Numeric classification as an aid to spectral mapping of vegetation communities

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Abstract

This study demonstrates a vegetation mapping methodology that relates the reflectance information contained in multispectral imagery to traditionally accepted ecological classifications. Key elements of the approach used are (a) the use of cover rather than density or presence/absence to quantify the vegetation, (b) the inclusion of physical components as well as vegetation cover to describe and classify field sites, (c) development of an objective land cover classification from this quantitative data, (d) use of the field sample sites as training areas for the spectral classification, and (e) the use of a discriminant function to effectively tie the two classifications together. Land cover over 39 000 ha of Australian chenopod shrubland was classified into nine groups using agglomerative hierarchical clustering, a discriminant function developed to relate cover and spectral classes, and the vegetation mapped using a maximum likelihood classification of multi-date Landsat TM imagery. The accuracy of the mapping was assessed with an independent set of field samples and by comparison with a map of land systems previously interpreted from aerial photography. Overall agreement between the digital classification and the land system map was good. The units that have been mapped are those derived from numeric vegetation classification, demonstrating that accepted ecological methods and sound image analysis can be successfully combined.

Introduction

Remote sensing has demonstrated a significant contribution to vegetation mapping and monitoring, and to understanding terrestrial ecosystem function, primarily through relationships between reflectance and vegetation structure and greenness. After two decades of earth remote sensing with satellite-based multispectral imagers, the consensus is that existing remote sensing data can effectively detect structural type, amount and condition of vegetation cover but is less able to discriminate different species or variations in composition within vegetation communities (Graetz 1989; Hobbs 1989). Research emphasis has been on vegetation structure, cover and temporal dynamics, the attributes most clearly portrayed by surface reflectance in the visible and near infrared wavelengths.

However, Stoms & Estes (1993) argue that remote sensing technology also has an important role to play

in assessing biodiversity at a range of scales, a role that has been largely neglected. Perhaps this role has not been fully explored because of the gap between conventional ecological research paradigms and methods and those employed within remote sensing, a discontinuity which has been remarked by several authors (Graetz 1989; Roughgarden et al. 1991; Wickland 1991). The exchange between ecology and remote sensing needs to be two-way. Ecology needs to re-evaluate its approaches to community description and classification, and to many ecosystem properties such as diversity, in order to take full advantage of the wealth of data remote sensing has to offer, while on the other hand, practitioners of remote sensing need to be better informed of ecological concepts in their development of scene models.

This study addresses some of the challenge implicit in these critiques, that of extracting information about plant species and community composition

from remotely sensed data. This has been called the 'difficult third dimension' of vegetation description (Graetz 1989), the other two dimensions being structure and cover, both of which have been successfully addressed by remote sensing. Whilst 'difficult' for remote sensing, an understanding of the specific types and composition of vegetation is essential to many areas of conservation and environmental management. For example, forest and habitat mapping is usually based on structure and dominant species, and rangeland managers assess pasture condition according to species palatability and biomass, geologists frequently detect mineral outcrops through their geo-botanical associations, and managers of wilderness and natural habitats assess their conservation value according to biodiversity and disturbance history.

This paper proposes a vegetation mapping methodology that bridges the gap between quantitative ecology and remote sensing. It acknowledges the spectral limitations of conventional remote sensing sources, but argues that their predictive mapping power can be used more effectively in conjunction with appropriate ground data. The approach outlined aims to relate the reflectance information contained in multi-spectral imagery to traditionally accepted ecological classifications.

Given more than 20 years of applied remote sensing research, surprisingly little attention has been given to the nature of relationships between spectral classes and vegetation classes that are of interest to the ecologist. These relationships are often not made explicit, and remain part of the professional 'art' of vegetation mapping with remote sensing. Similarly, the attention given to spectral characteristics of the mapping units is often at the expense of adequate description and quantification of their ecological characteristics.

Notable attempts to demonstrate the nature of relationships between spectral and vegetation classes include the use of multiple discriminant analysis to predict community type on the basis of spectral variables (Ustin et al. 1986., Pando et al. 1992; Hobbs et al. 1989; Ghitter et al. 1995), statistical association between the distributions of spectral classes and independently mapped vegetation classes (Price et al. 1992), and statistical comparisons between spectral and either numeric or subjective vegetation classifications (Catt et al. 1987; Toth et al. 1991; Treitz et al. 1992; Lewis 1994). The methodology presented here develops that used by Lewis (1994), and further tests its applicability in an arid landscape.

Study site

The study was conducted at Fowlers Gap Arid Zone Research Station, a 39 000 ha pastoral property managed by the University of New South Wales which straddles a northern extension of the Barrier Ranges in far western New South Wales, Australia (31°S, 141°45'E; Figure 1). The land comprises a spine of sandstone and quartzite ranges rising to heights of 280 m, bisected by several ephemeral creeks, most of which flow out onto extensive alluvial plains to the east. The climate is arid, characterised by hot dry summers and mild winters, with highly variable annual rainfall (mean over 28 years of records=195 mm p.a.). The vegetation, typical of much of the southern Australian arid zone, comprises low open chenopodiaceous shrublands, some low open *Acacia* and *Casuarina* woodlands and grasslands on the plains. The land systems and vegetation of Fowlers Gap have been comprehensively described by Mabbutt (1973) and Burrell (1973).

Methods

Image analysis

Work by Hobbs et al. (1989) has demonstrated the benefit of multi-date imagery for vegetation discrimination in Australian sclerophyll vegetation. The use of single-date imagery for classification depends on adequate spectral contrast between different vegetation types at that time, something which may be difficult to achieve where the dominant species display considerable morphological similarity. The use of seasonally contrasting images, however, takes advantage of any phenological differences between vegetation types to improve discrimination in digital mapping. The value of multi-temporal sequences of satellite imagery for tracking short and long term trends in vegetation condition is well recognised (e.g., Robinove et al. 1981; Milne and O'Neill 1990; and review by Hobbs 1989) yet their use for classification and mapping of natural vegetation types has been limited. As pointed out by Graetz (1989), inclusion of the temporal dimension has greatly enhanced agricultural remote sensing, considerably improving the ability to discriminate crops, yet the same approach has rarely been translated into studies of natural vegetation. Notable exceptions are the global and continental scale classification of vegetation based on phenological patterns extracted from

Figure 1. Study site at Fowlers Gap Arid Zone Research Station, Australia.

extensive time sequences of NOAA AVHRR (Advanced Very High Resolution Radiometer) imagery (Justice et al. 1985; Townshend et al. 1991; Turcotte et al. 1993).

Australian arid landscapes, particularly in their dry state, typically lack spectral variability, with most differentiation related to soil brightness and vegetation cover. Hence it was expected that multi-date imagery would assist discrimination of the Fowlers Gap vegetation types, particularly if the scenes captured the vegetation in differing states.

Two contrasting Landsat Thematic Mapper (TM) scenes were used: one shortly after heavy rains in mid-summer (January 1993), the other in mid-winter six months later when the flush of ephemeral and grass growth had dried off (June 1993). It is the wet/dry contrast that was considered most important here, rather than the summer/winter timing, as rain is the key factor driving the environment and can fall at any time of the year. The timing of the images in relation to rainfall at the site is shown in Figure 2.

The January scene was registered to the Australian Map Grid using 22 control points located on a 1:100 000 orthophoto map. A linear polynomial with a resultant average RMS error of 32.0 m was used to transform the data, and the image pixels were resampled to the map grid with nearest neighbour resampling. The June scene was registered to the geo-registered January image, also with a linear polynomial (13 control points, average r.m.s. error 31.4 m) and nearest neighbour resampling.

The 12 visible, near and middle infra-red bands of data were converted to apparent ground reflectance using the radiometric correction equations provided by Markham and Barker (1987) for Landsat TM 5. The equations convert the raw digital counts of the image (0–255) to spectral radiance measured in $\text{W m}^{-2} \text{sr}^{-1} \mu\text{m}^{-1}$, using published calibration values for the sensor, and then correct for variable solar irradiance and elevation to convert the spectral radiance values to apparent surface reflectance in each band. The effects of atmospheric haze were removed by subtracting values predicted by the atmospheric models presented by Chavez (1988). The models calculate the relative correction required for each image band under a range of atmospheric conditions. The appropriate model is generally chosen through consideration of the magnitude of haze present in the shortest-wavelength image band, where atmospheric scattering is greatest. Moderately clear and very clear atmospheric models

were used to correct the January and June images respectively.

Ground data

A requirement of the proposed methodology was that ground data collection coincide as closely as possible with image acquisition, and field data was collected within a week of the June overpass. Since significant rain had fallen just before the January scene, but not between January and June, grass and herbaceous ephemerals were at their most luxuriant and greenest in January. This green biomass changed to dry standing biomass between January and June, while the vigour of the deeper rooted perennial trees and shrubs increased somewhat. The property is grazed by sheep and cattle, although at conservative stocking rates, so it can be reasonably assumed that the biomass, cover and composition of the vegetation did not change significantly between the two dates, although its greenness did.

One-hundred sample sites were chosen to be representative of the range of vegetation types and land systems present at Fowlers Gap (Figure 3). At each site a wheelpoint apparatus (Mentis 1981) was used to estimate percentage cover of all physical (bare ground, stone) and biotic (ephemerals, grass and perennial shrub and tree species) ground cover components. The wheelpoint is commonly used to estimate pasture composition in rangeland condition surveys (Graetz and Ludwig 1978) and has been used successfully to correlate ground composition with image variables in several remote sensing studies (e.g., Graetz et al. 1988; Bastin et al. 1993). Parallel transects comprising a total of 800–1000 points traversed each sample area of 250×250 m or 6.25 hectares, and the proportion of wheelpoint 'hits' on each ground cover component or species used to estimate its overall percentage cover within the sample plot.

The choice of sample plot size was influenced by considerations of landscape scale and variability, and the accuracy with which plots could be located in the field and image. The 1:100 000 map used for image rectification, the largest scale map available for the study area, conform to Australian National Mapping Council standards, with a 99% probability that well defined points will be mapped within ± 50 m of their true positions. The satellite images were registered to this map with errors approximating ± 30 m. Plot centres were located with a single non-geodetic Global Positioning System (GPS) field unit averaging

Figure 2. TM image acquisition dates in relation to rainfall.

Figure 3. Location of 50 6.25 ha sample sites (squares) and 50 validation sites (circles). Sample sites are labelled with the cover classes to which they have been assigned by the agglomerative classification of percentage cover data.

40 readings over 3 minutes. The mean PDOP (Position Dilution of Precision) for all readings was 3.4, with all readings less than 5, the PDOP considered satisfactory for positioning (Pinkney and Trotter 1992). With Selective Availability in operation 95% of readings with the single GPS should be within 100 m of the true position (Leick 1995). Averaging readings over several minutes can improve this accuracy (Pinkney & Trotter 1992), and trials conducted by the author suggest that an r.m.s. error of 40 m is achievable by averaging readings from a single GPS (Lewis & Grierson 1992).

These errors in field and image geo-positioning may in the worst case be additive, with the result that sample centres identified in the image could be up to 120 m from their ground positions. To allow for these possible errors, as well as provide an adequate number of pixels per sample site, sample plots of 250×250 m were used, designed to correspond to blocks of 8×8 30-m TM pixels. This size of ground sample in relation to the accuracy of positioning and pixel resolution is consistent with recommendations of Justice and Townshend (1981). In addition, to further reduce the effects of possible misalignment of plots and pixel blocks, the samples were sited within relatively homogeneous areas, away from any apparent land system boundaries. Fifty of these sites were used as 'training areas' to calibrate relationships between spectral and field data, and the remaining fifty were used as validation sites to test the spectral classification.

Nomenclature for species follows Jessop & Toelken (1986), amended by Jessop (1993).

Vegetation classification

Wheelpoint data for all biotic and physical ground cover components from the 50 training sites was converted to percentage cover and used in an agglomerative hierarchical classification procedure (Wilkinson et al. 1992) to detect objective groupings of sites. Euclidean distance was used as the measure of dissimilarity between sites and Ward's minimum variance method used to sort sites into clusters, resulting in a dendrogram that shows progressive aggregation of similar sites into larger groups. To compare the resultant cover groupings with a more conventional vegetation classification, the same procedure was rerun using the 50 training sites but using only the vegetative cover components. Finally, to assign field cover classes to the validation sites, the classification was run using all 100 samples and all cover components.

Relationships between ground and spectral data

Both training and verification ground sample sites were located in the image using central co-ordinates collected in the field with the GPS unit. Blocks of 64 pixels around these central points, corresponding to the 6.25 ha ground sample sites, were designated as spectral training areas. The 50 training sites were labelled according to their corresponding ground cover class and canonical variate analysis used to develop a spectral discriminant function that would adequately separate the classes. The training sites were then used to generate a supervised classification using a maximum likelihood decision rule using all 12 spectral bands of the multi-date image. The resultant 50 spectral classes were allocated into nine map classes on the basis of their corresponding training site cover classification.

Accuracy assessment

Comparison with site-specific field data is the most reliable test of image classification (Congalton 1991), but it can be difficult to collect sufficient samples to meet the requirements for statistical comparison of classifications with many classes. Congalton (1991) recommends a minimum of 50 samples per land use or cover category. In this study 50 samples were used to develop the image classification comprising nine classes, and the same number used to assess its accuracy. As a result statistical assessment of classification accuracy must be approached with caution. The quantification of cover, used to characterise field sites and assign them to categories in the numeric cover classification, was time consuming, and would have required approximately 40 person-days to achieve the recommended number of samples. However, the benefit of this field validation data is that it provides reliable information about cover at specific locations, has been collected in the same manner as the data used to generate the initial classification, and can be categorised into groups consistent with the classification being tested.

An alternative approach, often used to assess the accuracy of digital classifications, is comparison with existing land cover maps. This approach allows the collection of large numbers of map/classification sample points without laborious field work. However, as discussed by Congalton, traditional maps derived from photointerpretation employ mapping conventions that are not entirely compatible with pixel-based image classifications. Distinct boundaries are usually drawn

between map classes, and the vegetation within classes assumed to be homogeneous. Variations in cover class within map categories are often wrongly interpreted as errors in the digital classification, rather than as generalisations in the traditional map.

The adequacy of the spectral discriminant function and accuracy of the vegetation mapping were tested in three ways: by testing the discriminant function developed on the training sites with the independent set of 50 validation sites, by comparing image class with field class for the 50 validation sites, and by comparing the image classification with an existing land system map of Fowlers Gap. Ground cover classes for the validation sites were determined from the classification dendrogram of all field sites. The discriminant function developed on the training sites was re-run with the validation sites and the resultant predicted and actual ground classifications compared. The 50 validation sites were also located in the image and the image class compared with the ground class. In many instances the 64 pixels within the validation sites contained a mixture of spectral classes because of localised variation in cover, and so the majority class was used in accuracy assessments.

The image classification was also compared with the land systems of Fowlers Gap mapped by Mabbutt et al. (1973) from panchromatic aerial photography. A land system is defined as 'an area or group of areas throughout which there is a recurring pattern of topography, soils and vegetation' (Christian & Stewart 1953). This integrated approach to landscape mapping was more consistent with the geology-soil-vegetation complexes mapped in the present study, than the purely floristic mapping of Fowlers Gap vegetation by Tkachenko (1987). The Mabbutt land system map was digitised, geo-registered to the TM imagery, overlain on the cover classification map in a geographic information system, and the two land classifications compared on a pixel by pixel basis.

Agreement between classifications for each of these accuracy assessments was tested with X^2 and also with Cohen's Kappa when both classifications contained the same number of classes. Kappa is frequently used to assess the accuracy of image classifications, and is considered a useful measure of overall agreement because it incorporates omission and commission errors as well as the proportion of correctly classified samples, and because it can statistically tested (Congalton 1991, Fitzgerald & Lees 1994).

Results

Vegetation classification

The dendrogram summarising the ground cover classification shows four broad groupings of the sample sites and nine classes at higher levels of similarity (Figure 4). These classes were reproduced when all 100 field sites were used in the classification. When bare ground, stone and litter cover were excluded, and only vegetation abundances used in the analysis, an approach more typical of conventional vegetation ecology classification, eight groups emerged with site allocations similar to the total ground cover classification. These two classifications were significantly associated ($X^2 = 220$, 56 d.f., $p < 0.001$).

Mean percentages of ground cover components and species were calculated for the vegetation groups determined from the cover dendrogram, and are presented in Figure 4 with the composition of the communities summarised in Table 1. The groups are discriminated largely on proportions of bare ground, stone, grass, ephemeral and perennial species, and on species dominance and composition of the perennial component of the vegetation. Exposed soil and surface rock dominate most of the groups, ranging from 30% in the grasslands of the alluvial plains, to almost 70% in the uplands and ranges. Green grass and ephemeral herbaceous plants contribute about 25% of cover in groups B, C and E, and dominate group A at 70%, but otherwise contribute less than 10–15% in groups F, G, H and I. Perennial shrub and tree cover is as low as 5% in groups B and C, and typically less than 15%, although increases to 20 and 30% in groups I and G.

A suite of three interrelated communities dominates the eastern alluvial plains: dense *Astrelba* spp. grasslands (A), and varying mixes of *Maireana aphylla*, ephemerals and grasses occurring as localised mosaics (B and C). Copses of *Acacia victoriae* are characteristic of the shrublands on the plains, but were recorded in very low percentages in the field samples. The plains give way to the *Maireana sedifolia*, *M. astrotricha* and *Atriplex vesicaria* shrublands of the central quartzite and sandstone ranges (H and I), which also carry scattered groves of the small and trees, *Acacia aneura* and *Casuarina pauper*. The lower slopes of the ranges and an extensive calcareous plateau to the west carry shrublands dominated by *Atriplex vesicaria* in varying combinations with *M. astrotricha* and ephemeral *Scerolaena* spp. (D, E and F). One distinctive and restricted community charac-

Table 1. Composition of vegetation groups discriminated through agglomerative hierarchical classification and mapped with Thematic Mapper imagery

Vegetation group	Landform	Vegetation structure	Dominant species	Mean % cover in samples
A	Alluvial plains	Grassland	<i>Astrebla</i> spp.	47
			<i>Maireana aphylla</i>	1
			<i>Maireana pyramidata</i>	2
B	Alluvial plains	Low open shrubland with grasses and ephemerals	<i>Maireana aphylla</i>	3
			<i>Astrebla</i> spp.	27
			<i>Sclerolaena</i> spp.	17
			<i>Acacia victoriae</i>	0.1
C	Alluvial plains	Low open shrubland with grasses	<i>Maireana aphylla</i>	2
			<i>Astrebla</i> spp.	19
D	Slopes flanking ranges	Low open shrubland	<i>Atriplex vesicaria</i>	6
			<i>Maireana sedifolia</i>	1
			<i>Maireana pyramidata</i>	1
			<i>Acacia aneura</i>	1
E	Outwash from ranges	Low open shrubland with ephemerals	<i>Atriplex vesicaria</i>	14
			<i>Sclerolaena</i> spp.	23
F	Calcareous plains and flanks of ranges	Low open shrubland	<i>Atriplex vesicaria</i>	10
			<i>Maireana astrotricha</i>	2
G	Valley in quartzite ranges, outcropping shale	Low open woodland	<i>Eucalyptus gillii</i>	18
			<i>Maireana astrotricha</i>	6
			<i>Atriplex vesicaria</i>	4
H	Sandstone ranges	Low open shrubland	<i>Atriplex vesicaria</i>	9
			<i>Acacia aneura</i>	2
			<i>Maireana sedifolia</i>	1
			<i>Maireana astrotricha</i>	1
I	Quartzite ranges	Low open shrubland	<i>Maireana astrotricha</i>	9
			<i>Atriplex vesicaria</i>	4

Table 2. Canonical coefficients showing relative weightings of image bands for the first four canonical variates. Weights are standardised by within-group standard deviations

	Image	Band	CV1	CV2	CV3	CV4
January image	blue	0.45–0.52 μm	1.47	–0.30	4.26	1.10
	green	0.52–0.60 μm	–3.76	2.84	–5.01	1.38
	red	0.63–0.69 μm	5.19	–3.60	1.59	–5.68
	near infrared	0.76–0.90 μm	–1.23	0.30	0.67	–0.68
	mid infrared	1.55–1.75 μm	2.28	2.64	3.11	1.27
	mid infrared	2.08–2.35 μm	–4.29	0.26	–4.04	0.02
June image	blue	0.45–0.52 μm	–0.53	–1.08	–1.34	1.08
	green	0.52–0.60 μm	3.19	0.66	0.82	–6.07
	red	0.63–0.69 μm	–4.78	–2.34	4.77	9.81
	near infrared	0.76–0.90 μm	1.52	1.64	–5.00	–0.45
	mid infrared	1.55–1.75 μm	–1.68	1.40	–0.41	–3.74
	mid infrared	2.08–2.35 μm	1.85	–1.42	0.87	2.11

Figure 4. Dendrogram showing vegetation groups formed from the 50 field samples, overall ground cover composition and percentage cover of the dominant perennial species.

terised by stands of curly mallee (*Eucalyptus gillii*) has been clearly separated in the vegetation classification (group G).

Image classification

The first four canonical variates explained 40%, 25%, 16% and 10%, respectively, of the between-groups to within-group separation. The first canonical variate is a contrast in reflectance between the two images, and is most strongly weighted by the green, red and mid infra-red bands of both dates (Table 2). High val-

ues of this variate were recorded for areas with high soil exposure, and which changed little between the two dates, while low values were recorded for areas with the highest plant cover and which changed considerably between the two dates. The second variate represents total scene brightness over the two dates minus bands 1 and 3 (blue and red) for both dates and band 6 (middle infra-red) for the winter scene, and emphasises different soil and rock colours as well as topographic shadowing. The third and fourth variates are also weighted contrasts between the two dates, the

Figure 5. Plots of variate means for 50 training sites against canonical variates 1, 2, 3 and 4. Sites are labelled according to ground cover group assigned from numerical classification of field data: A = grassland, B = *Maireana aphylla* low open shrubland, grass and ephemerals, C = *M. aphylla* low open shrubland and grasses, D = *Atriplex vesicaria* low open shrubland, E = *A. vesicaria* low open shrubland with ephemerals, F = *A. vesicaria* and *Maireana astrotricha* low open shrubland, G = *Eucalyptus gillii* low open woodland, H = *A. vesicaria* and *Maireana* spp. low open shrubland, I = *M. astrotricha* and *A. vesicaria* low open shrubland.

third with a heavy positive weighting on the visible red bands (band 3), and the fourth emphasizing the blue bands (band 1).

Table 3. Comparison of cover class and class predicted by the discriminant function for 50 training sites

Cover class	Predicted class									Total
	A	B	C	D	E	F	G	H	I	
A	4	1								5
B	1	8								9
C		1	2							3
D				6		1		1		7
E			1		3					3
F				1		8				9
G							2			2
H								6		6
I									6	6
Total	5	10	2	7	3	9	2	6	6	50

$\chi^2 = 332.5$, 64 d.f., $p < 0.001$.

Plots of the training sites against the first four canonical variates of the discriminant function are shown in Figure 5. The first variate separates sites which have decreased dramatically in vegetation greenness between the wet and dry images, namely the grassland communities A and B, from those which have changed little or have increased in greenness over the six month period, the perennial-dominated groups G and I. The second variate forms a continuum relating to overall scene reflectance. At one extreme groups C and D with high percentages of bare ground and a pavement of white calcite pebbles score high values, and at the other extreme group I, with large exposures of dark grey-brown quartzite and perennial shrubs, has the lowest scores. The third variate appears to separate sample sites and groups on soil and rock redness, group H on the red-brown Nundooka sandstone at one extreme and group G on green-grey shale at the other. The fourth variate is difficult to interpret in relation to the vegetation groups, but when represented in image form by adding the image bands weighted by their respective canonical coefficients, seems to represent a gradient relating to shadow in the scene. Topographic shadows on the western side of ranges are accentuated, while the vegetation types with significant tree canopies (*Eucalyptus gillii* low open woodland G) or dense cover (grassland A) contrast with the more open shrublands B, E and D.

Although the function adequately discriminates the 9 ground classes, a comparison of predicted vs actual ground cover class (Table 3), together with examination of the canonical variate plots indicates some difficulty in separating groups A, B and C, and groups

D and F. These classes are also similar in ground cover composition as shown by the classification dendrogram. For example A and B and C are part of the same major group, and likewise D and F. A, B and C all occur on similar soils on the eastern alluvial plains and are characterised by varying proportions of the same components, namely bare soil, grass, ephemerals and the same perennial species. While D and F are separated in the cover classification because of their differing proportions of bare ground, stone and *Atriplex vesicaria*, the majority of the surface stone comprises very bright milky-white quartz pebbles. This is a significant contributor to the spectral signature in these regions, and is no doubt a major factor in their spectral similarity.

The final image classification, in which 50 spectral classes have been assigned to their corresponding ground cover classes, is presented in Figure 6. In general the distribution of communities shown reflects that observed in the field. The eastern plains flanking Fowlers Creek clearly show the complex mosaic of grassland, *Maireana aphylla* low open shrubland and ephemerals that dominate this area. Occurrences of the *Maireana aphylla* shrubland however have been over-estimated to the west of the ranges: the species rarely occurs there, although areas with similar high proportions of grasses and ephemerals do. The two low open shrubland communities dominating the ranges have been well distinguished. The vegetation classification assigned them to different groups because of differences in species dominance, *Atriplex vesicaria* vs *Maireana astrotricha*, as well as differences in proportion of exposed soil and rock, while the spectral mapping has distinguished them on differences in rock colour as well as vegetation cover. Stands of *Acacia aneura* are more common in group H on the northern ranges (2% cover). The woodlands of *Eucalyptus gillii*, restricted to a single valley in the ranges, have been well delineated, although the classification has also identified additional areas of the characteristic grey-green shale that underlies this community, but which do not carry the trees. The suite of *Atriplex* dominated shrublands flanking the ranges have been quite accurately mapped. Occurrences on richer soils, which are accompanied by considerable ephemeral growth, have been separated from the pure *A. vesicaria* stands, and those combined with *M. astrotricha* on the calcareous plains to the west.

When applied to the verification site data, the discriminant function produced an acceptable classification, although with somewhat lower accuracy than

Table 4. Comparison of cover class and class predicted by the discriminant function for 50 validation sites

Cover class	Predicted class									Total
	A	B	C	D	E	F	H	I		
A	5	1							6	
B	1	4	1	2	2	2			10	
C		4	1						5	
D				2	1	3	1		7	
E	1		1			1			3	
F				1		4			5	
G								2	2	
H					1	3	4	2	10	
I							1	1	2	
Total	7	9	3	5	4	11	6	5	50	

$$X^2 = 144.4, 56 \text{ d.f.}, p < 0.001.$$

Table 5. Comparison of cover class and image class for 50 validation sites

Cover class	Image class									Total
	A	B	C	D	E	F	G	H	I	
A	3	3								6
B		5	1	2		2				10
C			4	1						5
D			1	1		4		1		7
E	1			1		1				3
F				2		3				5
G							2			2
H					1	3		4	2	10
I									2	2
Total	4	13	2	6	1	13	2	5	4	50

$$X^2 = 149.3, 64 \text{ d.f.}, p < 0.001, \text{Kappa} = 0.31, p < 0.001.$$

for the original training sites ($X^2 = 114, 56 \text{ d.f.}, p < 0.001$; Table 4). The least satisfactory of the group predictions were B, D and H, where the actual field vegetation group fell across three or four predicted classes. The function also failed to correctly allocate the two curly mallee verification samples (group G), although the training sites for this community were clearly segregated.

A comparison of mapped image class with actual ground class for the 50 verification sites yielded a Kappa of 0.3 ($p < 0.001$) and a significant X^2 (149, 64 d.f., $p < 0.001$; Table 5). Although these figures suggest overall agreement between predicted and actual vegetation class, the accuracy of mapping for individual vegetation types varied considerably from

Figure 6. Vegetation classification for Fowlers Gap Arid Zone Research Station based on maximum likelihood classification of multi-date TM imagery, with 50 spectral classes allocated to cover classes derived from numeric classification of field cover data. Land systems mapped by Mabbutt et al. (1973) are overlain in black. Key to land systems: C, Caloola; Cn, Conservation; Fw, Faraway; Gh, Gap Hills; Ls, Limestone; Ma, Mandelman; Md, Mulga Dam; Nk, Nundooka; Nn, Nuntherungie; Oh, Old Homestead; Sc, Sandy Creek; Ss, South Sandstone; St, Sandstone Tank.

100% for the *Maireana astrotricha*-*Atriplex vesicaria* shrublands on the ranges and the *Eucalyptus gillii* open woodland, to 15% for *A. vesicaria* shrublands on the western uplands. These figures need to be treated with caution however, and have not been used in an accuracy assessment of individual classes since the number of samples in each type is low.

Comparison of the 9 image classes with Mabbutt's 14 land systems by means of a cross-classification matrix of all pixels within the map of the property indicated significant agreement (Table 6: $X^2 = 689,883$, 104 d.f., $p < 0.001$). Despite the different number of categories in the two maps, there is clearly a general relationship between the cover classes mapped from TM imagery and the land systems subjectively mapped from aerial photography. Occurrence of a number of cover classes in each land system, and of differing proportions of the same cover classes across different land systems is not unexpected. By definition, each land system consists of several land units with different geology, soil and vegetation characteristics. For example, Mabbutt et al. (1973) describes Nundooka Ranges land system as comprising five land units: rocky crests and faces, cuestas, uplands and bevelled ridges, minor drainage tracts and major drainage tracts, each with different soils, and vegetation. The dominant vegetation is recorded as *Atriplex vesicaria* and *Maireana sedifolia* shrublands with scattered stands of *Acacia aneura*. This variation is reflected in the cover groups that have been mapped in the ranges: groups D and H dominated by *Atriplex vesicaria* and *Maireana sedifolia* with *Acacia aneura*, and minor occurrences of other groups with differing proportions of *Atriplex vesicaria*, *Maireana* species, ephemerals and grasses (groups B, F and I).

However, several aspects of this matrix suggest that some combination of both image and land system classes would achieve a clearer comparison of the classifications. Several land systems such as Caloola, Fowlers, Mulga Dam, South Sandstone, Limestone and Old Homestead are relatively small, each covering less than 1400 ha or 4% of the mapped area. Similarly, some of the image classes covered small proportions of the mapped area. Class G, the *Eucalyptus gillii* low open woodland, has no direct equivalent in Mabbutt's classification, being incorporated in the Faraway Hills land system. The smaller land system classes were merged with larger classes with the most similar geological and vegetation composition, reducing the land system map to 7 classes. Class G was merged with I of

the image classification, and D with E, also producing 7 classes.

A cross tabulation of these revised maps showed significant agreement between the two classifications X^2 (605,830, 36 d.f., $p < 0.001$) and a Kappa of 0.41 (standard error 0.001, $p < 0.001$: Table 7). The Kappa index of agreement for individual classes, using the land systems as the reference map, is shown in Table 8. Following Landis & Koch (1977), Fitzgerald & Lees (1994) suggest ranges of $K < 0.4$ (poor), $0.4 \leq K \leq 0.75$ (good) and $K > 0.75$ (excellent) for the agreement shown by Kappa. The strongest relationships occur between the Faraway land system and combined cover classes G and I ($K = 0.64$) and between combined Nuntherungie, Limestone, Old Homestead and South Sandstone land systems and cover class F ($K = 0.59$). The grass-dominated floodplain land systems Mandelman and Caloola also show a strong relationship with cover class A ($K = 0.55$). The low Kappa scores for the Sandy Creek and South Sandstone land systems indicate that they do not closely correspond to the *Maireana aphylla* and *Atriplex vesicaria* cover classes C, D and E with which they have been compared in this cross tabulation. Indeed, Table 7 shows that the Sandy Creek land system is mapped by a relatively even mix of classes A, B, C, D and E, and that Sandstone Tank comprises a mix of B, D, E and F.

Comparison with Mabbutt's land systems should not be considered a strict test of accuracy of the digital image classification, since the two maps have quite different origins – one an expert subjective photointerpretation of integrated landscape units, the other objectively derived from quantitative land cover data and digital imagery. However, the strong general agreement between the two indicates that the TM imagery and the numeric classification have effectively captured many of the land attributes Mabbutt et al. (1973) incorporated in their classification.

Discussion

Although it is often suggested that conventional satellite remote sensing cannot delineate sufficient variation in vegetation composition to be used for many ecological applications, this study demonstrates that it is possible to discriminate associations that correlate with land systems and with objective numeric vegetation classifications. Key elements of the approach used here are (a) the use of cover rather than density or presence/absence to quantify the vegetation, (b) inclu-

Table 6. Comparison of 9 cover classes from TM image classification and 14 land systems mapped by Mabbutt (1973). Cell values are percentages of the total of 415,366 pixels. $X^2 = 689,883$, 104 d.f., $p < 0.001$

Land system	Image class									Total
	A	B	C	D	E	F	G	H	I	
Caloola	1.7	1.4	0.2		0.1	0.1				3.6
Mandelman	4.5	2.0	0.2							6.7
Conservation	4.7	13.9	2.5	1.3		0.3		0.3		23.0
Gap Hills	1.5	6.0	1.5	2.6	0.6	1.4		0.4	0.1	14.1
Sandy Creek	1.5	2.8	1.6	1.3		0.3		0.1		7.7
Fowlers	0.7	0.8	0.1	0.1		0.1				1.7
Mulga Dam	0.1	0.3	0.2	1.5		0.2		0.9		3.1
South Sandstone				0.1	0.1	0.5			0.1	0.8
Limestone				0.1		1.1		0.3	0.1	1.6
Sandstone Tank		1.5	0.2	0.9	1.5	2.2		0.1	0.1	6.5
Nuntherungie	0.1	0.4	0.0	2.1		6.1	0.1	0.1	0.4	9.4
Old Homestead	0.2	0.1	0.0	0.2		1.2	0.1		0.2	2.1
Nundooka	0.1	0.7	0.3	2.9		0.9	0.1	5.1	0.8	10.8
Faraway				0.1	0.1	2.2	1.0	0.5	5.1	8.9
Total	15.1	29.9	6.9	13.1	2.4	16.6	1.3	7.8	7.0	100.0

Table 7. Comparison of 7 cover classes from TM image classification and 7 combined land system classes mapped by Mabbutt (1973). Cell values are percentages of the total of 415,366 pixels. $X^2 = 605,830$, 36 d.f., $p < 0.001$; Kappa = 0.41, standard error 0.001, $p < 0.001$

Land system	Image class							Total
	A	B	C	D, E	F	H	G, I	
Mandelman Caloola	6.5	3.4	0.5					10.4
Conservation Fowlers Gap Hills	6.8	20.6	4.1	4.8	2.0	0.9	0.2	39.3
Sandy Creek	1.4	2.6	1.6	1.2	0.2	0.1		7.1
Sandstone Tank		1.6	0.2	2.3	2.4		0.1	6.5
Nuntherungie Limestone Old Homestead South Sandstone	0.2	0.5		2.6	8.7	0.5	0.7	13.2
Nundooka Mulga Dam	0.1	1.0	0.5	4.5	1.0	6.0	1.0	14.0
Faraway	0.1			0.2	1.4	0.5	6.4	9.5
Total	15.0	29.7	6.8	15.5	16.9	7.9	8.3	100.0

Table 8. Kappa index of agreement for 7 combined land systems and cover classes

Land system	Kappa
Mandelman Caloola	0.55
Conservation Fowlers Gap Hills	0.32
Sandy Creek	0.17
Sandstone Tank	0.23
Nuntherungie Limestone Old Homestead South Sandstone	0.59
Nundooka Mulga Dam	0.37
Faraway	0.64
Overall	0.41

sion of physical as well as vegetation cover to describe and classify field sites, (c) development of an objective land cover classification from this quantitative data, (d) use of the same sample sites as training areas for the spectral classification, and (e) use of a discriminant function to effectively tie the two classifications together.

The inclusion of physical as well as biotic ground cover components to characterise the vegetation is particularly important in this arid environment since perennial and ephemeral vegetation cover rarely over 30%, and the underlying soils and rocks form a significant portion of the landscape. In addition, the same dominants may occur across several land systems. Use of soil and rock as well as vegetation variables to classify the landscape allows segregation of sites that may have the same dominants, but which vary in relative cover, a difference also likely to be captured by image reflectance, and which is relevant for management of the land. While a few previous studies have attempted to relate objective vegetation classifications to spectral classification, failure to achieve good correspondence has often been attributed to variations in structure, cover and soil type with a community or to spectral similarity between different species (Catt et al. 1987; Treitz et al. 1992). Use of percentage cover,

and of soil-vegetation complexes rather than purely botanical associations to classify land cover, analyses the environment in terms more directly relevant to remote sensing, and is more likely to lead to stronger relationships between the two.

Discriminant analysis has proven to be a useful tool for testing the spectral separability of vegetation classes and for establishing relationships between ground and spectral classes, although it has generally been applied to subjectively mapped vegetation classes (e.g., Hobbs et al. 1989; Ghitter et al. 1995). Pando et al. (1992) developed a predictive discriminant function between objectively classified chenopod shrublands and Landsat Multispectral Scanner (MSS) digital data in a rangeland environment similar to Fowlers Gap, but did not apply the relationship to image-based mapping. They found the relationship held up at the fenced paddock level, i.e., over areas up to 1000–3000 ha, but could not be applied over larger distances. The present study is significant in that the discriminant function has linked objectively derived cover classes with spectral classification, successfully applied this over a broad area, and assessed the accuracy of class prediction with an independent set of field data. This close linking of ground cover and spectral classifications demonstrates that sound image analysis and accepted ecological methods can be successfully combined.

This approach has considerable potential value for vegetation mapping programs. Many national and regional vegetation mapping agencies promote the use of standardised classification systems (e.g., Australian Land Information Group 1990, and the U.S. National Parks Service/United States Geological Survey 1994), and sometimes seek to make these compatible with objectively derived communities. For example, several recent biological surveys in Australia have employed numeric classification to group field sites into vegetation types which are then identified with associations in standardised classification systems (Forwood & Robinson 1996). The mapping of these vegetation units is usually based on traditional photo or image interpretation and definition of homogeneous polygons. Use of pixel-based digital imagery could refine this approach in that it more accurately portrays sub-polygon variation in vegetation and complex natural patterns of distribution. As shown by the present study, such image classification can be linked to numeric vegetation groupings which are also compatible with standardised vegetation and land system classifications.

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