Comparison of object oriented and pixel based classification of satellite data for effective management of natural resources
천연 자원의 효율적인 관리를 위한 위성자료의 객체 및 픽셀기반의 비교

자야쿠마[1] · 허준[2] · 손홍규[3] · 이정빈[4] · 김종석[5]
S.Jayakumar · Heo Joon · Sonh, Hong Gyoo · Lee, Jung Bin · Kim, Jong Suk

[1] 연세대학교 사회환경시스템 공학부 박사후과정(E-mail:sjayakumar_1@yahoo.com)
[2] 연세대학교 사회환경시스템 공학부 조교수(E-mail:jheo@yonsei.ac.kr)
[3] 연세대학교 사회환경시스템 공학부 부교수(E-mail:sohn1@yonsei.ac.kr)
[4] 연세대학교 사회환경시스템 공학부 석사과정(E-mail:ortolan@yonsei.ac.kr)
[5] 연세대학교 사회환경시스템 공학부 석사과정(E-mail:kjsppk2@naver.com)

요 지

이 논문은 고해상도 Quickbird 영상을 이용하여 세부레벨계획을 위한 토지피복분류를 수행하였으며 고해상도 영상을 이용한 토지피복분류를 위하여 객체기반분류와 ISODATA 기법을 적용하였다.
객체기반분류는 eCognition 소프트웨어를 사용하였으며 ISODATA 기법의 토지피복분류 결과와 비교분석을 수행하였다. 연구 대상지역은 인도의 Sukkalampatti이라 하는 작은 유역을 대상으로 연구를 진행하였다. 고해상도 영상의 사용으로 토지피복분류에 있어서 공간 해상도에 따른 토지피복의 세부레벨분류 정확도를 향상 시킬 수 있는 이점을 확인 할 수 있으며 또한, 객체기반분류와 ISODATA 기법의 분류 결과는 eCognition을 사용한 객체기반 토지피복분류결과가 ISODATA의 픽셀기반의 분류방법보다 높은 정확도를 보였다.

1. Introduction

Till recent times, the classification of land cover was based on traditional pixel-based methods (Ahmad et al., 1997; Hayder et al., 1999; Menges et al., 2000). The land cover may be misclassified if they are spectrally similar but compositionally different. Typical objects in an image are not characterized by one color, but by a characteristic texture of colors, as well (Steinnocher, 1997). The spectral heterogeneity of the land cover can lead to rogue pixels appearing within classes creating a 'salt and pepper' effect (Whiteside, 2000). Most classification algorithms are based on the digital number of the pixel itself and/or texture attributes in a certain defined vicinity around a pixel (Landgrebe et al., 1976). Furthermore, it is very difficult to integrate context information in pixel-oriented approaches. Topology and spatial relationship features are also missing. The increased amount of spatial information often leads to an inconsistent classification of pixels.

Baatz et al., (2004) and Benz et al., (2004) suggested that the object-oriented classification methods suitable for medium to high resolution satellite imagery provide a valid alternative to 'traditional' pixel-based methods. By this method, not single pixels are classified but homogenous image objects are extracted. Neimeyer and Canty (2003) claim that object-oriented classification has greater possibilities for detecting change in higherresolution imagery and Manakos et al. (2000) found that the ancillary data utilized within object-oriented classification is advantageous in improving the classification. Most papers 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).

In this paper the results of an object-oriented and pixel based supervised classifications for land cover mapping using QUICKBIRD satellite data were compared in part of the Eastern ghats of India.

2. Study area

For this study A small forest area covering 120 ha and a small non-forest area covering 95 ha have been selected in the Eastern Ghats of Tamil nadu, India (Figure 1a, b). The altitude is ranging from 200 to 1200 m above MSL. Geologically, it is occupied by acid charnockite. The study area comprises plateau, valley and foothill. A tribal settlement called Sukkalampatti is situated in the non-forest area. In the forest region patches of deciduous, southern thorn and scrub forests are present. Agriculture is the main source of income of the people. The mean annual rainfall is 1318 mm and mean maximum and minimum temperature is 35 and 18 C respectively.

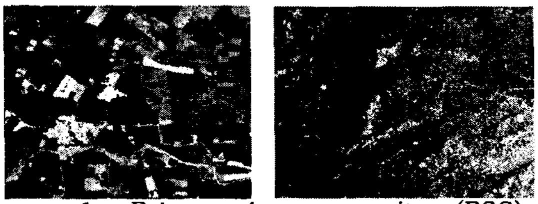

Figure -1. False color composite (FCC) of QuickBird satellite data, Band combination 4,3,2 in RGB, a) Non-forest area, b) Forest area

3. Materials and methods

QuickBird satellite data of 2006 (Figure 1a,b), 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 using the maximum likelihood algorithm and the Definiens' software product, eCognition was used for object-based classification. The methods followed are defined in the figure - 2.

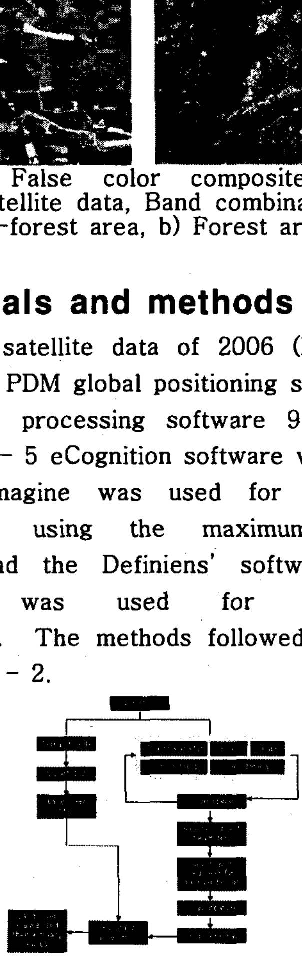

Figure 2. Methodology flow chart

3.1 Object-oriented 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).

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. 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 level. 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.

3.2 Pixel-based supervised classification

The pixel-based classification was undertaken using ERDAS Imagine v9.1 image processing software. The supervised classification method (Jensen, 1996; Lillesand and Kiefer, 2000) involved the selection of training areas representative of the 9 land cover classestotally in forest and non-forest areas. A number of training areas were selected to represent each class. The signature (or spectral mean) of the training area was then used to determine to which class the pixels were assigned.

3.3 Accuracy assessment

Accuracy assessments of both classifications were undertaken using confusion matrices and Kappa statistics (Congalton, 1991). The accuracy of the classified image was assessed using a range of reference data including field data collected in the study area. Producer and user accuracies for each class were calculated along with the overall accuracies and Kappa statistics (Congalton and Green, 1999).

4. Results

Thepixel based classification output shows many small groups of pixels or individual pixels, where as the object oriented classification shows multi-pixel features (Figure 3a - d).

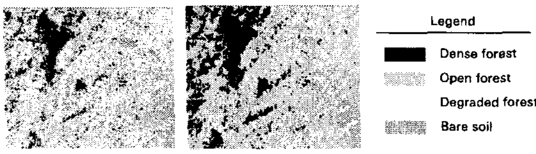

Figure 3. Classified images a) Pixel based classification of non-forest area, b) Object oriented classification of non-forest area, c) Pixel based classification of forest area, d) Object oriented classification of forest area.

4.1 Comparison of area

Table 1. Area and accuracy statistics of pixel based and object oriented classification of forest area

Class name	Area in hectare		Accuracy of pixel based classification			Accuracy of object-oriented classification		
	Pixel based	Object - oriented	Producer (%)	User (%)	Kappa	Producer (%)	User (%)	Kappa
Dense Forest	10.35	20.93	58.33	70.00	0.6053	75.00	81.82	0.7608
Open forest	48.47	68.04	46.15	40.00	0.1892	78.57	64.71	0.5098
Degraded forest	38.88	9.26	47.06	57.14	0.3506	57.14	80.00	0.7222
Barren soil	22.83	21.79	75.00	54.55	0.4589	90.00	75.00	0.6875
			Overall accuracy = 54.00%			Overall accuracy = 74.00%		
			Overall Kappa = .03814			Overall Kappa = .0.6524%		

Table 2. Area and accuracy statistics of pixel based and object oriented classification of non-forest area

Class name	Area in hectare		Accuracy of pixel based classification			Accuracy of object-oriented classification		
	Pixel based	Object - oriented	Producer (%)	User (%)	Kappa	Producer (%)	User (%)	Kappa
Residential	2.61	7.66	40.00	40.00	0.3077	40.00	36.36	0.2657
Dry crop	37.22	23.69	72.22	61.90	0.4987	73.91	94.44	0.9199
Wet crop	3.64	6.07	66.67	60.00	0.5455	83.33	100.00	1.000
Plantation	18.07	22.79	27.27	20.00	0.0625	60.00	33.33	0.2308
Fallow land	32.77	34.15	48.15	68.00	0.5066	80.00	88.89	0.8485
			Overall accuracy = 52.00%			Overall accuracy = 70.67%		
			Overall Kappa = 0.03834			Overall Kappa = 0.6285%		

The total forest area is 120 ha and the total area of non forest area is 94 ha (Table 1 and 2). In the case of forest, except the barren soil class there are drastic differences in the area between pixel based and object oriented classification. In the case of non-forest area except fallow land all other classes show more variation in the area between these classifications.

4.2 Accuracy of Classification

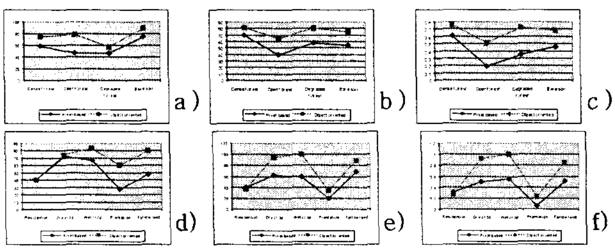

Figure -4. Accuracy assessment of forest and non-forest area, a) producer accuracy of forest area, b) user accuracy of forest area, c) kappa statistics of forest area, d) producer accuracy of non-forest area, e) user accuracy of non-forest area, f) kappa statistics of non-forest area.

For accuracy assessement, 125 pixels have been selected randomly in both forest and non-forest areas and their agreement with ground truth has been analyzed. Then, error matrix has been generated and given in table 1 and 2. This table includes the accuracies such as producer's, the user's and the kappa statistics.

In the case of forest the object oriented classification attains more weightages when compared to the pixel based classification. The user accuracy of dense forest and producer accuracy of degraded forest could be more or less related to the object oriented classification accuracies (Figure 4a and b). In all the other classes the accuracy is always higher in the object oriented classification. when comparing overall accuracy and Kappa statistics the object oriented classification attains 20% more value than the pixel based classification and in the Kappa statistics the object oriented classification is almost 100% better than the pixel based classification (Table 1 and Figure 4c).

In the case of non-forest area the classes such as residential and dry crop has similar producer accuracy between these two classifications. Wet crop, plantation and fallow lands have accurately been classified in the object oriented classification than pixel based one. The overall accuracy also show more variation and the Kappa statistics is very high in the object oriented (0.6285) but it is very less in the pixel based classification (0.03834) (Table 3 and Figure 4 d-f). The residential and plantation classes have been classified with low producer accuracy of 40 and 60 even in the object oriented classification. This may be due to the spectral similarity and irregular shape of these classes. The wet crop class has been classified with 100% user accuracy by the object oriented classification. All in all in this study the object oriented classification has produced better results when compared to the pixel based classification both in the forest and non-forest areas.

5. Conclusion

In the both the area the object oriented method using eCognition has produced better classification results with more producer, user and Kappa accuracy statistics.

1. QuickBird satellite data is suitable for land cover mapping on 1: 5000 or beyond

2. All the ground cover classes can easily be identified from the QuickBird data

3. Pan sharpened QuickBird can also be used for classification in object oriented method

4. Object oriented classification is proved to be superior than pixel based classification types

5. Object oriented classification of QuickBird satellite data will serve as good source of information for micro level planning

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