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OBJECT-ORIENTED CLASSIFICATION OF ASTER IMAGERY FOR LANDCOVER MAPPING IN MONSOONAL NORTHERN AUSTRALIA.

Tim Whiteside[1,2] & Waqar Ahmad[2]

Author affiliation:

[1]Natural and Cultural Resource Management, School of Health and Sciences, Batchelor Institute of Indigenous Tertiary Education, Batchelor, NT 0845.

ph: 08 89397307, fax: 08 89397123, email: tim.whiteside@batchelor.edu.au

[2]Remote Sensing and GIS Group, Faculty of Education, Health and Sciences, Charles Darwin University, Darwin, NT 0909.

Abstract

This paper looks at the suitability of object-oriented analysis of ASTER imagery for the classification of land cover within the Top End of the Northern Territory. Classification based purely on spectral values of pixels has its limitations. The nature of land cover in tropical Australia can lead to problems in classification using conventional pixel-based methods; for example, the misclassification of spectrally similar but compositionally different land covers as well as the difficulty in classifying spectrally heterogeneous cover. The method used here involved the segmentation of image data into objects at multiple scale levels. Class rules for the objects were then developed using spectral signatures, shape and the contextual relationships of the objects. These rules were used as a basis for classification of the image and DEM. The accuracy of the results using this method are promising, indicating object-oriented analysis has great potential for extracting information from satellite imagery captured over tropical Australia.

Introduction

The Northern Territory contains large tracts of land with little land resource information. Until now, most land cover classifications derived from remotely sensed data in northern Australia have been conducted using pixel-based methods of classification (e.g Ahmad *et al.* 1997; Hayder *et al.* 1999; Menges *et al.* 2000). Recent studies in the region under investigation are focus on mapping fire regimes (Edwards *et al.* 2001) and the expansion of forests (Bowman *et al.* 2001).

Classification based purely on spectral values of pixels has some limitations. The nature of land cover in tropical Australia can lead to problems in classification using conventional pixel-based methods; for example, the misclassification of spectrally similar but compositionally different land covers as well as the difficulty in classifying spectrally heterogeneous cover (Whiteside 2000). While ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) data has been used previously to map land cover (Gomes and Marçal 2003), with a resolution of 15 metres it could prove problematic when conducting a pixel-based classification. With the increase in resolution over multispectral Landsat imagery, areas that may have been considered homogeneous areas at 30m resolution might appear heterogeneous with tree crowns and canopy gaps displaying spectrally different values.

Object based classifications offer an alternative method that could prove suitable for mapping land cover in northern Australia. By segmenting an image into objects, geographical features such as shape and length, and topological entities, such as adjacency and found within, can also be called upon in the classification process (Benz *et al.* 2004). Using this contextual knowledge a knowledge base of the attributes of sample objects can then be developed.

This paper looks at the suitability of object-oriented analysis of ASTER imagery for the classification of land cover within the Top End of the Northern Territory. This work is ongoing and preliminary findings are presented here.

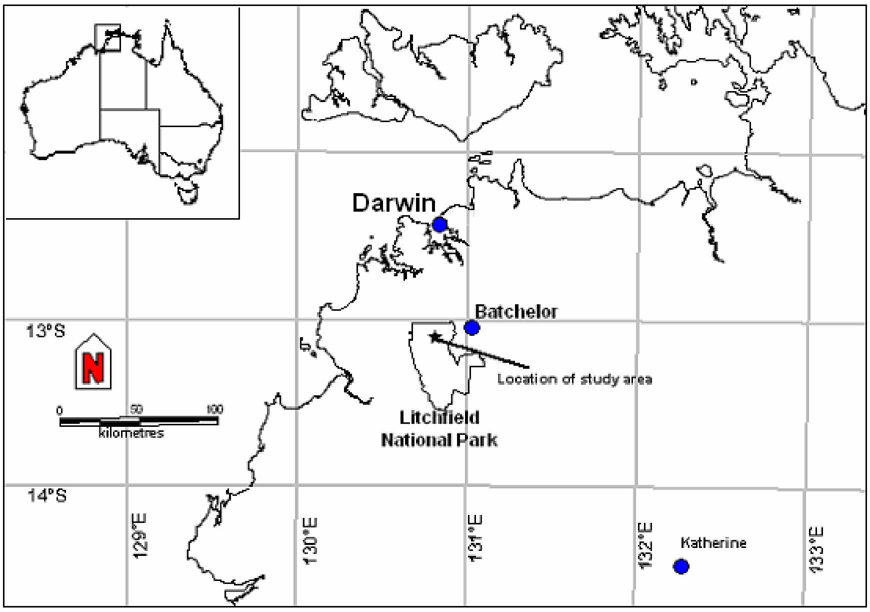


Figure 1: Location of the study site.

Methods

The study area is located in the Florence Creek region of Litchfield National Park, in the monsoonal north 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 attractions, Florence Falls and Buley Rockhole. Both these features are visited by hundreds of thousandths of locals and tourists every year.

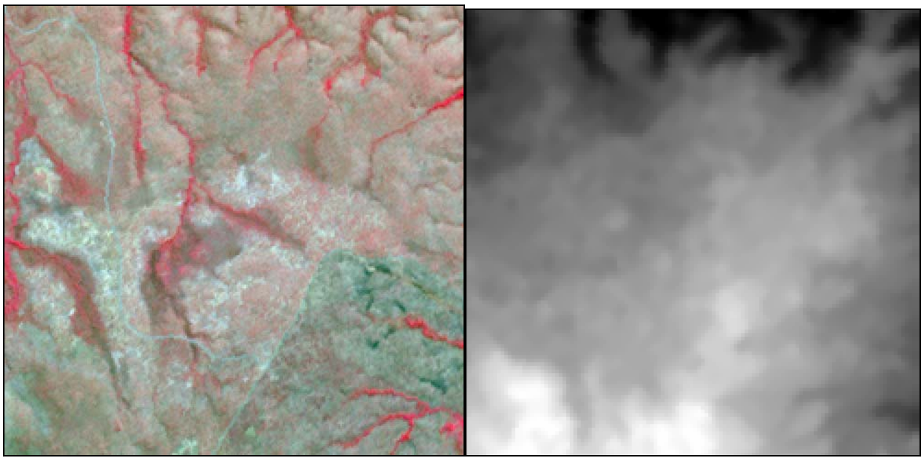
The region's climate is characterised by a long dry season (May – September) with little to no rainfall, while over 75% of the nearly 1500 mm of annual rainfall falls in the period between November and March. Records for nearby Mango Farm (latitude 13.74° S, longitude 130.68° E) indicate the maximum daily temperatures vary from just under 32°C in June and July (31.5°C) to over 36°C in October and November (37.2°C and 36.5°C respectively).

Vegetation is predominantly open forest and savanna woodland with a canopy dominated by *Eucalyptus* spp. (mostly *E. tetradonta* and *E. miniata*) and an 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 section of the study area consists of plateau surfaces intersected by drainage lines. Low lying areas subject to inundation are located to the north.

ASTER data for the area was captured on 28 July 2000. A level 1B processed granule was acquired in May 2002. ASTER products provide 14 spectral bands, 3 in the visible and near infrared (0.52-0.86 µm), 6 in the shortwave infrared (1.60-2.43 µm) and 5 in the thermal infrared.bands (8.12-11.65 µm) (Yamaguchi *et al.* 1998). The near infrared band 3 is captured at nadir (3N) and backwards looking (3B), creating a stereo pair of images. The relative DEM based on ASTER bands 3N and 3B was requested and acquired in October 2002.

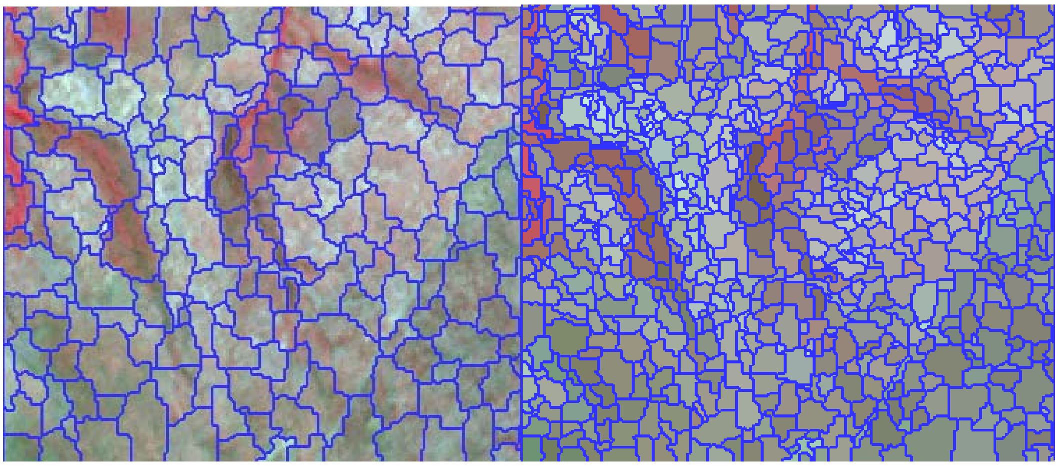
Preprocessing was conducted using ERDAS Imagine image processing software. Subsets for the study area were then created from the ASTER VNIR bands and the DEM (figure 2).



(a) (b)

Figure 2: (a)The subset of ASTER data for 28 July 2000 covering the study area. RGB represent Bands 3N, 2, 1 respectively. (b) Corresponding DEM subset.

The subset image was segmented into objects using eCognition software (Baatz *et al.* 2004). Segmentation occurred on two scale levels (figure 3). The image objects were based on parameters such as the spectral characteristics of pixels and the size and shape of the objects determined at each scale level. The homogeneity criterion for the objects is established in the weighting of these parameters. Values for the weighting of the parameters were determined using a visual inspection of the objects resulting from variations in the weighting of the parameters (table 1).



(a) (b)

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

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.

Table 1: Segmentation parameters.

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

The image was classified using eCognition software's method of fuzzy logic (Baatz*, et al.* 2004). After classification image objects have degree of membership to several classes. The class with the highest probability value is assigned as the best class for each object (Benz*, et al.* 2004).

The accuracy of the fuzzy classification was estimated using the mean probability of the best classification and the mean stability of each class (Baatz*, et al.* 2004). The mean stability is the difference between the probability of objects belonging to the best class and the probability of objects belonging to the next class - the higher the value the greater the stability. The accuracy of the classified image was the assessed using field data collected in the study area over a five-year period as reference data. Further verification was done using aerial photographs of the area. Producer, user and overall accuracies were calculated along with the Kappa statistic (Congalton and Green 1999).

Results

The image resulting from the object-oriented classification is shown in figure 4. The number of objects classified and the area (ha) assigned each class are presented in table 2. According to the classification the land cover class occupying the largest area is Eucalypt woodland (376 ha) with the number of objects identified as belonging in that class being 675. The land cover with the smallest area within the study site is Grassland occupying only 15 ha and consisting of just 21 image objects.

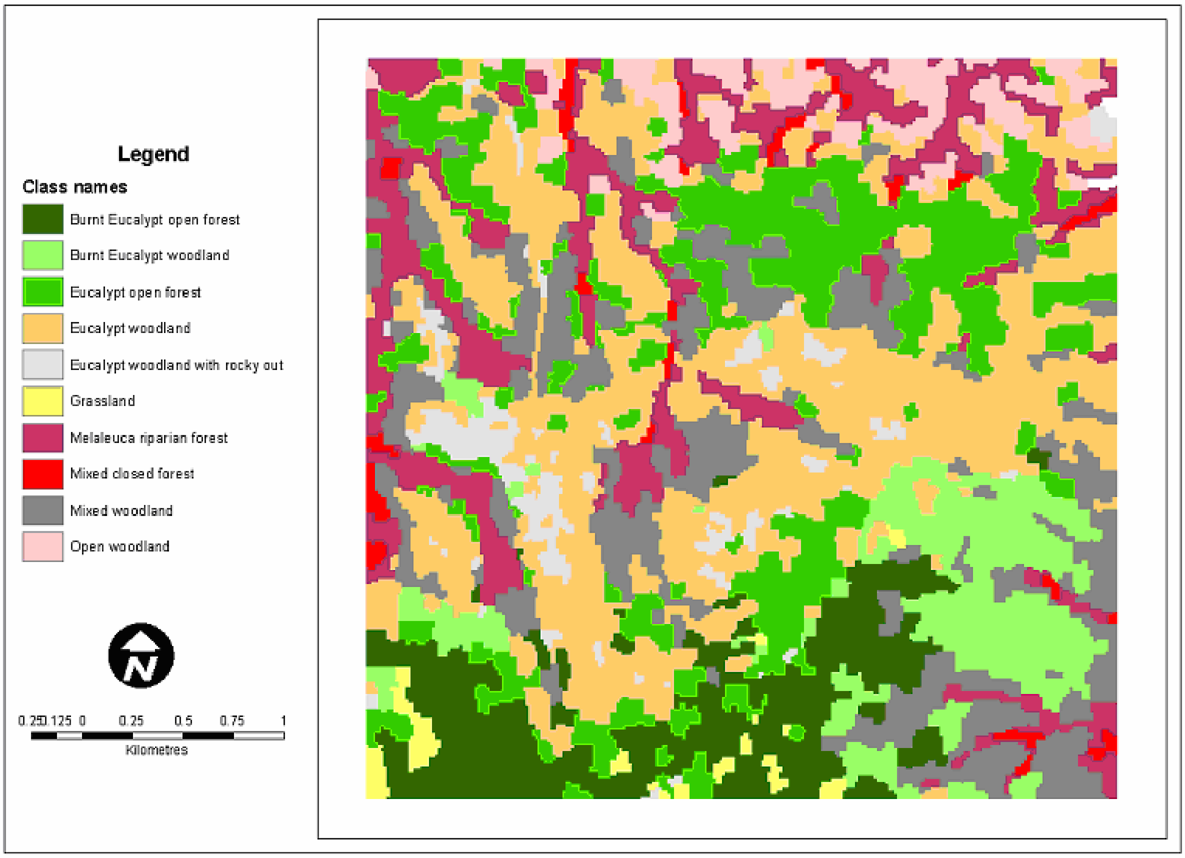


Figure 4: Classified image

A summary of the accuracy assessment of the fuzzy classification is presented in table 3. The Mean p_{1st} column displays the mean probability of objects belonging to that class. Nearly all classes have a mean p_{1st} value over 0.8 suggesting that the probability of image objects being assigned the best class was high. The class with the lowest value is Open woodland suggesting that objects assigned this class have only have a probability of 0.68 of being classed correctly. Within the Mean stability column most of the classes display stability in their classification. Only the Eucalypt open forest, *Melaleuca* riparian forest and Mixed woodland classes have a Mean stability value under 0.1. This suggests that a number of objects within these classes may not have been assigned to the correct class.

Table 2: Areas (ha) classifed.

Class ID	Class code	Class name	No. objects	Area (ha)
	1	Burnt Eucalypt open forest	128	228.38
	2	Eucalypt open forest	205	140.54
	3	Mixed closed forest	35	19.58
	4	*Melaleuca* riparian forest	215	168.09
	5	Eucalypt woodland	675	376.02
	6	Burnt Eucalypt woodland	118	114.39
	7	Eucalypt woodland with rocky outcrops	83	42.59
	8	Open woodland	71	57.55
	9	Mixed woodland	214	208.84
	10	Grassland	21	15.18

Table 3: Fuzzy classification accuracy assessment.

Class	Class name	Mean p_{1st}	Mean stability
1	Burnt Eucalypt open forest	0.880	0.136
2	Eucalypt open forest	0.827	0.092
3	Mixed closed forest	0.810	0.362
4	*Melaleuca* riparian forest	0.796	0.048
5	Eucalypt woodland	0.832	0.145
6	Burnt Eucalypt woodland	0.856	0.373
7	Eucalypt woodland with rocky outcrops	0.839	0.362
8	Open woodland	0.676	0.373
9	Mixed woodland	0.874	0.048
10	Grassland	0.840	0.138

The results of the confusion matrix accuracy assessment are summarized in table 4. Producer's accuracy was low (<70%) for the *Melaleuca* riparian forest Eucalypt woodland with rocky outcrops and Grassland classes. User's accuracy was low (<70%) and the Kappa statistic was below 0.7 for the Mixed closed forest, Mixed woodland and Grassland classes.

Table 4: Confusion matrix for classification accuracy.

	Class code	1	2	3	4	5	6	7	8	9	10
Accuracies	**Producer (%)**	92.00	81.82	100.00	68.18	77.50	85.71	66.67	87.50	70.00	50.00
	User (%)	74.19	75.00	66.67	78.95	91.18	80.00	100.00	87.50	46.67	50
	Kappa	0.68	0.73	0.66	0.75	0.88	0.78	1.00	0.87	0.43	0.51
	Overall accuracy = 78%										
	Overall kappa = 0.7389										

Discussion

The application of object oriented classification to map land cover has been demonstrated. Although this work is only in its preliminary stages the results indicate that object-oriented analysis has great potential for extracting information from multispectral satellite imagery captured over tropical Australia.

While the accuracy of most classes was reasonable or higher, the classification of a couple of classes was not satisfactory. In particular, the classification accuracies of the Mixed woodland and Grassland classes was exceptionally low. The accuracy of the Grassland within the confusion matrix is partially attributed to the low number of points selected (only 6). Other inaccuracies within the assessments may be a result of the scale parameters used. Boundaries of the objects at the level 1 segmentation level are in some cases displaying linear patterns along the edge of a row or column of pixels. This pattern is then transferred to the classification. Further assessment of a range of segmentation parameters including scale is required.

Future studies intend to incorporate larger areas to include a greater range of land cover types. Study is also to be carried out on improving the knowledge base of image objects such as providing more contextual information, particularly the relationships of neighboring objects. The incorporation of other information such as a slope layer derived from the DEM would also increase the opportunity for building the knowledge base of objects. The inclusion of spectral information from the SWIR bands of the ASTER data is also to be considered.

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