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A COMPARISON OF OBJECT-ORIENTED AND PIXEL-BASED CLASSIFICATION METHODS FOR MAPPING LAND COVER IN NORTHERN AUSTRALIA.

T. Whiteside [1,2], Ahmad, W.[2]

[1]School of Health, Business and Science, Batchelor Institute of Indigenous Tertiary Education, Batchelor, NT.
[2]Faculty of Education, Health and Science, Charles Darwin University, Darwin, NT.
tim.whiteside@batchelor.edu.au

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ABSTRACT

The development of robust object-oriented classification methods suitable for medium to high resolution satellite imagery provides a valid alternative to ‘traditional’ pixel-based methods. This paper compares the results of an object-oriented classification to a supervised pixel-based classification for mapping land cover in the tropical north of the Northern Territory. The object-oriented approach involved the segmentation of image data into objects at multiple scale levels. 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 imagery. The supervised pixel-based classification involved the selection of training areas and a classification using maximum likelihood algorithm. Accuracy assessments of both classifications were undertaken. A comparison of the results shows better overall accuracy of the object-oriented classification over the pixel-based classification. This object-oriented method provided results with acceptable accuracy; indicating object-oriented analysis has great potential for extracting land cover information from satellite imagery captured over tropical Australia.

BIOGRAPHY OF PRESENTER

Tim Whiteside is a lecturer within the Natural and Cultural Resource Management Unit in the School of Health, Business and Science at Batchelor Institute of Indigenous Tertiary Education. His teaching areas include plant ecology, vegetation management, GIS and remote sensing. Tim’s research interests focus mainly on the application of remote sensing and GIS technologies as tools for resource management.

Tim is also currently a PhD candidate in spatial science at Charles Darwin University.

INTRODUCTION

The Northern Territory of Australia is characterised by large areas of land and a very small population. This situation ideally suits itself to the use of remote sensing data and technologies to effectively map natural resource information. A range of remotely sensed data has previously been used to map land cover in northern Australia, however until recently, land cover classification was based on traditional pixel-based methods [Ahmad *et al.*, 1997; Hayder *et al.*, 1999; Menges *et al.*, 2000]. The nature of land cover in tropical Australia creates some issues relating to pixel-based method of classification [Whiteside, 2000]. For example, spectrally similar but compositionally different land cover may be misclassified. Similarly, the spectral heterogeneity of the land cover can lead to rogue pixels appearing within classes creating a 'salt and pepper' effect. 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.

The development of robust object-oriented classification methods suitable for medium to high resolution satellite imagery provides a valid alternative to 'traditional' pixel-based methods [Baatz *et al.*, 2004; Benz *et al.*, 2004]. Object-oriented classification involves segmenting an image into objects (groups of pixels). These objects have geographical features such as shape and length, and topological entities, such as adjacency and found within, [Baatz *et al.*, 2004]. These attributes make a knowledge base for the sample objects, which can be called upon in the classification process. There has been recent interest within the Northern Territory in using the object-oriented approach to map land cover [Whiteside and Ahmad, 2004; Crase and Hempel, 2005].

While there has been some studies comparing object-oriented and pixel-based classification techniques little has been conducted in northern Australia. 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]. Neimeyer and Canty [2003] claim that object-oriented classification has greater possibilities for detecting change in higher resolution imagery and Manakos *et al.* [2000] found that the ancillary data utilised within object-oriented classification is advantageous in improving the classification.

This paper compares the results of an object-oriented classification to a supervised pixel-based classification for mapping land cover in the tropical north of the Northern Territory.

METHODS

The study area

The study area is part of the Florence Creek region of Litchfield National Park, in the northwest of the Northern Territory of Australia (figure 1). The site with an area of 1373 ha is located near two of the park's major features, Florence Falls and Buley Rockhole attracting hundreds of thousandths of visitors every year.

The region's climate is characteristic of the wet/dry tropics; consisting of a long dry season (May – September) with little to no rainfall, with over 75% of the annual rainfall (1500 mm) occurring in the period between November and March. Maximum daily temperatures vary from just under 32°C in June and July to over 36°C in October and November.

The vegetation within the study area is predominantly open forest and savanna woodland with a *Eucalyptus* spp. (mostly *E. tetradonta* and *E. miniata*) dominated canopy and annual grass understorey (*Sorghum* spp.) [Griffiths *et al.*, 1997]. Patches of monsoon rain forest are located on springs near the base of the escarpment and other areas of permanent water. *Melaleuca* forests occur along creek lines and share overlapping species with the monsoon rain forest (i.e. *Xanthostemon eucalyptoides and Lophostemon lactifluus*) [Lynch and Manning, 1988]. The southern porttion of the study area is generally plateau surfaces intersected by drainage lines, while low lying areas subject to inundation are located to the north.

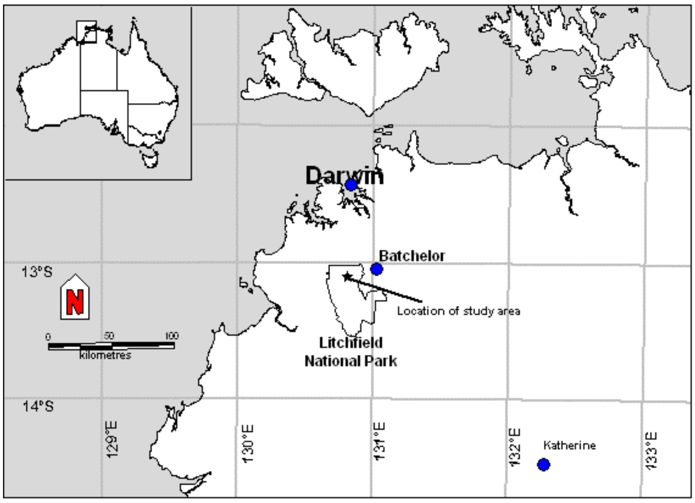


Figure 1: Location of the study site

Data

ASTER data for the area was captured on 28 July 2000 providing 14 spectral bands; three in the visible and near infrared (0.52-0.86 µm), six in the shortwave infrared (1.60-2.43 µm) and five in the thermal infrared. (8.12-11.65 µm) [Yamaguchi *et al.*, 1998]. The near infrared band 3 is captured at nadir (3N) and backwards looking (3B), producing a stereo pair of images that can be used to create a DEM [Hirano *et al.*, 2003]. The relative DEM based on ASTER bands 3N and 3B was requested and acquired in October 2002.

Geometric correction of the imagery was undertaken using ERDAS Imagine v8.6 image processing software and subsets for the study area were created from the ASTER VNIR bands and the DEM (figure 2).

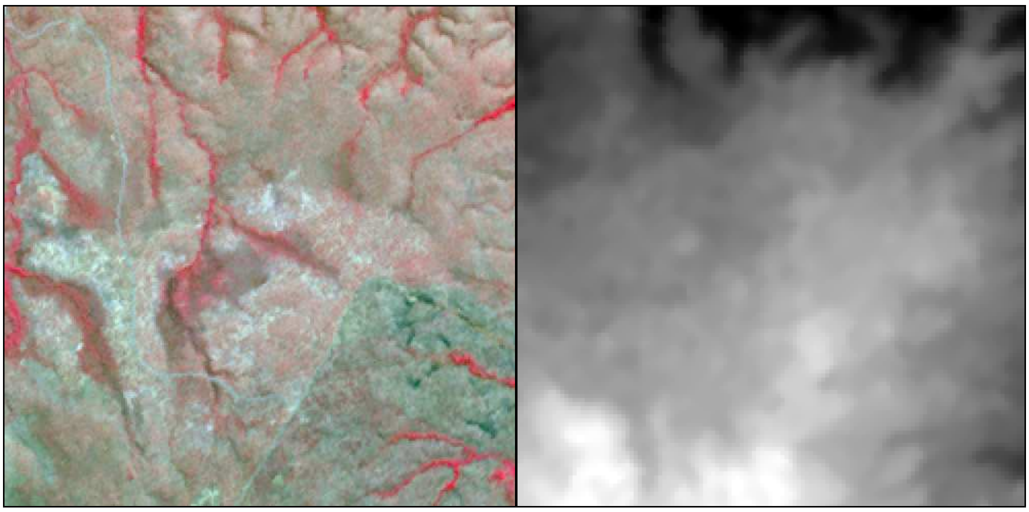


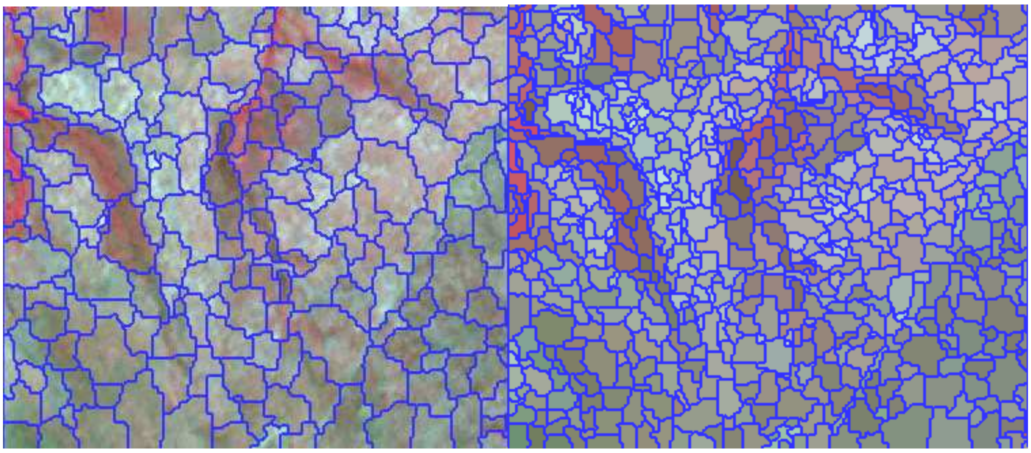
Figure 2: Subsets of ASTER VNIR bands and DEM

Object-oriented classification

The object-oriented classification conducted using eCognition v4 software [Baatz *et al.*, 2004] has previously been described [Whiteside and Ahmad, 2004]. The process can be split into two steps, segmentation and classification.

Multi-scale segmentation

The object-oriented approach first involved the segmentation of image data into objects on two scale levels (figure 3). 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].



(a) (b)

Figure 3: A section of the study area showing hierarchical segmentation at scale level 2 (a) and level 1 (b).

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 (table 1).

Scale level	Scale parameter	Shape factor	Compactness	Smoothness
2	10	0.4	0.7	0.3
1	5	0.2	0.7	0.3

Table 1: Segmentation parameters

Classification

Sample objects were selected as representative of land cover classes. A total of ten land cover classes for the study area were identified based on the structural formation of the vegetation and characteristic Genus. Two of these classes were introduced to include areas of the study site that were identified as recently burnt. Class rules for the objects were then developed using spectral signatures, shape, location and the contextual relationships of the objects. These rules were then used as a basis for classification of the image and DEM. 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.

Pixel-based supervised classification.

The pixel-based classification was undertaken using ERDAS Imagine v8.6 image processing software. It was a standard supervised classification using the maximum likelihood algorithm [Jensen, 1996; Lillesand and Kiefer, 2000]. This involved the selection of training areas representative of the ten land cover classes. 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.

Accuracy assessment

Accuracy assessments of both classifications were undertaken using confusion matrices and Kappa statistics [Congalton, 1991]. The accuracy of the classified image was the assessed using a range of reference data including field data collected in the study area over a five-year period and interpretation of aerial photography of the area. Producer and user accuracies for each class were calculated along with the overall accuracies and Kappa statistics [Congalton and Green, 1999].

RESULTS

A visual comparison of the resultant land cover images shows the differences between the classifications (figure 4). While both methods produce aggregations of pixels based on land cover classes, the object-oriented classification yields multi-pixel features whereas the pixel-based classification contains many small groups of pixels or individual pixels. This produces classes with mixed clusters of pixels as displayed by the heterogenic nature of the image.

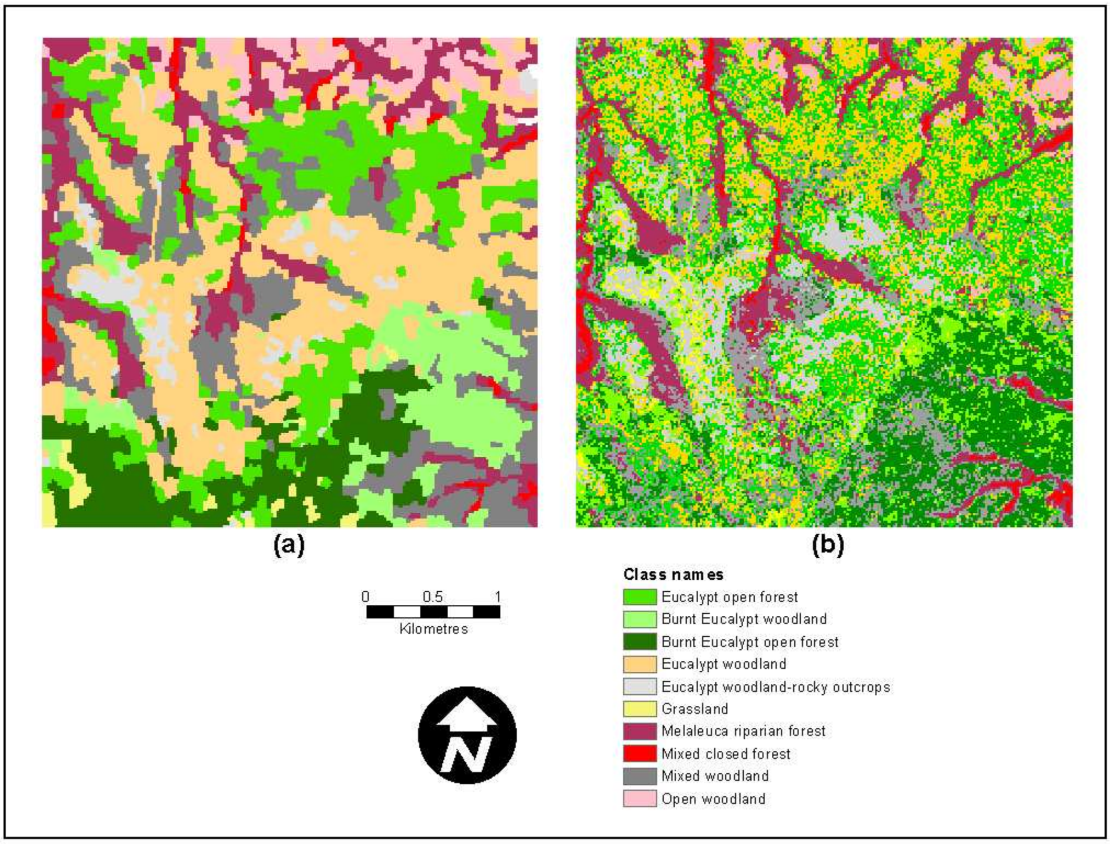


Figure 4: Results of the object-oriented (a) and pixel-based (b) classifications.

The areas of the Mixed closed forest, *Melaleuca* riparian forest and Grassland classes are relatively similar in both classifications (table 2). The Eucalypt woodland classes appears noticeably under-represented in the pixel-based classification, while there is an apparent over-representation of the Eucalypt open forest and Eucalypt woodland with rocky outcrops classes.

	Area (ha)	
Class name	Object –oriented	Pixel-based
Burnt Eucalypt open forest	228.38	188.53
Eucalypt open forest	140.54	302.24
Mixed closed forest	19.58	21.94
Melaleuca riparian forest	168.09	173.68
Eucalypt woodland	376.02	256.10
Burnt Eucalypt woodland	114.39	77.38
Eucalypt woodland with rocky outcrops	42.59	118.19
Open woodland	57.55	37.59
Mixed woodland	208.84	180.86
Grassland	15.18	16.11

Table 2: Areas of classes determined by object-oriented and pixel-based classifications

From the results of the confusion matrices, the overall accuracy of the object-oriented classification was better than for the pixel-based classification, 78% versus 69.1% respectively (table 3). This was also the case for the overall Kappa statistic. The object-oriented classification had an overall Kappa of 0.7389 while the pixel-based classification's overall Kappa statistic was 0.6476. The producer and user accuracies were greater for the majority of the classes in the object-oriented classification. The land cover classes that were more accurately classified using the pixel-based method were *Melaleuca* riparian forest, Mixed closed forest. The classes that had poor accuracy in both classifications were Mixed woodland and Grassland. This is possibly due to small number of reference data points for those classes. Object-oriented classification appears to be able to differentiate more accurately the Eucalypt open forest and woodland classes.

	Object oriented classification			Pixel-based classification		
Class name	Producer (%)	User (%)	Kappa	Producer (%)	User (%)	Kappa
Burnt Eucalypt open forest	92.00	74.19	0.68	63.64	65.63	0.6054
Eucalypt open forest	81.82	75.00	0.73	75.00	57.45	0.5048
Mixed closed forest	100.00	66.67	0.66	91.67	100.00	1.0000
Melaleuca riparian forest	68.18	78.95	0.75	87.10	90.00	0.8862
Eucalypt woodland	77.50	91.18	0.88	49.21	75.61	0.6781
Burnt Eucalypt woodland	85.71	80.00	0.78	76.92	55.56	0.5318
Eucalypt woodland with rocky outcrops	66.67	100.00	1.00	64.62	86.96	0.8516
Open woodland	87.50	87.50	0.87	83.33	76.92	0.7579
Mixed woodland	70.00	46.67	0.43	84.21	51.61	0.4773
Grassland	50.00	50.00	0.51	66.67	40.00	0.3856
	Overall accuracy = 78.00 %			Overall accuracy = 69.14 %		
	Overall Kappa = 0.7389			Overall Kappa = 0.6476		

Table 3: Summary of confusion matrices for the accuracy of object-oriented and pixel-based classifications.

DISCUSSION

The object-oriented method use in this paper provided results with an acceptable accuracy better than the pixel-based classification. This suggests that object-oriented analysis has great potential for extracting land cover information from satellite imagery captured over tropical Australia. This will be the case particularly with the increasing application of higher resolution imagery and the greater information content it holds. The visual difference between the classifications is obvious. Pixel-based classifications do misclassify pixels, particularly in land covers that are spectrally heterogenous, such as Eucalypt open forest and woodland. . Object-oriented classification appears to overcome some of the problems encountered using pixel-based methods to classify Eucalypt land cover types and their characteristic spatial heterogeneity, while it is evident that pixel-based classification is still quite successful in classifying land cover of a homogenous nature (ie closed forest). To improve the accuracies of the object-oriented classification, further work refining the process is continuing. The use of multi-sensor data and ancillary data, such as derivative data sets and existing GIS layers, is being investigated. There is also to be further development of the contextual information to be applied to objects.

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