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Object-oriented Classification and QuickBird Multi-spectral Imagery in Forest Density Mapping

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Abstract : Forest cover density studies using high resolution satellite data and object oriented classification are limited in India. This article focuses on the potential use of QuickBird satellite data and object oriented classification in forest density mapping. In this study, the high-resolution satellite data was classified based on NDVI/pixel based and object oriented classification methods and results were compared. The QuickBird satellite data was found to be suitable in forest density mapping. Object oriented classification was superior than the NDVI/pixel based classification. The Object oriented classification method classified all the density classes of forest (dense, open, degraded and bare soil) with higher producer and user accuracies and with more kappa statistics value compared to pixel based method. The overall classification accuracy and Kappa statistics values of the object oriented classification were 83.33% and 0.77 respectively, which were higher than the pixel based classification (68%, 0.56 respectively). According to the Z statistics, the results of these two classifications were significantly different at 95% confidence level.

Key Words : Object oriented classification, NDVI, Forest density, Eastern Ghats, High-resolution data

1. Introduction

Forest cover mapping using satellite remote sensing is well established as it provides an opportunity to monitor and understand spatial patterns of vegetation and to inform the understanding of biotic and abiotic processes related to those patterns. There are many studies in which the physical and spectral properties associated with vegetation cover and surface morphologic structures observed by remote sensing are being continuously refined (Bradley & Mustard, 2005; Okin & Painter, 2004; Okin *et al.*, 2001; Weeks *et al.*, 1996) especially with the incorporation of spatial patterns of vegetation (Caylor *et al.*, 2004; Okin & Gillette, 2001; Privette *et al.*, 2004; Scholes *et al.*, 2004). In recent times, the technical advances in remote sensing sensor provides high spatial resolution, which enables direct imaging of plant individuals that are at least the size of the ground resolution of the remote sensing image (Schlesinger and Gramenopoulos 1996; Phinn *et al.* 1996; Okin and Gillette 2001).

The classification of remote sensing data by various procedures is so far based on the radiometric

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information in the image bands. Ideally pixels are expected to be, to a degree, more or less grouped in the multi-spectral space in clusters corresponding to different land cover types (Price, 1994). Classic classification approaches classify an image pixel by pixel and one pixel can only be classified into one class, thus produces a hard classification. This approach performs well but the ability for resolving inter-class confusion is limited. The land cover may be misclassified if they are spectrally similar but compositionally different. Similarly, the spectral heterogeneity of the land cover can lead to rogue pixels appearing within classes creating a 'salt and pepper' effect (Whiteside, 2000). In addition to this, the increased application of higher resolution imagery is problematic as it is difficult to classify accurately using traditional pixel-based methods. The increased amount of spatial information often leads to an inconsistent classification of pixels, as a result, in recent years, and following advances in computer technology, alternative strategies have been proposed, particularly the use of artificial neural networks, decision trees, methods derived from fuzzy set theory, and the incorporation of secondary information such as texture, context and terrain features (Tso and Mather, 2001).

The object-oriented classification is a new method, in which new image-analysis tools are introduced. Here, in contrast to methods used until now, group of pixels called objects, not the individual pixels of the image themselves are examined during the classification process. The object-oriented classification methods suitable for medium to high resolution satellite imagery provide a valid alternative to 'traditional' pixel-based methods (Baatz *et al.*, 2004; Benz *et al.*, 2004). With object oriented image analysis approach, not only the spectral information in the image will be used as classification information, the texture and context information in the image will be combined into classification as well (Baatz *et al.*, 2004). Most studies claim that object based classification has greater potential for classifying higher resolution imagery than pixel-based methods (Willhauck *et al.*, 2000; Mansor *et al.*, 2002; Oruc *et al.*, 2004). Neimeyer and Canty (2003) claimed that object-oriented classification has greater possibilities for detecting change in higher resolution imagery and Manakos *et al.* (2000) found that the ancillary data utilized within object-oriented classification is advantageous in improving the classification.

In India, the Forest survey of India (FSI) estimates the forest cover of India once in two years using medium resolution satellite data such as Landsat MSS, TM, IRS 1B LISS II and IRS 1C/1D LISS III data from 1983 onwards. Till 1999 FSI adopted visual classification technique on 1: 250,000 scale and from 2001 onwards it adopted the NDVI based digital classification technique on 1:50,000 scale. Apart from FSI, there are number of forest cover density studies carried out in India using medium resolution data following the traditional pixel based classification method, but object oriented classification using medium or high-resolution satellite data is very much limited. Therefore in the present study, pixel and object oriented classification methods were tested for forest density classification in a forest region, in the Eastern Ghats of Tamil nadu, India using QuickBird multi-spectral data (2.4 m spatial resolution).

2. Study Area

A forest region covering 601 ha has been selected for the present study, which is situated the Easter Ghats of Tamil Nadu, India (Fig. 1).

The Geographical coordinates of the area range

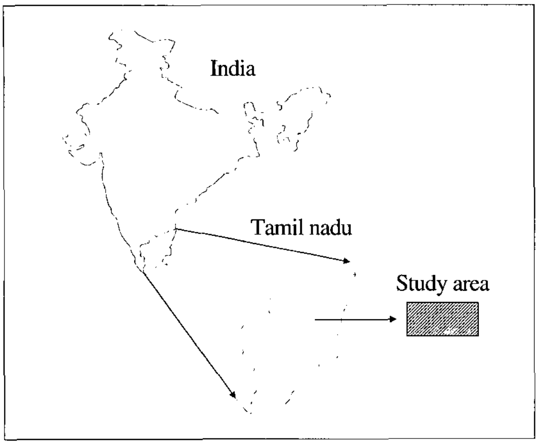


Fig. 1. Location map of the study area.

between 78° 25′ 37″ to 78° 27′ 26″ E and 11° 18′ 10″ to 11° 19′ 08″ N. The altitude is ranging from 200 to 1100 m above MSL. Geologically, it is occupied by acid charnockite. The study area comprises plateau, valley and foothill. In the forest region patches of semi-evergreen, deciduous, southern thorn and scrub forests are present. The mean annual rainfall is 1318 mm and mean maximum and minimum temperature is 35° and 18°C respectively.

3. Materials and Methods

QuickBird satellite data of July, 2006 (Fig. 2 a-e), Leica GS 20 PDM global positioning system (GPS), Erdas Image processing software 9.1, Definiens Professional -5 eCognition software were used. ERDAS Imagine was used for pixel based classification and the Definiens' software product, eCognition was used for object oriented classification.

4. Object-oriented Classification

The process can be split into two steps, segmentation and classification. The object-oriented approach first involved the segmentation of image data into objects on the defined scale level. The subset images were segmented into object primitives or segments using eCognition. The segmentation of the images into object primitives is influenced by three parameters: scale, colour and form (Willhauck *et al.*, 2000).

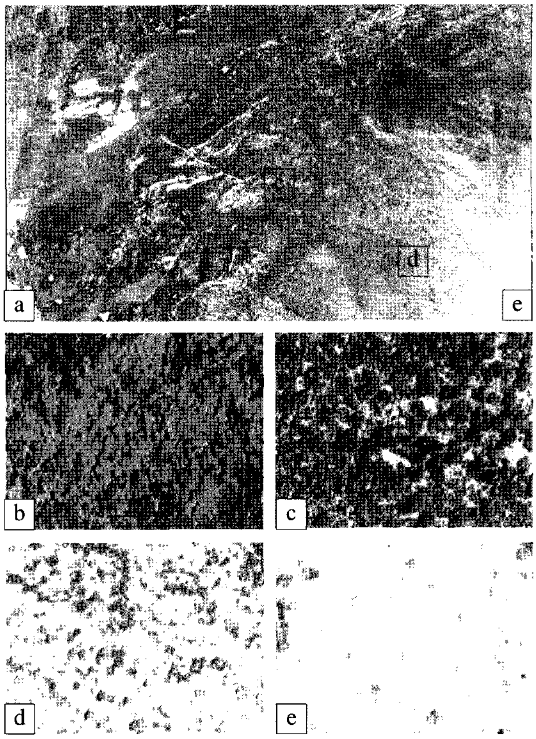


Fig. 2. a. QuickBird satellite data of the study area, b. Dense forest, c. Open forest, d. Degraded forest, e. Bare soil.

The scale parameter set by the operator is influenced by the heterogeneity of the pixels. The colour parameter balances the homogeneity of a segment's colour with the homogeneity of its shape. The form parameter is a balance between the smoothness of a segment's border and its compactness. The weighting of these parameters establishes the homogeneity criterion for the object primitives (Definiens, 2006). A visual inspection of the objects resulting from variations in the weightings was used to determine the overall values for the parameter weighting at each scale

Table 1. Segmentation parameters for object oriented classification of forest density classification.

Classification	Scale parameter	Color	Shape factor	Compactness	Smoothness
Forest	60	0.9	0.1	0.5	0.5

level (Table 1).

Samples for each class were selected from the image objects to act as training areas for the classification. Objects were assigned class rules using spectral signatures, shape and contextual relationships. The rules were then used as a basis for the fuzzy classification of the data with the most probable/likely class being assigned to each object.

5. Pixel-based (NDVI) Classification

The pixel-based classification was undertaken using ERDAS Imagine v9.1 image processing software. A normalized difference vegetation index (NDVI) (Jensen, 1996; Lillesand and Kiefer, 2000) was generated from the QuickBird satellite data. An interactive method of display was used to assign threshold values for each density class viz., dense (>40% crown cover), open (10-40%) and degraded (<10%), on the basis of field knowledge (Rawat *et al.*, 2003), and a density map of the forests was prepared. Majority filter (3×3) was run on the classified map to remove salt and pepper effect. Further, sieve and clump functions were also used to remove group of pixels less than four. As the pixel size of QuickBird multispectral data is 2.4 m a group of 2×2 pixels (23 m^2) was set to be the minimum mapping unit.

6. Accuracy Assessment

The classified forest cover density map of pixel/NDVI based and object oriented were printed on 1:5,000 scale using an HP plotter. Accuracy check was carried out in 150 points in each map (Table 2 and 3) using a GPS to estimate the accuracy of classification (Congalton, 1991).

The accuracy sample points were distributed randomly in the classified map in proportion to the area of each class. The latitude and longitude values of the accuracy check points were noted, and in the field, the location of each point was identified with the help of the GPS. Given that the GPS accuracy was found to be less than 5 meters in all places, the location of each point was judged to have been identified accurately. Once all of the points were checked, the producer and user accuracy of the individual class as well as the overall accuracy of the

Table 2. Accuracy assessment table for pixel based classification of forest density.

	Dense forest	Open forest	Degraded forest	Bare soil	Row Total
Dense forest	19	7	6	0	**32**
Open forest	9	31	5	0	**45**
Degraded forest	0	6	35	2	**43**
Bare soil	0	0	13	17	**30**
Column total	**28**	**44**	**59**	**19**	**150**

Table 3. Accuracy assessment table for object oriented classification of forest density.

	Dense forest	Open forest	Degraded forest	Bare soil	Row Total
Dense forest	24	4	4	0	**32**
Open forest	7	36	2	0	**45**
Degraded forest	0	2	41	0	**43**
Bare soil	0	0	6	24	**30**
Column total	**31**	**42**	**53**	**24**	**150**

classification were calculated. The Kappa statistics for each and every individual class were also calculated. The variance of Kappa and Z statistics were computed with 95% confidence level for both classifications (Congalton and Green, 1999).

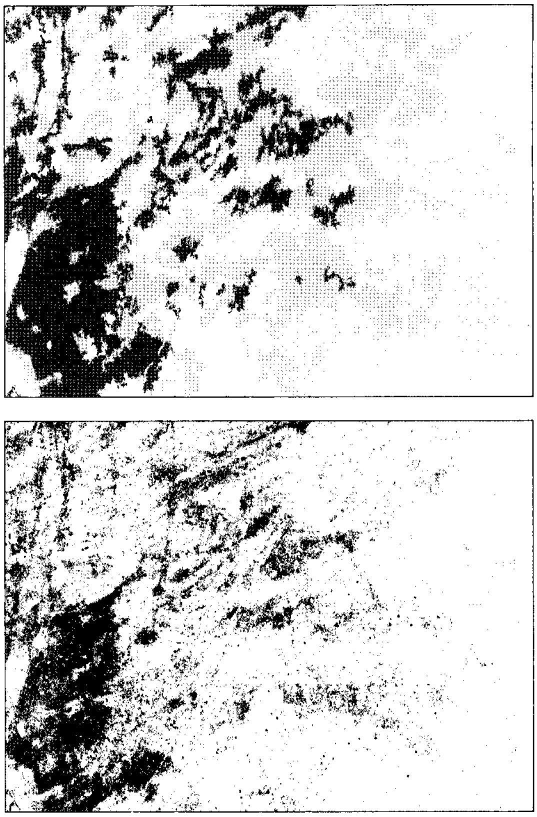
7. Results and Discussion

The study area comprised of 601 ha (Table 4). There were semi-evergreen, deciduous, southern thorn and southern thorn scrub forest types. The results of density classification of pixel based and object oriented are discussed below. The visual observation of results of two classifications showed wide variations.

The result of pixel based density classification had salt and pepper effect all through the area (Fig. 3). The dense forest occupied 92.36 ha in pixel based classification whereas it occupied 113.39 ha in object oriented classification. Accuracy point of view the producer and user accuracy of the dense forest class based on object oriented method were high (77.42 and 75.00 % respectively) when compared to pixel based method (67.45 and 59.38% respectively) (Table 5). In the case of open forest, the area occupied under pixel based and object oriented classifications were 155.0 and 203.9 ha respectively (Table 4). The producer, user and kappa statistics were also higher in the object oriented classification

Table 4. Forest cover density and areal extent of each class in the study area.

Sl. No.	Forest cover density	Area in hectare	
		Pixel based	Object oriented
1	Dense	92.36	113.39
2	Open	155.33	203.90
3	Degraded	228.74	185.0
4	Bare soil	124.98	99.12
		601.41	601.41



Dense forest Open forest
Degraded forest Bare soil

Fig. 3. a. Forest density classification by object oriented methods, b. Forest density classification by pixel based method.

compared to pixel based methods (Table 5).

The degraded forest class of pixel based classification occupied more area (124.98 ha) when compared to object oriented method (99.12 ha). But accuracy point of view, the object oriented classification had more producer (77.36%) and user (95.35%) accuracies when compared to the pixel based classification. The kappa statistics value also was higher in object oriented classification (0.92) than pixel based classification (0.69) (Table 5). The bare soil class occupied 124.98 ha and 99.12 ha in pixel based and object oriented classification respectively. The overall classification accuracy and overall kappa statistics were 68.0 % and 0.56 in pixel based classification,

Table 5. Accuracy assessment values for object oriented and pixel/NDVI based classification methods.

Sl. No	Forest cover density	Accuracy of pixel based classification			Accuracy of object oriented classification		
		Producer (%)	User (%)	Kappa	Producer (%)	User (%)	Kappa
1	Dense	67.45	59.38	0.5005	77.42	75.00	0.6849
2	Open	70.45	68.89	0.5597	85.71	80.00	0.7222
3	Degraded	59.32	81.40	0.6933	77.36	95.35	0.9281
4	Bare soil	89.47	56.67	0.5038	100.0	80.00	0.7619
		Overall accuracy = 68.00%			Overall accuracy = 83.33%		
		Overall Kappa = 0.5641			Overall Kappa = 0.7744		
		Variance = 0.002655643			Variance = 0.0016866097		
		Z statistics = 3.1916					

whereas it was 83.33 % 0.77 in the object oriented classification respectively. The Z-statistics calculated at 95% confidence level proved that these two classifications were significantly different as the value (3.1916) is more than 1.96 (Table 5).

Among the four classes, the bare soil was classified with 100% producer accuracy and the degraded forest was classified with 95.3 % user accuracy in the object oriented classification. In the case of dense and open forest categories, the pixel based classification occupied lesser area when compared to object oriented classification. This is due to the classification methods. The object oriented classification considers group of pixels based on the scale factor rather than single pixel during classification but the pixel based approach considers only individual pixels. Therefore, the salt and pepper effect was totally avoided in object oriented method. Apart from these, the pixel based classification results in a model of the terrain that does not match with the representation of geographical objects, such as parcels and water bodies (Fisher 1997, Stein *et al.* 1999). As a consequence, the output maps need to be extensively edited before they can be stored into GIS databases. Object-oriented classification techniques based on image segmentation overcame this inconvenience and generated geo-information that could be immediately usable (Crosset *et al.*, 1988, Franklin and Wilson, 1991, Johnsson, 1994).

8. Conclusion

The use of QuickBird multi-spectral high-resolution image and object-oriented classification technique were highly suitable for forest density studies. Compared to the more traditional NDVI based (pixel based) density classification technique, object-oriented method proved to be significantly different. The object oriented method produced vector maps ready to be integrated and analyzed in a GIS database. In future, forest cover density mapping with object oriented classification method using QuickBird satellite data can be tried for entire India, so that not only the accuracy of classification can be improved, but also the limitations related to spatial resolution of satellite data can be overcome.

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