OBJECT ORIENTED CLASSIFICATION: CASE STUDIES USING DIFFERENT IMAGE TYPES WITH DIFFERENT SPATIAL RESOLUTIONS

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ABSTRACT:

This paper presents the case for information extraction from images using what has been termed “object oriented classification” (OOC). Traditional methods of computer classification of images focus of the colour or spectra of individual pixels. However, human interpretation of images uses many more image attributes, including relative size, shape, distribution (texture and pattern) and context of groups of pixels which are spatially associated together to form “objects”. Image segmentation, a process of examining the spatial clustering of pixels which display some degree of homogeneity at a particular scale, has been used in the last decade to assist image classification, particularly when the spectral dimensionality of an image is low. More recently, OOC has become available in off the shelf software. OOC provides a process of computer based learning in respect to not only colour, but also in respect to size, shape, orientation, texture and to some extent, context of groups of pixels.

This paper illustrates the use of OOC image classifiers via the use of four examples. Firstly in the stratification of ecological zones an Australian desert using six banded Landsat TM data, the software eCognition™ from Definiens was used with better results compared with pixel based methods. Secondly the results of classification of high resolution multi-spectral and panchromatic QuickBird satellite imagery over South Australian vineyards, which was the subject of undergraduate UniSA student research by Martin Nolan, are presented. In his work Nolan was trying to achieve or exceed 96% accuracy as compared with human interpretation combined with field work. Results of using the object oriented classifier, in this case Feature Analyst™ from Visual Learning Systems, showed improvement over the use of traditional supervised classification, but did not meet the high tolerances required for this technique to be universally adopted. Thirdly, OOC was applied to classifying urban features in a rural township in South Australia. Feature Analyst™ was again used on multi-spectral Quickbird imagery and compared with supervised classification. Whilst in the main good results were observed, shadows from tall trees, and larger buildings created classification uncertainty. Finally, the paper examines the results of applying OCC to very high resolution (pixel size of 0.15m) aerial, multi-spectral orthophotos over an urban area, where the objective was to automatically extract building roof information. Results show that OOC software, in this case Feature Analyst, provided a very quick method of directly extracting GIS polygons from the imagery. Hierarchical learning used in the project requires that context from landuse and cadastre is utilized to assist the differentiation of grey roof tops from roads. Other learning is based on the shape of roofs versus the shape of paved driveways, which share similar areas and colours to some roof tops, but different shapes. Again shadows presented significant problems for the OOC algorithm and suggest that whilst humans interpret object height from shadows, this attribute needs to be explicitly injected into the computer classification methodology. Airborne laser scanning (ALS) is currently being evaluated for provision of this additional attribute. However, it is noted that relief displacement in the orthophoto imagery will cause geometric displacement of roofs relative to their correct position and that observed in the ALS data.

In conclusion the paper summarizes accuracy from the four examples to show how, for at least images exhibiting low spectral dimensionality, object oriented techniques are superior to the traditional pixel based methods, but still inferior to human interpretation.

1.INTRODUCTION

1.1 Background

Hay and Castilla (2006) proposed that ‘Object-based Image Analysis (OBIA) ia a sub-discipline of GIScience devoted to partitioning of remote sensing (RS) imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale.” Amongst its strengths and weaknesses Hay and Castilla (2006) provided some comments on its strengths such as:

- Object texture, shape and contextual relationships with other objects are more useful to assist recognition than individual pixel algorithms.
- Image objects are more easily integrated into vector GIS than pixel classifications.

Weaknesses can be associated with:

- A poor appreciation and hence implementation of hierarchical relationships between objects at different scales and resolutions.
- Results are variable based on chosen algorithms and variation of image attributes such as pixel depth.
- Processing time for large images (e.g. aerial photographs) can be extreme and requires parallel processing for efficiency.

Typically object oriented classification (OOC) has been applied to images where spectral dimensionality of images is low (1 – 4 multi-spectral bands) and where spatial resolution is high. Kux and Araujo (2006) and Kamagata *et al* (2006) both applied OOC to high resolution Multi-Spectral (MS) imagery (QuickBird and Ikonos respectively) with improved results over traditional techniques.

The applications reported in this paper also attempt to move from purely spectral classification at the pixel level to spectral and spatial classification at the object or multi-pixel level. There are a number of approaches to this problem; some of these commence with single band image segmentation at different scales, whilst other use hierarchical learning from Artificial Neural Networks (ANN). Some methods use additional information which is non-imaged based to assist the OOC.

1.2 Case Studies

Four case studies of OOC are presented in this paper. Three examples are located in rural regions of the state of South Australia (SA) and one is located within the metropolitan city of Adelaide, the capital city of South Australia. Table 1 summarizes the characteristics of the four case studies / sites.

Site Code	Site Character	Imagery	OCC Software	Main objects classified
A	Rural – Arid Zone	Landsat TM	eCognition	Trees, shrubs, open ground
B	Rural - horticulture	Quickbird MS and Pan	Feature Analyst	Grape Vines
C	Rural - settlement	Quickbird MS	Feature Analyst	Houses, roads, shops
D	Urban	Colour Ortho-photograph	Feature Analyst	Buildings

Table 1. Characteristics of OCC example sites

Site A, located in an arid zone in South Australia north of the town of Whyalla, featured red brown soils some of which are covered with a biological soil crust (BSC), low salt tolerant chenopod shrubs and small trees which are dominated by acacia or eucalyptus species. The region was the focus of a PhD study by Ghorbani (2007), who's objective was to examine the nature, distribution and spectral characteristics of BSC with a view to using BSC as a rangelands indicator.

Site B was a series of vineyards in the central Mount Lofty Ranges close to the city of Adelaide. The region has rolling hills and a temperate Mediterranean style climate not only suitable for growing vines, but also suitable for horticultural crops of apples, pears and cherries. The study was undertaken by undergraduate student Nolan in 2006 as part of an assessment by the Phylloxera and Grape Industry Board of SA into to the automatic or semi-automatic mapping of vineyards in the state of SA.

Site C is based upon a rural town, Mount Barker, also located in the central Mount Lofty Ranges close to Adelaide. The town has a rapidly expanding population and the objective was to undertake mapping of the expansion of houses, shops and commercial buildings via use of multi-temporal high resolution satellite imagery.

Site D constituted urban buildings and roads within a University campus. These buildings are two to three stories high and have varying roof structures and roof materials. The imagery utilised here was colour orthophotography supplied by the company AEROmetrex. The site was also measured with an airborne laser scanner (ALS) by Airborne Research Australia (ARA). The height data from the ALS was utilised in an improved object extraction process.

2.METHODOLOGY

2.1 General Approach

The general approach applied at the four example sites was to firstly develop accuracy assessment data through he used of field trips, collection of information re "true" object identification and location via GPS or DGPS methods and through manual digital image interpretations of aerial images. The result was a series of "true" GIS polygons against which image classifications could be compared.

Image classifications generally occurred through traditional unsupervised and supervised pixel based algorithms (IsoData and Maximum Likelihood respectively). In all cases this was followed by OOC using either Definiens' eCognition^{TM} and / or Visual Learning Systems Feature Analyst software. Stratified random sampling of each of the classifications proceeded using the GIS polygons as the basis for accuracy assessment.

2.2 Site A

Site descriptions and methods have been more extensively reported in Ghorbani and Bruce (2006). In summary a Landsat 5 TM image for the study area was acquired in August 2003. Geometric correction of the imagery was undertaken and the imagery subseted for the study area. A GIS was created of land units (see Laut *et al.*, 1977) and a Digital Elevation Model (DEM), was created from spot heights and contours.

2.2.1 Visual Interpretation of Landsat Data

The principle objective of the study at site A was BSC monitoring using ground-based and remotely-sensed data. It was observed from a reconnaissance field visit that there was strong relationship between BSC distribution and shrubland communities and a negative relationship with woodland dominated communities. Moreover, there was negative relationship between BSC and some landforms such as crest and water courses, and sandy soil textures. Thus stratification, which was undertaken using visual interpretation, aimed to separate this diversity and delineate shrubland communities for BSC ground sample locations. This became the basis for accuracy assessment.

2.2.2 Pixel-based Classification

Pixel-based standard supervised processing was conducted using the Maximum Likelihood Classification (MLC). The supervised process involved the selection of multiple training areas representative of seven land cover classes as shown in Table 3. These types of classes show a typical ecological gradation with many features of one class contained within another. This frequently results in confusion in the classification process. The signatures of the training areas were then used to determine to which class image pixels were assigned.

2.2.3 Object-based classification

Object-oriented classification was undertaken using eCognition v4 -2005. The process was split into two steps: segmentation and classification:

Multi-resolution Segmentation

The subset image was segmented into smaller regions (object primitives) or segments on two scale levels (Table 2 & Figure 1). The segmentation of the image into objects was influenced by three parameters: scale, colour/shape ratio and form/spatial properties (smoothness / compactness ratio) (Baatz *et al.*, 2004). The scale parameter set by the operator is influenced by the heterogeneity of the pixels. The colour parameter is a balance between the homogeneity of a segment's colour and the homogeneity of its shape. The form parameter balances the smoothness of an object's border with its compactness (Whiteside & Ahmad, 2004). The homogeneity criterion for the objects was established within the weighting of these parameters. The image objects were based on parameters such as the spectral characteristics of pixels, the size and shape of the objects determined at each scale level. A visual inspection of the objects resulting from variations to parameter weighting was used to determine the overall values for the weighting of the parameters at each scale level.

Classification

Training sample objects were selected as representative of land cover classes from segmented components. Objects were assigned class rules using spectral signatures, shape and contextual relationships. These rules were then used as a basis for classification of image data using assignment of fuzzy membership and fuzzy logic. After classification image objects have degree of membership to several classes. The class with the highest fuzzy membership value was assigned as the best class for each object (Baatz *et al.*, 2004).

Scale level	Scale parameter	Shape factor	Compactness	Smoothness
2	10	0.05	0.02	0.98
1	5	0.05	0.02	0.98

Table 2. Segmentation parameters

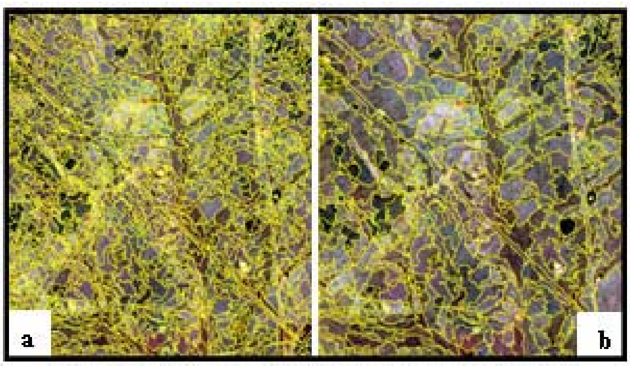

Figure 1. Segmentation, a) Level 1 and b) Level 2 for a section of the Landsat imagery (see Table 2 for segmentation parameters)

2.2.4 Accuracy Assessment

Accuracy assessments of both classifications were undertaken using confusion matrices and Kappa statistics. The accuracy of the classified image was assessed using field data collected in the study area over a two year period and visual interpretation of Landsat 5 TM imagery. Producer and user accuracies for each class were calculated along with the overall accuracies and Kappa statistics. It should be noted that, because the main project objective was to avoid bare ground, sandy soil, woodland community and water courses and crest land forms in the selection of homogeneous sites for BSC monitoring, accuracy assessment and ground truthing in these communities and landforms was not considered and ground truth data were not collected for those strata.

2.3 Site B

The process of comparing pixel based with object oriented methods at site B was similar to that of site A. Differences between the sites were that the resolution of the satellite imagery was 0.6m (Pan) and 2.4m (MS) from QuickBird satellite imagery and that ground truth consisted of vectors from extensive ground truthing and observation of high resolution orthophotographs (0.15m). Additionally the OOC software utilized was that of VLS Feature Analyst. The object of the exercise was to map vineyards versus other land covers, and in particular separate vineyards from other horticultural crops which shared similar image characteristics. Vineyards consist of parallel rows of trellised vegetation with a width of approximately 1.5 m, separated from each other by either bare ground, mulched ground, or sometimes vegetated ground (weeds or low crops). The space between the rows is approximately 3m and the height of the vines between 1.5 and 2m. This latter dimension generates shadow effects which are dependant on the elevation and aspect of the sun, the orientation of the vine rows and on the topographic slope and aspect. Figure 2 illustrates the some of these characteristics.

Figure 2. Illustration of grape vine orientations and patterns.

2.3.1 OCC Software

VLS Feature Analyst applies hierarchical artificial neural networks (ANN) to undertake OCC. This commences with the user identifying samples (from prior knowledge / ground truth) and parameters to undertake an initial classification. The shape, size, pattern and spectra of the samples are used in the ANN to detect other objects of similar characteristics. Errors of commission and omission are identified at the end of the first iteration so that the ANN can improve its learning. Aggregation and minimum size parameters can also be set. The process continues until the analyst is satisfied that the process has culminated.

2.3.2 Imagery

Quickbird Pan and MS imagery was utilised in both single image mode and in pan-sharpened mode. Since the object of interest was of similar size to the MS pixel resolution it was thought that higher spatial resolution would be of benefit. However, the higher spatial resolution data was single and broad banded and thus a principal component resolution merger was performed to combine the spectral and spatial resolution attributes of Pan and MS imagery.

2.3.3 Accuracy Assessment

Accuracy assessment was applied to both the supervised maximum likelihood and the OOC. 50 vineyard and 50 non-vineyard accuracy assessment sites were generated and producer's, user's and overall accuracy computed together with kappa coefficients.

2.4 Site C

QuicBird MS imagery was again utilized at Site C. The objective was to classify urban features (roads, residential houses, commercial and light industrial buildings) in the rural township of Mount Barker in South Australia. This township has a rapidly expanding population and the research was part of a multi-temporal study of the changing urban growth boundaries of the town. Again OOC using VLS Feature Analyst was compared with MLC for the 2006 image of this township.

2.5 Site D

At site D colour (R,G,B) orthophotography with a spatial resolution of 0.15m was derived from photography flown over suburbs of Adelaide in SA. A number of sub-sites were utilised, with the sub-site reported in this paper coming from the University of SA's Mawson lakes campus. This campus is characterised by a number of two and three story medium sized buildings, minor roads, footpaths, lawns, tress and shrubs. The objective was to extract the building roof lines. The Campus was also flown with a Riegl LMS-Q560 ALS system by ARA, with an approximate ground sampling distance of 0.25m. The research here was to compare results of using OCC using Feature Analyst with those from OCC with the additional information on object height.

3.RESULTS AND DISCUSSION

3.1 Site A

Graphic results for one rangeland paddock are presented in Figures 3, 4 and 5 which show visual interpretation (based on ground truth), supervised classification and OOC. Numerical accuracy assessments are presented in Table 3.

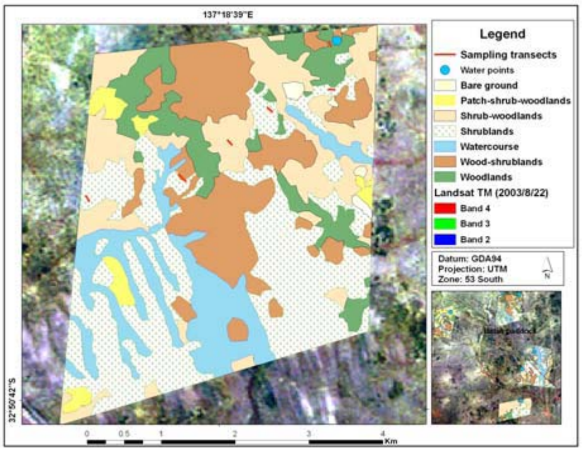

Figure 3. Visual interpretation based on image information and ground truth of one rangeland paddock at site A into 7 classes.

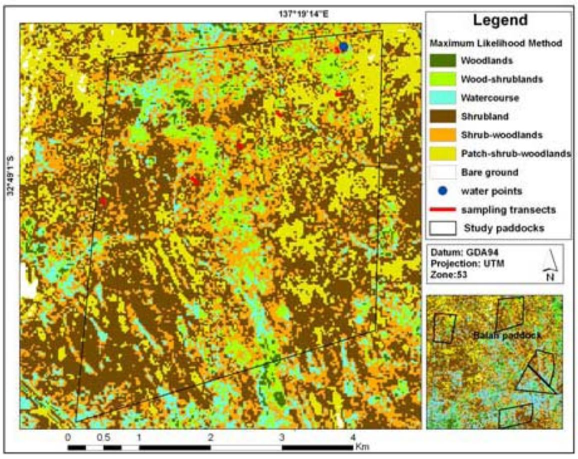

Figure 4. Supervised MLC of one rangeland paddock at site A into 7 classes.

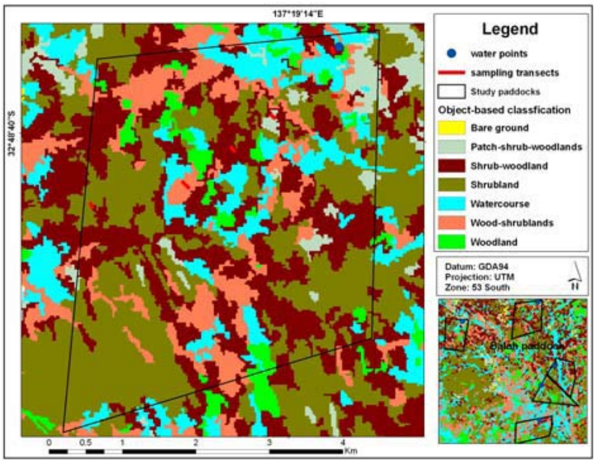

Figure 5. OOC of one rangeland paddock at site A into 7 classes.

Class Name	Supervised MLC		OOC		
	Producer (%)	User (%)	Producer (%)	User (%)	Kappa
Bare Ground	-	-	-	-	-
Patch Shrub-Woodlands	50	33	50	50	0.07
Shrublands	40	55	43	75	0.57
Shrub-Woodlands	25	25	50	67	0.37
Woodlands	0	0	100	50	1.0
Wood-shrublands	0	0	67	40	0.22
Water course	-	-	-	-	-
Overall accuracy	33%		50%		
Overall Kappa	0.09		0.37		

Table 3. Summary of confusion matrices for the accuracy of pixel-based and object-oriented methods (accuracy assessment was not undertaken for bare ground and water course classes)

Results support those of Whiteside and Ahmad (2004) who conclude that pixel based remote sensing has greater limitation for stratification in rangelands than object oriented methods. The object oriented technique provided results with higher accuracy than the pixel based classification, though this statement must be qualified by observing that overall accuracies are not high. Contributing factors to these poorer than desired results can be the size of objects of interest compared with the resolution of the imagery; in this case 30m, and the overlap between classes. Whilst the former issue can potentially be improved via the use of higher resolution imagery, the latter remains, as ecological stratifications typically present these kinds of classes.

3.2 Site B

Figures 6, 7 and 8 provide graphic illustrations of object oriented classification of QuickBird imagery over vineyards and Table 4 presents numeric results.

Results at Site B appear significantly better than at Site A. However, extension of the analysis across larger areas showed that only 62% of all vineyards were successfully mapped by the OOC method. As the size of the area of analysis increased the characteristics of vineyards underwent subtle change. It was noted that the size and orientation of shadow had a large impact on the change and thus further training was required. A positive side to the experiment at site B was that the best results were obtained from a combination of high spatial and low to medium spectral resolution.

Figure 6. OOC of a sample vineyard using the QuickBird Pan imagery. Red vector shows “truth”, the green the results of OOC.

Figure 7. OOC of a sample vineyard using the QuickBird MS imagery. Red vector shows “truth”, the green the results of OOC. The green vector on the right corresponds to a non-vine horticultural crop.

Figure 8. OOC of a sample vineyard using the QuickBird Pan-sharpened imagery. Red vector shows “truth”, the green the results of OOC.

Classification Method	Producer’s Accuracy (%)	Users’s Accuracy (%)	Overall Accuracy (%)	Kappa (Vine Class)
MLC	91	60	77	.40
OCC - Pan	97.5	79	88.5	.65
OCC - MS	98.8	82	90.5	.69
OCC – PanSharp	98	98	98	.96

Table 4. Accuracy statistics for vine classifications using two classification methods and three imagery combinations

3.3 Sites C and D

Table 5 summarizes the results from the classification of urban buildings at sites C and D and Figure 9 shows results at site D.

Classification Method	Producer's Accuracy (%)	Users's Accuracy (%)	Overall Accuracy (%)	Kappa (Vine Class)
SITE C				
MLC	56	60	62	.36
OCC	87.5	75	78	.55
SITE D				
OCC	81	80	80	.62
OCC + 3D	85	79	84	.74

Table 5: Summary of classification statistics at sites C and D

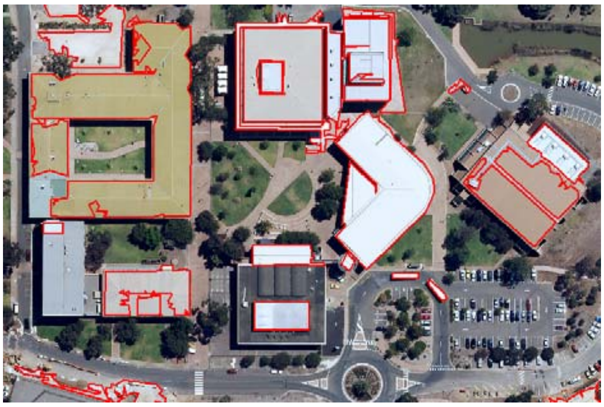

Figure 9. OCC (red vectors) of roof tops at site D.

4.CONCLUSIONS

Numerical comparisons of the results from the four sites shows that accuracy increases within the use of OOC compared with pixel based classification. Qualitative comparison of the results shows that there is a relationship between image spatial resolution, the size of objects to be classified and the accuracy of OCC. When image resolution is equivalent or smaller than the typical object size (e.g. site A and site B (MS imagery)) then classification accuracies are not high. As image resolution increases to be greater than object size (e.g. site B (Pan imagery) and site C), then accuracies improve. At site D, where the image resolution exceeded object size by many times, the accuracy improvement over pixel based classifiers, whilst still observable, was not as marked.

In sites B, C and D shadows of 3D objects created problems for both pixel based and object oriented classifications. In the case of vines the size of shadows varied with the orientation and height of vine trellises as well as the slope and aspect of the topography. In sites C and D shadow orientation was constant but also varied with object height and shape. The use of additional data on object height assisted the classification accuracy at site D. However, it was noted that mis-registration of ALS height data with orthophotography, due to differing geometries, contributed to edge classification errors.

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