Trans. Inst. Indian Geographers
Vol. 32, No. 2, 2010

Comparison of Visual Interpretation and Object Based Classification Techniques for Urban Land Cover Mapping, Using High Resolution Images

Seema Jalan, Jaipur, Rajasthan

Abstract

Information extraction of urban areas from very high resolution satellite images requires methods which can incorporate spatial, textural and contextual information content of the image in the classification process along with the spectral characteristics of the pixels in a multi-scale environment. This approach is effectively followed in visual interpretation and is the fundamental basis of object based image analysis technique. This paper compares the performance of visual interpretation and object based classification for land cover mapping of two representative types of urban landscapes using merged CARTOSAT-1 and IRS-P6 LISS-IV datasets. For object based classification nearest neighbour technique has been applied. Comparison is based on rigorous qualitative and quantitative measures of evaluation.

The results revealed that comparable classification accuracies can be achieved by both the methods for land cover mapping of dense urban as well as sub-urban fringe areas. Both the methods confront with difficulty in differentiating classes with indistinct image characteristics. Visual interpretation allows for effective integration of prior knowledge. Nevertheless, derived accuracies are conditioned by limitations of human vision and complexity of landscape. Object based classification technique has proved to be a fast, versatile and objective means of producing visually appealing outputs in a semi-automated manner with very close approximation to results obtained by visual interpretation approach. It can effectively be used for time effective extraction of land cover information in complex urban landscapes for such applications where concern is class area and high cartographic quality of boundaries is not required.

Introduction

Urban decision makers are confronted with a complex and dynamic environment. Formulation of policies aimed towards sustainable regional development requires up-to-date information supplied by efficient data extraction systems that support their decision making process (Voorde et al., 2004). Spatial applications like urban planning and environmental monitoring essentially require reliable and up to date information on land cover. Remote sensing datasets contain a wealth of land cover information at a range of spatial and temporal scales. The new generation very high resolution (VHR) satellite images provide unprecedented capabilities for the extraction of land cover information for extended urban areas with larger spatial details.

Visual interpretation (VI) and manual digitization has long been a preferred approach for thematic mapping from VHR satellite images for its ability to integrate

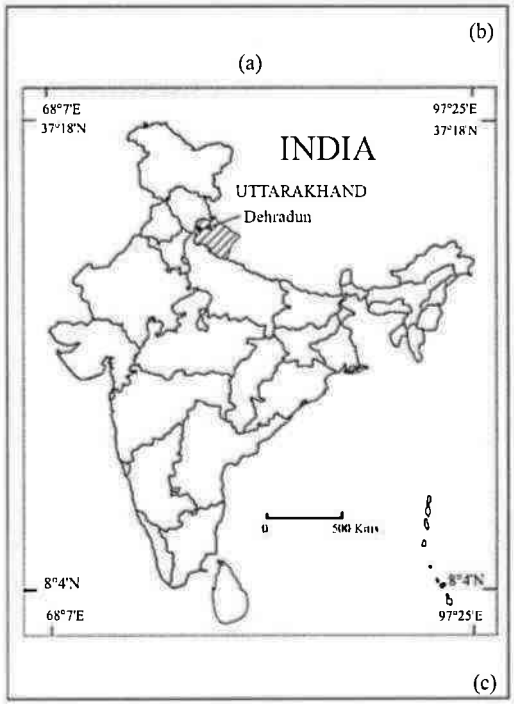


Fig. 1. Study area (a) Location map of Dehradun and Uttarakhand in India (b) Subset 1 - densely built urban area in Dehradun city and (c) Subset 2 - sub-urban fringe area located in southern part of Dehradun.

spatial information and expert knowledge derived from human perception, expertise and experience in the classification process at various scales at the same time. However, it has often been criticized for being time consuming and subjective, lacking flexibility and reproducibility; the derived accuracy being heavily contingent upon the skill and psyche of the interpreter. Moreover, the full exploitation of the information intrinsic in the image is constrained by the limitation of human vision to interpret only three layers of remotely sensed information at a time (Gao J., 2008). Ability to process large amount of data at a time, reproducibility, flexibility and objectivity associated with digital analysis techniques has consistently fuelled the efforts for development of automated or semi-automated computer assisted algorithms for classification of VHR datasets.

Because of high within class spectral heterogeneity and spatial variance in VHR datasets, conventional pixel based classification methods often result in 'speckled classifications', i.e., thematic maps that lack spatial coherence (Voorde et al., 2004). This limitation stems from the overemphasis on spectral properties of individual pixels and inability to integrate the spatial, textural and contextual measures in the classification process. Recently several studies have reported Object Based Image Analysis (OBIA) as a promising semi-automated tool for producing reliable and accurate land cover maps in a time efficient manner (Benz et al., 2004; Yan et al., 2006). OBIA divides the image into regions of similar pixels prior to classification, called as image segments or object primitives, which are then wholly assigned to a land cover class by a fuzzy classifier. These segments not only have spectral properties but also region based metrics such as shape, texture, structure, size and context (Frauman and Wolff, 2005). Therefore "imitating the approach followed in manual image interpretation, such methodology exceeds the limits of a subjective classification, by making a process that can be reproduced and homogenous and also exceeds the problems of traditional classification techniques" (Barrile and Bilotta, 2008).

This paper compares the merits and limitations of traditional VI and OBIA method for information extraction from VHR satellite images of urban areas. The relative efficiency of two techniques has been evaluated and compared in

a statistically rigorous way. Owing to the high spatial variation in landscape configuration within a single urban scene, the utility of a method of information extraction is contingent upon its ability to provide results of comparable accuracy for different types of urban landscapes. Hence both the methods have also been evaluated individually with regard to the classification accuracy achieved for two different urban and sub-urban sub scenes.

Materials and Methodology

Study area and data used

The analysis was done on CARTOSAT-1 (PAN) and IRS-P6 LISS-IV (MS) fused image of Dehradun, India. Dehradun is an important urban centre situated in the foothills of Himalayas and is the capital of Uttarakhand state [Fig. 1(*a*)]. The city is located in western part of the state in Dehradun district extending between longitude 78°00' E and 78°10' E, and latitude 30°15' N and 30°25' N.

Two image subsets were extracted from the larger scenes for the purpose of analysis. Subsets have been chosen so as to include representative samples of urban and sub-urban land-cover to compare the efficiency of techniques in areas with potential difficulties. Sub-set 1 comprises of a densely built urban area [Fig. 1(*b*) See page 166] Major part of the sub-scene comprises of commercial and residential area with intermittent institutional set ups. It is characterised by a complex intermixing of built up forms, buildings - single as well as multi-storeyed - roads and narrow lanes with intermittent vacant plots and vegetation patches. The eastern part of the sub-scene comprises of a large stretch of informal settlement along a more or less dry river bed. The extreme eastern part is dominated by a heterogeneous vegetation cover comprising dense along road vegetation, orchards, grass and wild vegetation. Sub-set 2 [figure 1(*c*) (See page 166] is a part of rapidly developing southern fringe area of the city. Traversed by a highway and rail route, the south-west portion of the sub-scene is an institutional area with a complex mixture of open forest, underlying tea gardens and embedded buildings. The remaining area is predominantly agricultural interspersed with medium density residential settlement mainly along the roads. The eastern part is traversed by a dry river bed flanked by dense intermix of bare ground, cropped and non-cropped agricultural land, orchards and unutilized vacant land.

Toposheet of Dehradun on 1:50000 scale was used for geometric rectification of CARTOSAT-1 image. Field data were obtained for designing classification scheme, identifying sample sites for classification and reference data for accuracy assessment.

Methodology

Image pre-processing

CARTOSAT-1 image was geometrically rectified using the geo-referenced toposheet as reference. Resampling was performed by nearest neighbour technique in order to preserve the original radiometry of the image. The LISS-IV image was registered to CARTOSAT-1 image and resampled using the same technique. Subsequently, the two subsets were extracted from the co-registered larger CARTOSAT-1 and LISS-IV images. This entire exercise was implemented in ERDAS imagine version 9.1. This provided two sets of co-registered subsets which were then fused.

Image fusion

Spectral fidelity of the fusion result is important for visual image interpretation and more specifically for automated image classification (Zhang, 2002; Ehlers, 2007; Ehlers, et al., 2008; Gangkofner, et al., 2008). Image fusion was performed using Gram- Schmidt spectral sharpening method in ENVI version 4.3. Jalan (2009) evaluated the spectral and spatial quality of the Gram-Schmidt fused image and found it capable of minimizing colour distortion while retaining the spatial improvement of the standard data fusion algorithms.

Image classification and generation of land cover maps Classification scheme

Following a preliminary reconnaissance survey of both the study areas, a composite three-tier hierarchical classification scheme was devised for both the sub-sets. Built up (BU) and non built up land at the highest level were differentiated into buildings (B), transportation (TR) [roads (RD) and railway track (RT)], built up with vegetation (B_Veg), cropped land (CL), vegetation -tree covered land [V (T)], vacant land (VL) and water body (W) [river bed (R)] at lower levels. Vacant land category is a comprehensive class including multifarious types of land - bare non vegetated land, open unutilized vacant plots in city area with or without wild vegetation, degraded land, agricultural fallow fields, grassed patches - hence is characterized by high intra-class spectral as well as spatial heterogeneity along with high spectral similarity with river bed and cropped land. 'Built up with vegetation' as a mixed land cover category corresponds to areas with intricate inseparable mix of built up structures, vegetation and bare ground.

Visual image interpretation and on-screen digitization

Fig. 2 succinctly illustrates the methodology followed for visual image interpretation and mapping. Digitization was performed in Arc GIS version 9.2 at a scale of 1:5000 with a minimum mapping unit (MMU) of 3mm x 3mm. Final maps were prepared at 1: 10000 scale. Due to high spatial variability inter-class inclusions of different categories were unavoidable. The map units were delineated and labelled on the basis of predominant category in cases where: (i) the alien category formed a minimal proportion of the predominant category and was located such that it could not be merged with other features of its kind, or (ii) it was smaller than the MMU hence could not be delineated as a separate unit. At 2.5 m spatial resolution the inter-class boundary is in the form of transition zone. Boundaries between classes were placed at the centre of respective zones. Shadows were assigned to the category which formed the ground land cover type beneath the shadow.

Object based classification (OBC)

The OBIA of both the images was performed using eCognition Professional 4.0. A precise illustration of the steps and methodology followed for OBC has been given in figure 2 (*b*).

Quality of image segmentation directly affects the accuracy of subsequent classification. OBIA effectively addresses the multi-scale hierarchy of objects in an urban scene by allowing classification at different object levels corresponding to the scale of various target objects.

For image segmentation, beginning with a very small scale parameter at base level

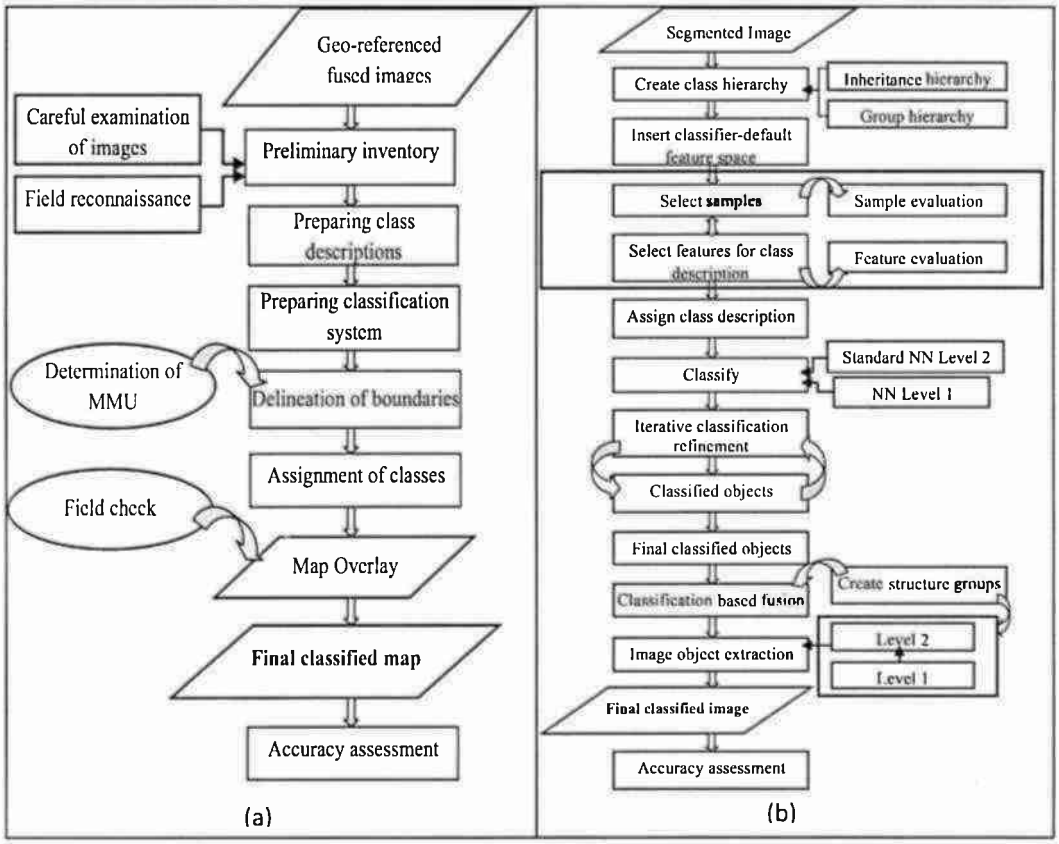


Fig. 2: Workflow for visual image interpretation and on-screen digitization (b) Workflow for object based classification.

it was gradually increased to arrive at the appropriate levels corresponding to target features of various classes. In both subsets layer weights were assigned in accordance with the predominant land-cover class. A higher shape and smoothness parameter was defined in order to avoid frayed boundaries of objects. Tables 1 and 2 show the two finally selected segmentation levels, corresponding feature classes and segmentation parameters for subset 1 and 2 respectively.

Sample objects were selected according to the ground truth and subsequently multi-scale iterative Nearest Neighbour (NN) classification was performed on both the segmented image subsets. For instance, in subset 2 the small scale objects like buildings and transportation features were classified at object level 1 and larger scale objects – cropped fields, vacant land, vegetation (trees), and river were classified at level 2. The class description for classification at level 1 comprised of features related to layer value (mean, ratio), shape (generic shape features) and textural features (Haralick texture measures). Class description for classification at level 2 comprised of a

combination of measures related to layer values (mean, standard deviation and ratio) and Haralick texture measures.

The initial classification yielded fairly promising results but there were several incorrectly classified and unclassified objects. To improve the classification, the wrongly classified and unclassified objects were assigned as samples to the respective classes and reclassification done till the final classification was achieved. At each level, the classified objects belonging to the same category were then fused. Thereafter both levels were projected at one single image object level. Standard false colour composites of original merged subsets, classified maps prepared by VI and manual digitization and results of OBC have been shown in figure 3(a)-(f) See page 181.

Accuracy

ation technique for the two different types of urban areas, and (ii) compare the performance of two methods with respect to each individual type of urban area. The comparison has been made both qualitatively (visually) and quantitatively. Quantitative assessment is based on accuracy measures derived from error matrix. The same set of sample points, determined through stratified random sampling, has been used for both the methods for each area. Use of the same samples for different classifications helps to ensure that the differences in accuracy can be attributed to the nature of the class allocation process used (Foody, 2004).

Overall agreement between the classification results of VI and OBC for each subset has been determined using single summary measures - overall accuracy (OA) and kappa coefficient of agreement (k). The statistical significance of the difference between the two accuracy statements has been determined using McNemar's test as suggested by Foody (2004) in cases when related samples are used in accuracy assessment of different thematic maps. Overall performance of an individual classification method for the two sub-scenes has been compared using OA and k.

Class wise accuracy derived from the two methods for each sub-scene has been compared on the basis of user's accuracy (UA), producer's accuracy (PA) and

Table 1. Segmentation parameters for subset 1§.

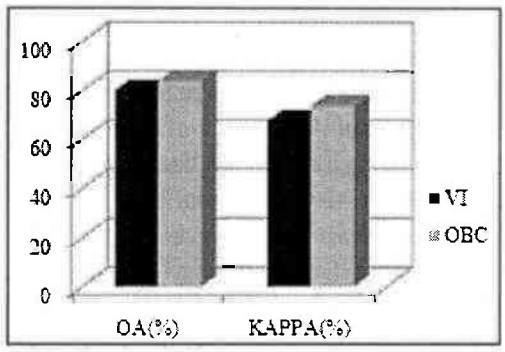
Level	Scale	Shape	Compactness	B	G	R	Classes
1	10	0.3	0.2	3	1	1	RD
2	14	0.3	0.1	1	1	1	B, R, VL,V(T)

§ The expanded forms of class codes have been given in sub-section 2.2.3.1.

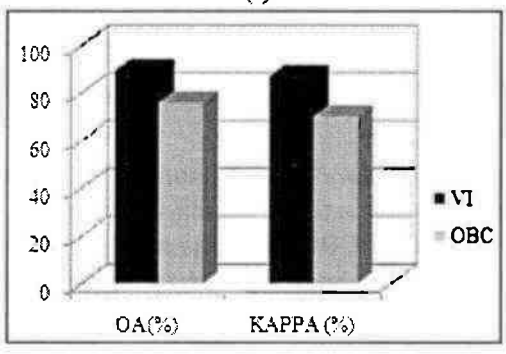
Table 2. Segmentation parameters for subset 2§.

Level	Scale	Shape	Compactness	B	G	R	Classes
1	22	0.3	0.1	1	1	3	B, RD
2	38	0.3	0.1	1	1	3	CL, R, VL,V(T)

§ The expanded forms of class codes have been given in sub-section 2.2.3.1.



(a)



(b)

Fig. 4. Single summary accuracy statistics obtained for (a) subset 1- dense urban area and (b) subset 2-fringe area. OA refers to overall accuracy.

conditional k (k_c) values. To ascertain the relative class wise accuracy achieved by each individual classification method in different land cover situations, only UA and PA were compared. k_c was not used for this purpose because "it is difficult to compare the values of k_c when the marginals vary from map to map, because accuracy is confounded with chance agreement" (Stehman, 1997) which will vary with difference in land cover.

The classified map from e-Cognition was exported as *.img file. The feature classes from ArcGIS were converted into raster as an *.img file with a cell size of 2.5 m. Subsequently, accuracy assessment was performed in ERDAS imagine 9.1.

3. Results and analysis

The resolution of the image coupled with high spatial heterogeneity and spectral overlap between classes posed substantial challenge not only for the digital classifier but also for VI and manual delineation of map units.

Visual assessment

With VI and manual digitization it was possible to differentiate between all classes up to third level of the selected classification scheme in both subsets. During the entire process of manual digitization the details as visible on the image were not sufficient to differentiate between certain classes precisely; especially vegetation and vacant land covered with vegetation in both subsets, and built up and small bare vacant plots in subset 1. Occlusion of details caused by shadows also posed a challenge. Major part of the road network in subset 1 is in form of narrow lanes embedded in dense residential and commercial area which was not differentiable in the image at the given resolution. Tonal and textural similarity with the surroundings, occlusion by shadows and roadside vegetation made it difficult to delineate them. Consistent use was made of higher resolution imagery of the area along with ground truth for delineation of roads. In both subsets, most of the roads were delineated as trend lines as the entire length and extent of roads was not distinctly visible in continuity.

OBC effectively extracted all classes, except transportation, up to second level of classification. Subset 1, with its complex intermingling of selected land cover classes posed an especially challenging task for the classifier. Nevertheless, all classes except

roads were well extracted. Indistinctive signature owing to the reasons described above and high within class tonal variation hindered extraction of roads as continuous linear features and only fragmented sections could be derived during segmentation. Without high quality segmentation, accurate classification cannot be achieved. In subset 2 roads and railway track were well identified in relatively open areas where signatures were distinct. Misclassifications were mainly associated with classes having overlapping signatures viz. vacant land covered with wild vegetation and agricultural fields with standing crops, dry river bed and bare ground. The mixed class (built up with vegetation) was also difficult to define in terms of class description. Had the classes been mutually disparate the classification would have been much easier. At places subtle differences in tone and texture set in low contrast with the surroundings, were well detected as distinct map units (see box A in figure 3). These were not digitised during VI due to the constraint of mapping scale and MMU or because of being indiscernible due to low contrast.

The classified maps produced by VI have sharp and smooth boundaries hence are more visually appealing. The boundaries produced by OBC follow the raster boundaries hence seem relatively serrated (see box B in figure 3). Nevertheless, the smoothened boundaries created in VI entail generalisation hence a compromise with accuracy. In cases where the spectral overlap between adjoining classes is high, the objects created as map units in OBC lack a defined shape and fail to conform precisely to real world objects. The problem can be effectively mitigated if a higher spatial resolution data is used.

A qualitative assessment of the classification results suggests that a comparable land cover classification can be achieved using both the methods OBC is an efficient semi-automated tool to deal with high spatial and spectral heterogeneity inherent in high resolution datasets of urban areas. A multi-scale classification based on object features integrating spectral, spatial and textural characteristics of image objects yields classified map units having high correspondence with the real world geographical entities.

Comparison of performance based on error matrix

Since transportation features could not be fully extracted in the classified images obtained by OBC, for purpose of accuracy assessment, building and transportation classes were merged into a single built up class.

Comparison based on single summary measures

Single summary accuracy statistics for subset 1 and 2 has been compared in figure 4 (*a*) and (*b*) respectively. The accuracy (OA and k) obtained by VI was considerably higher than OBC for subset 2. Interestingly, OBC provided slightly better results in relatively more complex landscape of subset 1. Nevertheless, the results of McNemar's test reveal that the difference in overall accuracy of classified maps obtained by both the techniques was statistically insignificant. For subset 1 c^2 value was 1 which is insignificant at 5% level of significance. For subset 2 c^2 value was 5.55 which is insignificant at 1% level of significance.

OA of map classified using OBC was higher for subset 1 than subset 2. Nevertheless, the value of k (> 70%) for both the areas was almost equivalent and fairly high which suggests that the improvement over chance agreement provided by the classifier was significant and comparable for both the areas.

The classification using VI method achieved considerably higher accuracy in subset 2 as compared to subset 1.

Class-wise accuracy

Subset 1

Major part of the area is an intricate intermix of built up, vegetation and vacant land. The built up structures are intricately intermingled with small vacant plots which are highly similar in terms of spectral characteristics. In the eastern part of the sub-scene it was very difficult to differentiate between tree covered land and wild vegetation covered vacant land. The confusions were further compounded by the shadows which were mainly responsible for the misclassifications between built up and vegetation class. Hence at the quality and resolution of the image in hand high accuracy in digital classification of this area was not expected. Consistent reference was taken from a very high resolution image of the area during VI.

As evident from table 3 OBC has produced accuracies equivalent or higher than VI for all categories except vacant land [figure 5 (*a*)]. One notable observation for this area is the high omission error of VI for river bed class. The river in the area is dry bed, surrounded by a dense informal settlement which has extended well into the river bed. Hence, it was very difficult at some places to distinguish between the houses and the river bed (Box C in figure 3). The tonal distinction between the two was very low. Moreover textural differences were also not very marked. OBC was able to differentiate between the two on the basis of subtle textural features hence resulting into higher mapping accuracy.

Omission and commission errors for OBC were primarily associated with spectrally and spatially indistinct categories viz. vacant land or the inter class transitional zones. The classifier has successfully identified built up area with accuracies at par with VI. It has outperformed VI for vegetation (trees) category. Given the characteristics of the subset, accuracies achieved by OBC are clearly evident of the immense capabilities of the technique for classifying a complex urban land-cover.

Subset 2

Fairly high accuracies have been achieved by VI for all classes. Comparable accuracies were achieved by OBC for all classes except vacant land and built up with vegetation [Table 4 and figure 5(b)]. Both methods confused cropped land with vacant land with vegetation cover and tree covered ground. This can be attributed to intricate intermixed occurrence of the three land cover types in the area. By OBC poorest results have been derived for vacant land. It confused vacant land with all other classes. Vacant land being a comprehensive class had overlapping spectral and textural signatures with all other classes which explain the limitation imposed on the digital classifier. Misclassifications pertaining to vegetation (trees) category were mainly associated with small patches of vegetation embedded in large vacant tracts.

Table 3. User's accuracy, Producer's accuracy and Conditional Kappa for classification results obtained from subset 1.$

Class Code	Subset 1					
	User's Accuracy		Producer's Accuracy		Conditional KAPPA	
	VI	OBC	VI	OBC	VI	OBC
BU	85.71	89.29	85.71	86.21	0.68	0.74
VL	70	60	70	66.67	0.63	0.51
V(T)	66.67	87.50	75	87.50	0.60	0.85
B_Veg	100	100	100	100	1.00	1.00
R	100	100	50	100	1.00	1.00

$ Class codes have been explained in the text.

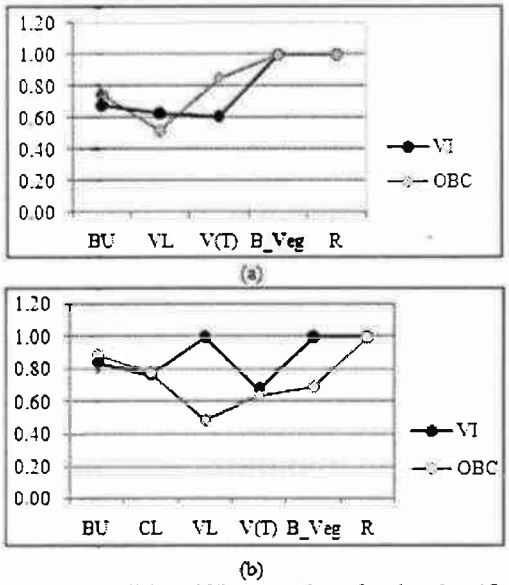


Fig. 5. Conditional Kappa values for the classification results obtained from visual interpretation and object based classification for (a) subset 1 and (b) subset 2. Values on vertical axis show values of Conditional Kappa coefficient. Class codes have been explained in the text.

These could have been identified at a smaller scale parameter. Other errors, especially related to built up category, pertained to transitional zones where signatures are merged hence indistinct. Commission errors pertaining to built up with vegetation class is explainable as the class is more a semantic class rather than a distinct distinguishable class in terms of the selected feature set. The class could have been more accurately identified had the rule base included class related features. Omission errors associated with river bed mainly pertained to spectrally and texturally identical dry bare ground in its vicinity. During VI it was identified and delineated on the basis of prior knowledge and field check.

Foregoing analysis of accuracy measures suggests that comparable classification results can be obtained by OBC and VI for both types of urban land cover. OBC has provided a satisfactory classification at the selected quality and resolution of the image. Given the complex intermingling of land cover the differentiation and delineation of classes up to the second level of classification hierarchy achieved using the technique is significant. Although detailed differentiation of built up category could not be achieved, built up area as a whole has been very well extracted in both the subsets with high user's and producer's accuracy. The performance of OBC is impaired if the classes of interest

are not clearly distinguishable in terms of some specific features. Misclassifications pertained to spectrally confused areas-inter-class transitional zones and land cover types like vacant land covered with wild vegetation and agricultural fields with standing crops, dry river bed and bare ground, built up with vegetation - as it was difficult to define in terms of class description. However, iterative sample definition and reclassification method addressed the problem of overlapping signatures to a considerable extent. Manual editing is also an effective method to deal with such overlapping classes. The rule-set applied for NN classification in this study was relatively simple. More complex rule sets or integration of contextual and class related features in class descriptions may further improve the classification accuracy.

Performance of individual classifiers in different land-cover situation

Figure 6 (*a*) shows the UA and PA achieved by object based classifier for land cover classes common in both subsets. It is evident from the figure that except for vacant land and built up with vegetation classes, OBC has produced comparable accuracies for both the areas. Nevertheless, for these two classes PA is almost equal in both the areas. Similar results have been obtained by VI. There is no significant difference in the accuracies achieved in both subsets except UA for vacant land category and PA for river bed.

Conclusion

In this paper classification results derived from visual interpretation (VI) and object based classification (OBC) have been compared with respect to land cover mapping of urban areas using merged CARTOSAT-1 and IRS-P6 LISS-IV image subsets. An in depth analysis of relative merits and limitations of both methods in different land cover situations has been done and classification accuracies achieved by both methods have been compared.

Comparable classification results have been achieved by OBC and VI for dense urban area as well as sub-urban fringe area

Table 4. User's accuracy, Producer's accuracy and Conditional Kappa for classification results obtained from subset 2. $

	Subset 2					
Class code	User's Accuracy		Producer's Accuracy		Conditional KAPPA	
	VI	OBC	VI	OBC	VI	OBC
BU	87.50	90.91	93.33	71.43	0.84	0.89
CL	81.25	81.82	100	69.23	0.77	0.78
VL	100	61.90	73.68	68.42	1.00	0.49
V(T)	72.73	70.59	80	85.71	0.68	0.64
B_Veg	100	71.43	100	100	1.00	0.69
R	100	100	100	77.78	1.00	1.00

$ Class codes have been explained in the text.

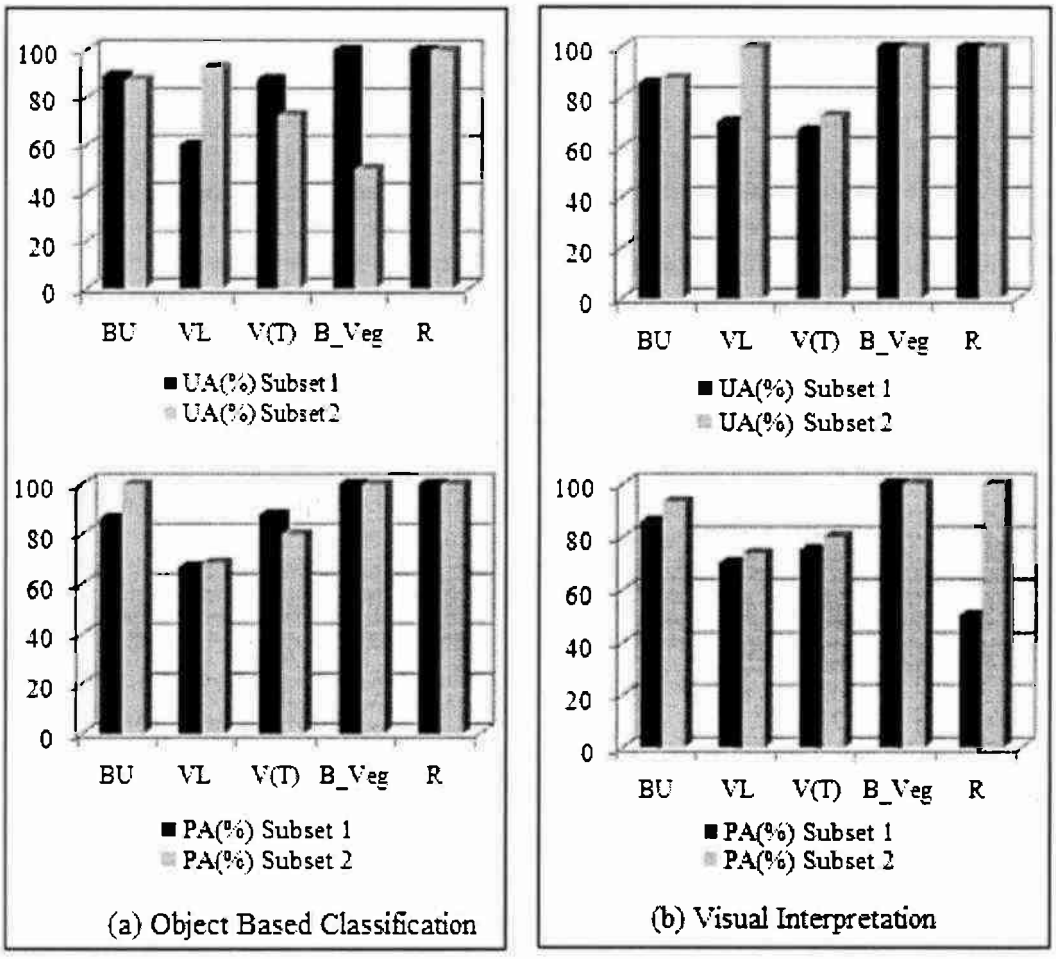


Fig. 6 : Comparison of classification accuracies for common land cover classes obtained from subset 1 and 2 by applying (a) object based classification and (b) visual interpretation. Abbreviations have been explained in text. UA refers to User's Accuracy and PA refers to Producer's Accuracy.

up to second level of selected classification hierarchy. Difference in overall accuracy achieved by both methods as revealed by McNemar's test for both areas is statistically insignificant.

VI Scores over OBC where high cartographic quality of boundaries is concerned. Integration of prior knowledge facilitates delineation in areas where features are indistinct in terms of image characteristics as in case of transport features or land cover classes are not precisely defined in terms of distinguishing features such as built up with vegetation and vacant land category. Smoothened boundaries generated by manual digitization, although generalized at times, are more visually appealing and conform to real world perception of objects. Operational utility of the method is limited by limitations of human vision and complexity of landscape.

OBC has proven very effective in delineating classes which have distinct spatial and spectral characteristics. Built up area has been very well extracted in both the subsets with high user's and producer's accuracy. At places subtle differences in texture, set in low contrast with the surroundings, were detected by the technique which was unidentified during VI. However, performance of the technique is impaired when classes have indistinct image characteristics. Overlapping spectral characteristics hinder effective segmentation and affect subsequent classification. Manual editing allows integration of prior knowledge.

Segmentation results underline the high potential of the technique for a speedy and automated region extraction or delineation of boundaries for scenes characterized by complex urban areas. A simple and elementary approach for OBC has been applied in this study. There is great potential for further improving the classification accuracies through refining and specialising the decision rule structure. The poor performance of the technique with respect to spatially indistinct and spectrally overlapping classes can be further improved by integrating relevant auxiliary layers in the process of segmentation and classification. At the resolution of the image used in this study the accuracies achieved by the selected unrefined classification approach are highly encouraging. Better results can be achieved with a higher resolution dataset where interclass differences are more marked.

OBIA may effectively be used in urban applications for time effective generation of land cover maps in a semi automated manner with very close approximation to results obtained by VI approach. The approach bears the potential of providing a fast, efficient, versatile, objective means of producing visually appealing outputs for information extraction from high resolution satellite datasets of urban as well as suburban areas. The method can effectively be used for urban applications like detection of urban impervious surfaces, determination of urban green space, study of urban sprawl, assessment of building density and vacant land, land cover change detection and other such applications where high cartographic quality of outputs is not required. At the given resolution and quality of pan-sharpened multispectral image acceptable accuracies in land cover mapping may be achieved by object based nearest neighbour classification method for applications where the concern is class area rather than visual quality of boundaries.

Acknowledgement

The author expresses heartfelt gratitude to Prof. B.S.Sokhi under whose able supervision this project was undertaken. Thanks are due to Dean, IIRS for images and institutional support, to Poonam S. Tiwari, Heena Pandey and Meenakshi for their valuable suggestions. Sincere thanks to the reviewers and Prof. R.D.Gurjar for their insightful comments for refinement of the script.

References

Barrile, V., & Bilotta, G. (2008): An Application of Remote Sensing: Object-Oriented Analysis of Satellite Data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 37, Part B8, Beijing 2008.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004): Multi-Resolution, Object-Oriented Fuzzy Analysis of Remote Sensing Data for GIS-Ready Information. *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 58: 239– 258.

Ehlers, M. (2007): New Developments and Trends for Urban Remote Sensing. In Q. Weng and D. A. Quattrochi (Eds.), *Urban Remote Sensing*, (pp. 357- 374). London: Taylor and Francis.

Ehlers, M., Klonus, S., & Astrand, P.J. (2008): Quality Assessment for Multi-Sensor Multi-Date Image Fusion. In *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 37, Beijing, pp. 499-505.

Foody, G. M. (2004): Thematic Map Comparison: Evaluating the Statistical Significance of Differences in Classification Accuracy. *Photogrammetric Engineering and Remote Sensing*, Vol. 70: 627-633.

Frauman, E., & Wolff, E. (2005): Segmentation of Very High Spatial Resolution Satellite Images in Urban Areas for Segments-Based Classification. *Proceedings of the ISPRS WG VII/1 "Human Settlements and Impact Analysis"* 3rd International Symposium Remote Sensing and Data Fusion Over Urban Areas (URBAN 2005) and 5th International Symposium Remote Sensing of Urban Areas (URS 2005) accessed online at *www.isprs.org/commission8/workshop_urban/frauman.pdf.*

Gangkofner, U.G., Pradhan, P.S. & Holcomb, D.W. (2008): Optimizing the High-Pass Filter Addition Technique for Image Fusion. *Photogrammetric Engineering and Remote Sensing*, Vol. 74: 1107-1118.

Gao, J. (2008): *Digital Analysis of Remotely Sensed Imagery*. New York: McGraw Hill.

Jalan, S. (2009): *Comparative Evaluation of Visual Interpretation and Object Based Classification Technique for Urban Land Cover Mapping using High Resolution Satellite Images*. Unpublished project report, PG Diploma 2009, HUSAD, Indian Institute of Remote Sensing, Dehradun, India.

Stehman, S.V. (1997): Selecting and Interpreting Measures of Thematic Classification Accuracy. *Remote Sensing of Environment*, Vol. 62: 77-89.

Voorde, T. Van de, Genst, W.D., Canters, F., Stephenne, N., Wolff, E., & Binard, M. (2004): Extraction of Land Use/ Land Cover Related Information from Very High Resolution Data in Urban and Suburban Areas. In R. Gossens (Ed.), *Remote Sensing in Transition*, Proceedings of the 23rd Symposium of the European Association of Remote Sensing Laboratories, Ghent, Belgium, 237-244.

Yan, G., Mas, J. F., Maathuis, B. H. P., Xiangmin, Z., & Van Dijk, P. M. (2006): Comparison of Pixel-Based and Object-Oriented Image Classification Approaches-A Case Study in a Coal Fire Area, Wuda, Inner Mongolia, China. *International Journal of Remote Sensing*, Vol. 27: 4039-4055.

Zhang, Y. (2002): Problems in the Fusion of Commercial High-Resolution Satellite Images as well as LANDSAT 7 Images and Initial Solutions. *International Archives of Photogrammetry and Remote Sensing (IAPRS)*, 34(4).

Dr. Seema Jalan
Lecturer
Government P.G. College
Dausa, Rajasthan
seemajalan1@gmail.com

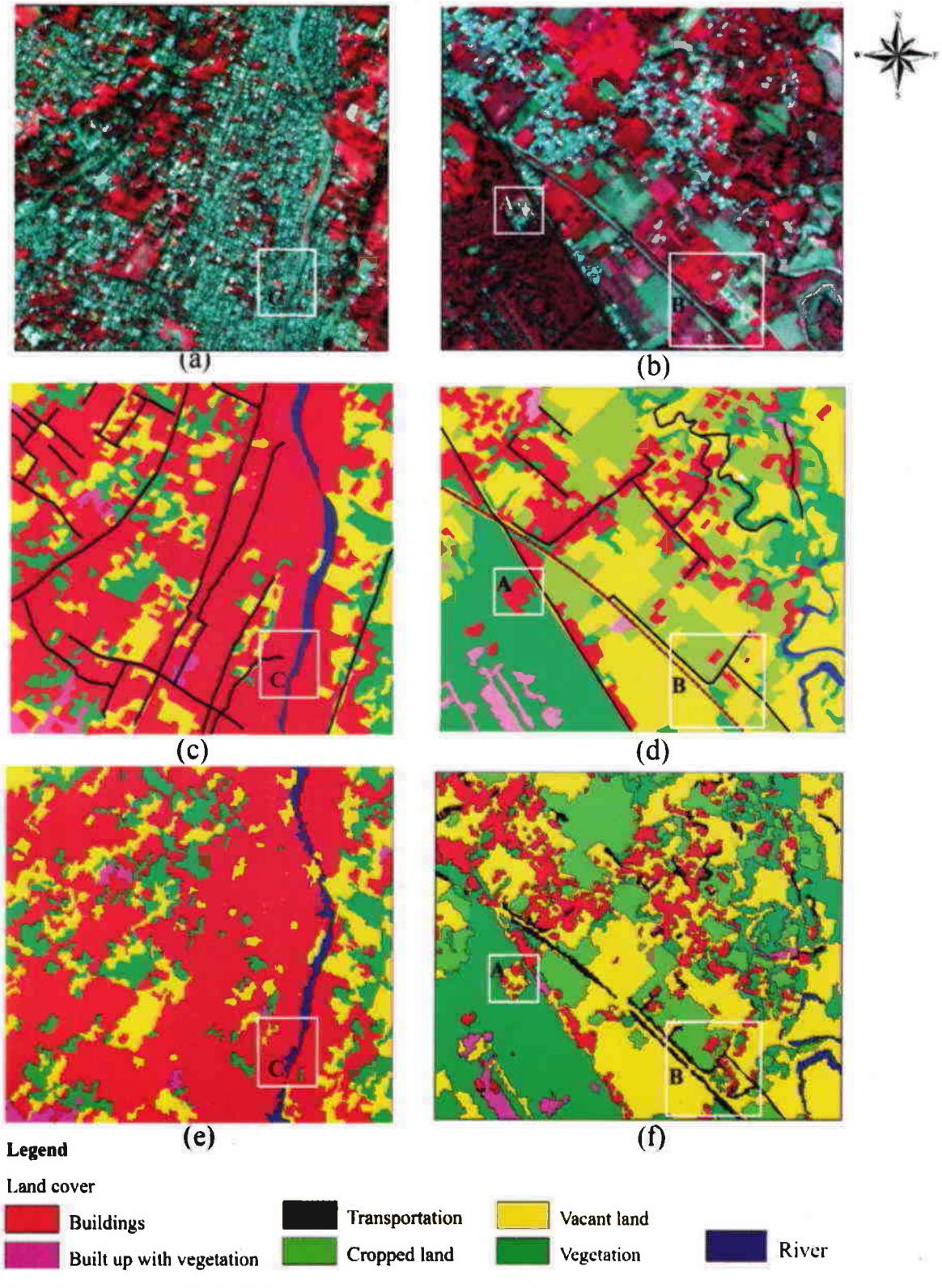


Fig.3: Original image subsets (False Colour Composites) and classification results obtained by applying visual interpretation (VI) and object based classification (OBC) (a) subset 1; (b) subset 2; (c) subset 1 classified by VI; (d) subset 2 classified by VI; (e) subset 1 classified by OBC; (f) subset 2 classified by OBC. Explanations for Boxes A, B and C have been given in section 3 of text.

Fig 1 b
"Subset 1 Densely Built Urban Area"

Fig 1 c
"Subset 2 Urban Fringe Area"