indian urban environment using high spatial resolution satellite data. Three different types of classifications were performed: the per-pixel classification, per-field GML classification and the per-field neural classification. Result showed that per-field classification improves overall classification accuracy up to 25% in comparison to per-pixel approach.

1.0 INTRODUCTION

The past five decades have seen a phenomenal increase in the growth of urban population in India. All this rapid and haphazard growth of urban sprawl and increasing population pressure is resulting in deterioration of infrastructure facilities, loss of productive agricultural lands and green open spaces besides causing air pollution, health hazards and micro-climatic changes. To address these issues effectively, one requires up-to-date and accurate data at regular intervals of time on the changing urban sprawl, urban land use, urban resources and urban environment. It is here that satellite remote sensing with its ability to provide reliable and accurate data may offers excellent possibilities to map, monitor and measure the various facets of urban development. Conventionally, land use maps derived using remote sensing data have been prepared using coarse resolution satellite data with per-pixel spectral (PPS) classifiers like minimum-distance-to-means and Gaussian maximum likelihood (GML) classification methods (Mather, 1985).

However, the levels of details that could be delineated were very limited. Later on the same techniques and features were used for classification with high-resolution satellite images of urban areas from SPOT HRV and Landsat TM sensors (Toll and Kennard, 1984). Unfortunately, the results were not encouraging. The main reasons for this apparent lack of success were that the conventional classification techniques and features were not sufficient for urban land use classification. Therefore, with the availability of high-resolution data some new alternative approaches need to be explored for information extraction.

Some of the new approaches which could be used for this purpose are based on artificial neural network, fuzzy approach, inclusion of spatial information in the classification process etc. Spatial information could be included in the form of texture or per-field basis. Inclusion of spatial information in the form of texture using the window-based approach has inherent drawback of choosing a suitable window size. The per-field or region base is important because a region as a whole contains more information than its individual pixels, but also because regions are atomic entities for structural and semantic analysis in middle and high level vision. This study presents investigation pertaining to the region-based approach of classification for a typical urban environment.

2.0 OBJECTIVE, STUDY SITE AND DATA RESOURCES

The experiments reported in this work were mainly implemented to achieve the following main objectives:

- To investigate suitability of per-pixel spectral classifier for high resolution data of urban environment.
- To investigate per-field method of incorporating spatial information in the classification process.
- To asses utility of the proposed per-field approach for classification of high spatial resolution satellite data.

The study has been carried for Lucknow city, the state capital of northern Indian state of Uttar Pradesh. It is situated in the upper Gangetic plains of the country, the geographical extent of study area lies within North latitudes $26^0 45'$ to 27^0 and the East longitudes 80^0 $50'$ to 81^0 $5'$. From the study of available maps, field visits and previous knowledge about these study sites, it was observed that for Lucknow study site 12 classes covered the majority of urban land use features (Table 1).

The satellite data products used for the study was procured from linear image self scanning (LISS)-III sensors on board IRS-1C satellite through National Remote Sensing Agency (NRSA), Hyderabad, India (Table 2). A central extract of 512 x 512 pixels covering major portion of urban areas was extracted from the satellite image for the study. In addition to these satellite data products corresponding topographic and land use maps were also used.

3.0 EXPERIMENTAL METHODOLGY

In the first part, per-pixel spectral classifications were carried out using GML approach with pure spectral features to asses its suitability for Indian urban environment. It was also intended for making comparison with the results obtained using other approaches. Initially, classification was carried out using 3 bands (B2, B3, B4) and then short wave Infra red band (SWIR) was added to see its effect on classification. The training and test pixels for different classes were selected with the help of various maps available for the city, field visits, and by employing the experience of the authors about various classes in the city. Sample size for training and test were calculated at a confidence level of 99% and a desired precision of ± 5% using equation suggested by Toratora (1976).

Table 1 Classes in the study area and their brief description

S. no.	*Name*	*Description*
1	Agriculture-1	Agriculture area having crops at middle stage of growth
2	Agriculture-2	Agriculture area having crops at early stage of growth
3	Commercial	Central business area of the city
4	Educational institutes	Various educational Institutions
5	Government establishment	Different Government establishments
6	Grassy land	Big patches of lands having grass only
7	High residential	Residential areas with more than 600 persons/hectare
8	Medium residential	Residential areas with 400 persons/hectare
9	Park	Parks for recreational activities
10	Reserve forest	A big portion of land reserved for forest
11	River	River Gomati flowing from left to right
12	Water body	Various small water bodies in the study area

Table 2 Satellite data characteristics for study area

Sensor	*Bands*	*Resolution (m)*	*Size (pixels)*	*Wavelength (μm)*	*Spectral Region*	*Path/Row Date*
LISS III	B2	23.5	512 x 512	0.52-0.59	Green	100/52
	B3	23.5	512 x 512	0.62-0.68	Red	
	B4	23.5	512 x 512	0.77-0.86	NIR	
	B5	70.5*	512 x 512	1.55-1.70	SWIR	
PAN	-	5.8	2048 x 2048	0.50-0.75	Panchromatic	

* resampled to 23.5 m.

Experimental methodology for per-field based classification is divided into four stages i.e. Determination of threshold, segmentation of imagery, refinement of segmented imagery followed by classification based on per-field approach (Figure 1). For finding threshold for a given spectral band, an approach modified after Nagao and Matsuyama (1980) was implemented. The investigations used three different thresholding methods, namely Otsu (1979), Trussel (1979) and Kapur *et al*. (1980). These algorithms were applied using a sliding window approach with 5x5 window size. Using thresholds obtained by using the aforementioned approach, the spectral bands were subjected to segmentation. There are two types of image segmentation that are based on detection of boundary or growth of region (Nevatia, 1982; Choo *et al*., 1990).

A region-based approach was preferred because finding precise edges in such images is extremely difficult. The approach calculates a merge-score. A merge-score less than one indicates a preference for merging, while values greater than one dictates against merging. It is possible to incorporate many segment attributes to determine the merger of segments. The segmentation algorithm operates in two phases. In the first phase, initial segments were grown from randomly selected seed pixels. After that the second phase started from the first pixel in the image by scanning from left to right and top to bottom. The second phase considered all those pixels that were not included in segments grown during the first phase.

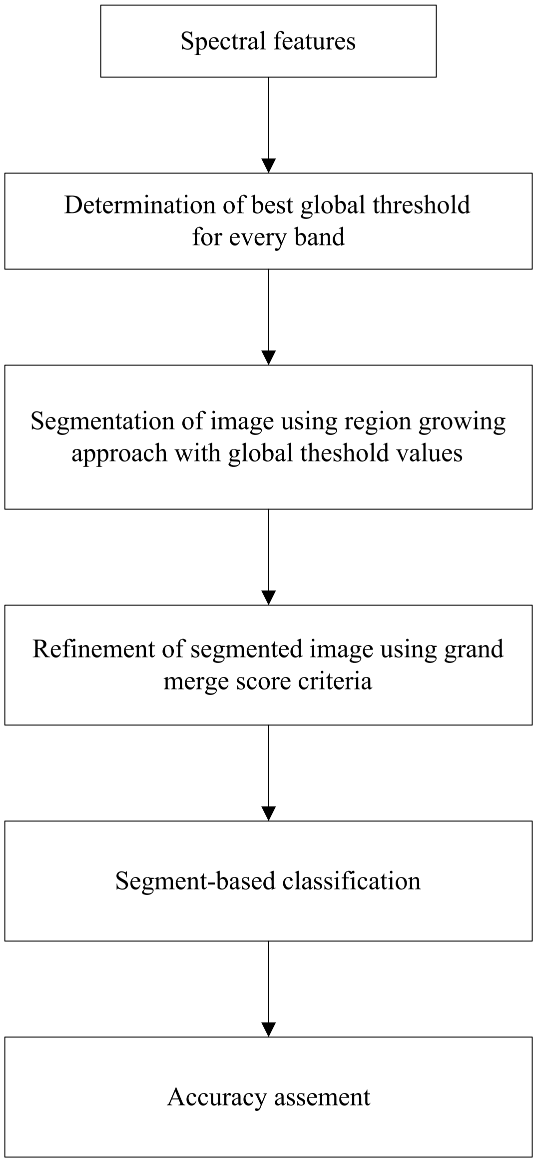

Figure1 Overall methodology for per-field classifications

The output of this process was a label image with a label number assigned to each segment. The label image obtained as a result of the initial segmentation was refined iteratively using region-merging approach proposed by Beveridge *et al*. (1989). After getting refined label image, various properties of segments like, minimum, maximum, mean, median, standard deviation, covariance, kurtosis and skewness values were calculated from spectral values of segments. Apart from these measures, texture measures *Mean*, *Con* and *Entropy* (Haralick *et al*., 1973) were also calculated.
In the final stage, these segments were classified using various spectral and textural properties of segments. Textural properties like standard deviation (SD), GLCM texture feature *Mean* were used. Three different types of classifications were performed, the per-pixel GMLC, perfield GMLC and per-field classification. For neural classification, Resilient Backpropagation method was used. The accuracy analysis was carried out using two approaches. The first measure of classification accuracy is based on the number of correctly classified segments. The other measure is based on κ-coefficient calculated using number of pixels corresponding to correctly classified segments. Pair-wise

statistical tests were performed to assess the significance of any differences observed between two classifications using a Z statistic (Congalton and Green, 1999).
For testing the proposed per-field based classification approach on high resolution data, a simulated high spatial resolution data set of study site was generated by image fusion using wavelet based substitute principal component analysis (SPCA) approach (Li *et al*., 1999). High spatial resolution PAN and low resolution LISS-III data were used for generating simulated high spatial resolution data set. Experiments were carried out using per-field based classification approach out in similar manner as it was done for normal data set.

4.0 RESULTS AND ANALYSIS

This section presents results of various experiments carried out to achieve various objectives and to study importance of spatial properties in the classification of urban environment.

4.1 Classification using spectral features

Classification results are presented in the Table 3. Classification accuracy for grassy land, reserve forest, river and water body was acceptable but for rest of the classes accuracy was poor. For classes commercial, educational institutes and government establishment κ - coefficient was lesser than 0.50. The overall accuracy was also very low.

This low accuracy may be due to the fact that most of the classes were highly heterogeneous, there were many classes with low separability values and few classes had similar biophysical environment. Analysis of results suggests that classification results are less than acceptable due to high heterogeneity and non-normal behaviour of most of the classes. These poor classification results also suggest that spectral features alone are not sufficient for urban land use classification having high heterogeneity and non-normal behaviour and some additional information like spatial information in the form of texture, size, shape may be required.

Table 3 also presents result of GML classification after including SWIR band with three spectral bands B2, B3 and B4. It was observed that with the inclusion of SWIR band, there was improvement in classification accuracy for most of the classes. Though, this increase in classification accuracy was statistically significant only for one class (commercial) but due to increase in accuracy of all other classes, overall accuracy improved in a statistically significant manner. This shows that, although SWIR band has poor spatial resolution but its spectral properties help in improving classification accuracy when separation amongst classes is poor and the classes are highly heterogeneous.

Table 3 Classification accuracy with spectral band

S. no.	*Class name*	*Training*			*Test*		
		a	*b*	Z_{ba}	*a*	*b*	Z_{ba}
1	Agriculture-1	0.65	0.75	1.33	0.74	0.78	0.71
2	Agriculture-2	0.61	0.82	3.16	0.73	0.77	0.58
3	Commercial	0.42	0.57	1.90	0.45	0.71	3.54
4	Educational institutes	0.44	0.51	0.91	0.49	0.53	0.49
5	Government establishment	0.15	0.19	0.69	0.05	0.11	1.49
6	Grassy land	0.87	0.92	1.02	0.87	0.89	0.49
7	High residential	0.80	0.85	0.83	0.75	0.81	0.81
8	Medium residential	0.81	0.91	1.90	0.74	0.85	1.77
9	Park	0.68	0.68	0.02	0.69	0.73	0.53
10	Reserve forest	0.94	0.93	-0.31	0.91	0.90	-0.26
11	River	0.95	0.95	0.00	0.92	0.92	0.00
12	Water body	0.84	0.87	0.44	0.92	0.93	0.29
	Overall	0.68	0.74	3.19	0.68	0.74	2.81

a 3 bands
b 3 bands + SWIR
z_{ba} *Z*-statistic between *b* and *a*

4.2 Classification using per-field approach

Threshold values were determined for all bands considered for the study. It was observed that results of Otsu and Kapur *et al*. methods were similar while threshold values from Trussel were slightly higher than other two methods. Threshold values obtained using Otsu method were chosen to carry out further analysis. After selecting suitable threshold values for all four bands, multispectral segmentation of bands was carried out. It was observed from segmented image that inclusion of band B5 in the segmentation process produced poor segmentation. This could be due to very small thresholds values obtained for band B5. Segmentation carried out using three bands (B2, B3 and B4), produced good segmented image. Therefore, further analysis was carried out using only these three bands.

Table 4 shows the results of per-field based classifications. It was observed from the results that accuracy in terms of number of correctly classified segments was lower than the number of correctly classified pixels. The reason for this becomes obvious when we see test accuracy of classes like commercial and educational institutes. In case of commercial class, only two out of eight segments have been correctly classified whereas in terms of number of pixels, more than 97% of the pixels have been correctly classified. Similarly for class educational institutes only one out of eight segments have been correctly classified whereas in terms of number of pixels, more than 90% of the pixels have been correctly classified for this class.

Table 4 Results of per-field based classification

S. no.	*Class name*	*Test accuracy*						
		In terms of segment			*In terms of pixels*			
		a	*b*	*c*	*d*	*e*	*f*	*g*
1	Agriculture-1	10	8	80.00	229	180	78.60	0.79
2	Agriculture-2	8	7	87.50	2623	1983	75.60	0.75
3	Commercial	8	2	25.00	2754	2691	97.71	0.98
4	Educational institutes	8	1	12.50	4943	4482	90.67	0.90
5	Government establishment	7	4	57.14	3477	3148	90.54	0.90
6	Grassy land	4	2	50.00	7768	7740	99.64	1.00
7	High residential	1	1	100.00	15558	15558	100.00	1.00
8	Medium residential	2	1	50.00	15412	15407	99.97	1.00
9	Park	5	2	40.00	1171	1125	96.07	0.96
10	Reserve forest	4	3	75.00	9954	7329	73.63	0.70
11	River	4	4	100.00	2297	2297	100.00	1.00
12	Water body	8	7	87.50	291	286	98.28	0.98
	Overall	69	42	60.87	66477	62226	93.61	0.92

a Number of segments for training / test
b Number of correctly classified segments
c % of correctly classified segments
d Number of pixels corresponding to training / test segments
e Number of correctly classified pixels
f % of correctly classified pixels
g κ -coefficient

Table 5 shows a comparison between classification results using perfield based GML and per-pixel GML classification approach. It was observed that except reserve forest, classification accuracy for most of the classes was statistically significantly higher using per-field based approach. The overall test accuracy in terms of κ -coefficient increased from 0.68 to 0.92 (increase of 24%). The classified image using per-field based approach looks more like a thematic map in comparison to per-pixel classified image.

For three fused bands obtained using wavelet based SPCA approach, threshold values were obtained from Otsu method. Segmentation of fused bands was carried out and subsequently merging was done for refinement of initially segmented image. Total of 550 iteration of segment merging algorithm were required before merging stopped. Corresponding to refined segmented image, per-pixel and per-field based GML classifications were carried out for simulated data set. The same approach of classification was adopted, which was used with the multispectral data set. Table 6 presents a comparison of per-field and per-pixel classification results. The overall test accuracy in terms of κ -coefficient increased from 0.70 to 0.95 (increase of 25%).

Table 5 Comparison of per-pixel and per-field based classification accuracy

S. no.	*Class Name*	*Training*			*Test*		
		a	*b*	z_{ba}	*a*	*b*	z_{ba}
1	Agriculture-1	0.65	0.61	-0.24	0.74	0.79	0.29
2	Agriculture-2	0.61	0.99	5.60	0.73	0.75	0.15
3	Commercial	0.42	0.99	8.29	0.45	0.98	6.87
4	Educational institutes	0.44	0.88	5.05	0.49	0.90	4.67

5	Government establishment	0.15	0.90	9.04	0.05	0.90	11.17
6	Grassy land	0.87	1.00	3.03	0.87	1.00	2.78
7	High residential	0.80	1.00	4.48	0.75	1.00	5.17
8	Medium residential	0.81	1.00	3.89	0.74	1.00	5.13
9	Park	0.68	1.00	6.20	0.69	0.96	2.87
10	Reserve forest	0.94	0.70	-3.26	0.91	0.70	-2.78
11	River	0.95	1.00	1.24	0.92	1.00	2.77
12	Water body	0.84	0.98	1.35	0.92	0.98	0.73
	Overall	0.68	0.93	7.26	0.68	0.92	6.60

a Per-pixel GML
b *Per-field* -based GML
z_{ba} *Z*-statistic between *b* and *a*

Table 6 Comparison of accuracy on fused image between per-pixel and Per-field based classification with fused image

S. no.	*Class name*	*Training*			*Test*		
		a	*b*	z_{ba}	*a*	*b*	z_{ba}
1	Agriculture-1	0.79	0.78	-0.46	0.57	0.70	9.18
2	Agriculture-2	0.90	1.00	35.30	0.66	0.89	50.50
3	Commercial	0.48	0.95	196.19	0.49	0.95	195.73
4	Educational institutes	0.47	0.95	126.16	0.46	0.93	125.45
5	Government establishment	0.28	0.36	18.44	0.28	0.36	18.35
6	Grassy land	0.84	0.99	101.36	0.85	1.00	108.40
7	High residential	0.77	1.00	201.69	0.77	1.00	201.25
8	Medium residential	0.65	1.00	213.30	0.64	0.98	213.69
9	Park	0.63	0.87	45.45	0.62	0.82	36.38
10	Reserve forest	0.83	1.00	165.30	0.83	1.00	165.75
11	River	0.65	1.00	147.36	0.65	1.00	147.28
12	Water body	0.70	0.82	16.66	0.69	0.82	16.62
13	**Overall**	0.71	0.96	388.40	0.70	0.95	390.24

a Per-pixel classification
b Per-field classification
z_{ba} *Z*-statistic between *b* and *a*

These results reveal that invariably for all the classes, accuracy increased in a statistically significant manner in case of per-field based classification approach. This clearly indicates that use of the proposed classification method would be appropriate even for high resolution data.

5.0 CONCLUSIONS

This paper has demonstrated the significance of spatial properties in the classification of urban environment using IRS-1C satellite data. This paper has also demonstrated that proposed approach of per-field (segment) based classification is suitable for classification of urban environment even with high resolution spatial data. The classification results with this approach showed significant improvement over per-pixel approach. The following conclusions can be drawn from the analysis carried out in this study:

- The poor classification results with pure spectral features suggest that spectral features alone are not sufficient for urban land use classification having high heterogeneity and non-normal behaviour. Therefore, some additional information like spatial information in the form of texture, size, shape may be required.

- Inclusion of SWIR band in the classification process with IRS-1C data helps in improving classification results for classes having high heterogeneity.
- Per-field based classification provides statistically significantly higher accuracy (up to 25%) than per-pixel approach.
- The per-field ANN classification provides slightly higher, though statistically insignificantly different, test accuracy than the per-field GML classification.
- Classified image obtained as a result of per-field based classifications looks more like a thematic map while making a comparison with results of per-pixel approach.
- Per-field based classification of fused data set obtained from high spatial resolution PAN and low spatial resolution LISS-III, provides significantly higher accuracy. This clearly indicates that per field approach would be appropriate for classification of urban environments from high spatial resolution satellite images.

REFERENCES

Beveridge, J. R., Griffith, J., Kohler, R. R., Hanson, A. R., and Riseman, E. M.,1989. *Segmenting Images using localised histograms and region merging.* International Journal of Computer Vision, 2, 311-347.

Choo, A. P., A.J. Maeder and B. Pham, 1990. *Image Segmentation for complex natural Scenes*,. Image and Vision Computing, vol. 8, pp. 155- 163.

Congalton, R. G. and Green, K., 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. CRC Press, Inc.,U.S.A.

Haralick, R. M., Shanmugam, K., and Dinstein, I., 1973. Textural features for image classification. *IEEE Trans. on Systems, Man, and Cybernetics*. SMC-3, 610-621.

Kapur, J. N., Sahoo, P. K. and Wong, A. K. C., 1985. *A new method for grey-level picture thresholding using the entropy of the histogram.* Computer Vision and Image Processing, 29, 273-285.

Li., J., Zoju, Y., and Li, D., 1999. *PCA and wavelet transform for fusing panchromatic and multispectral images.* SPIE's International symposium on Aero Scene: Image Exploitation and Target Reconstruction; Orlando, Florida, U.S.A, 3719, 5-9.

Mather, P.M., 1985. *A computationally efficient maximum likelihood classifier employing prior probabilities for remotely sensed data.* International Journal of Remote Sensing. 6 (2), 369-376.

Nagao, M. and Matsuyama, T., 1980. *A structural analysis of complex aerial photographs*. Plenum, New York.

Nevatia, R., 1982. *Machine Perception*. Printice-Hall, Englewood Cliffs, NJ.

Otsu, N., 1979. *A threshold selection method from grey-level histograms.* IEEE Trans. on systems, Man, and Cybernetics, SMC-9, 62-66.

Toll, D. L. and Kennard, R. E., 1984. *Investigation of SPOT spectral and spatial characteristics for discriminating land use and land cover in Prince George's county, Maryland.* In SPOT simulation Applications Handbook, Falls Church: American Society for Photogrammetry, 165-170.

Tortora, R., 1978. *A note on sample size estimation for multinomial populations. The American Statistician, 32 (*3) 100-102.

Trussel, H. J., 1979. *Comments on 'Picture thresholding using an iterative selection method'.* IEEE Trans. on Systems, Man, and Cybernetics, SMC-9 (5), 311.