2. POTENTIAL OF REMOTE SENSING IN THE MONITORING OF WEED INFESTATIONS ALONG POWERLINE CORRIDORS

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2.1 SUMMARY

The Chalumbin-Woree powerline corridor was examined in detail at seven locations. Percentage vegetation cover was measured and spectral reflectance data of weed species was collected in the field using a “Cropscan” Multispectral Radiometer. Imagery of the powerline corridor was acquired at two different spatial scales. One source was Ikonos multispectral satellite at four-metre resolution and the other was from an Airborne Data Acquisition and Registration (ADAR) system at approximately one metre ground resolution. This study examined the general criteria needed for quantitative ground measurements of reflectance to be used in classifying the spectral differences of weed species. The specific focus was the determination of the spatial, spectral and radiometric resolution required to detect the fractional quantity of each weed species at the sub-pixel level using "Spectral Mixture Analysis" (SMA).

Field measurements of the percent cover of weed species showed that within each square metre, one to three main species were present suggesting that SMA was a viable technique for determining the quantity of weed fractions in imagery at one metre spatial resolution. Signatures were made from the spectral reflectance measurements and found to be statistically separable.

To relate field spectral responses to the imagery an empirical calibration was employed, avoiding complex atmospheric corrections. However difficulty was experienced with calibration of the ADAR imagery due to an inherent interpolation algorithm in the camera's output.

The Spectral Mixture Analysis was found to be unsuitable as a classifier of the ADAR imagery because of poor camera performance. The spatial resolution of the Ikonos imagery was unsuitable for SMA, as there are only four spectral bands to unmix the contents of each 4 metre x 4 metre area on the ground.

There is definite potential to discriminate individual weed species using their spectral signatures. However, vegetation reflectance patterns are broad and the variability within a species is much higher than apparent differences between species. An image classifier that considers the variance in vegetation reflectance is required, together with a sensor with the spectral and radiometric qualities of the Ikonos satellite imagery but with the higher spatial resolution of an airborne camera ($1m^2$). Either a four camera airborne system giving a spatial resolution of $1m^2$ or a 4-band multispectral satellite sensor with two metre resolution (available 2005) can be expected to be far more successful than the imagery examined in this study.

2.2 INTRODUCTION

In the wet tropical zone of Queensland, the World Heritage Convention has protected much of the publicly owned tropical rainforest from logging and clearing, but other more insidious threats remain. Roads and electricity supply corridors create linear barriers through natural areas, fragmenting the WTWHA. Weed invasions along these corridors (see Section 1) contribute to fragmentation effects by competition with native species (shading, allelopathy), and inducing disturbances such as fire, edge effects (see Section 3) or the influx of generalist species. Thus, infrastructure corridors and invasive pest species have been identified as priority areas of research effort in the Wet Tropics World Heritage Area (WTMA 2000).

In addition to the significant threats posed by fragmentation, several invasive weed species, which are in the higher categories of significance for Weeds of the Wet Tropics Bio-region (Werren 2001), occur in the linear infrastructure corridors that traverse the World Heritage Area. WTMA (1999) identified a need to develop less field-intensive methods for the detection of invasions of new weed species, and to predict expansion of existing weed problems. Good information on the density and location of weeds is essential to monitor the effectiveness of control programs and management strategies (Lamb 2000). Ground surveys over large areas are labour intensive, costly and in the WTWHA, difficult to undertake during wet seasons. Remote sensing has the potential to provide a practical and cost-effective monitoring tool both for threats such as weed incursion or for the success of rehabilitation. It could give timely, up-to-date information on the distribution and abundance of weeds over wide areas, especially where seasonally wet roads prevent continuous access to some locations. Remote sensing has the capability to discern small patches at a local scale of square metres as well as surveying on broad scales of square kilometres. The ability of a Geographic Information System (GIS) to integrate remote sensing data also allows development of predictive modelling. Such a powerful tool could assist in monitoring the spread of an aggressive weed such as Pond apple (*Annona glabra*), and in design of control strategies.

2.3 POTENTIAL OF REMOTE SENSING AS A MONITORING TOOL FOR WEEDS – LITERATURE REVIEW

2.3.1 Introduction

Limited use and development of remote sensing in rainforest environments has occurred in Australia (Phinn *et al.* 2000). One reason for this could be due to the fact that rainforests are located in mountainous areas with rugged topography and frequent cloudy weather. Much of the groundwork in developing remote sensing as a useful tool has occurred in comparatively flat areas of temperate or semi-arid regions with consistently clear skies (Schetselaar and Rencz 1997; Hindle 1998; Lewis *et al.* 2000). Most quantitative work on plant material has been for agricultural crops that predominantly have uniform low canopies (McNairn *et al.* 2001; Nutter *et al.* 2001).

One difficulty, which is exacerbated by mountain environments, is relating one remotely sensed image to another image captured at a different time. An essential requirement of this is an adjustment of the levels of light recorded in each image, to a standard surface of known reflectance (calibration), while at the same time, accounting for all the variations in light levels arising from seasonal, view angle and atmospheric differences. The calibration of an image can be a difficult and complex task but can be avoided if one limits analysis to just spatial changes, rather than subtle spectral changes (Adams *et al.* 1995). Thus, remote sensing has been used for monitoring land clearing, but less frequently applied to detecting small changes in forest type.

2.3.2 Using Remotely-Sensed Imagery to Determine Canopy Composition

Satellite imagery is widely used to map broad vegetation or land use classes. However the highly complex mix of canopy types in rainforests presents difficulties when standard classification techniques are used on coarse resolution. To overcome similar problems in other environments, sub-pixel component analysis has been used with varying success for tasks such as arid-zone vegetation mapping (Lewis 1998) and agricultural weeds surveys

(Chewings *et al.* 2000, Hindle 1998). It shows promise for the mapping of forests in Australia (Dibley *et al.* 1998), and in recognition of its growing importance, several new versions of GIS packages have included modules for this new technique (often called "Linear Unmixing").

2.3.3 Spectral Component Analysis

Spectral component analysis is suited to the situation where the resolution of an image (e.g. a Landsat scene with a ground resolution of 25 metres) is larger than the size of the features of interest e.g. a patch of weeds.

Spectral component analysis can determine the proportions of each cover type or canopy species in each pixel, but only after three requirements are met:

1. Determination of the spectral reflectance characteristics of the canopy species occurring in each pixel;
2. Calibrated imagery; and
3. Imagery that has an equal or greater number of bands of information than the number of distinct canopy types occurring in each pixel.

The last requirement can be met by reducing the size of the ground resolution element (pixel) so that fewer species are present within it or by obtaining a larger number of bands in the imagery (the rationale behind hyperspectral imagery).

2.3.4 Measurements of Spectral Reflectance of Species

Spectral reflectance characteristics of individual species can be measured in the field with a hand held radiometer. Sampling the reflectance of plants *in situ* takes into account the reflectance of other components such as shade and bark, just as occurs in remotely sensed imagery. The spectral signal received by a sensor (whether it is near the canopy or above the atmosphere) is a mix of different components like leaves, flowers, stems, understorey, and is affected by shadow within the canopy (Dury *et al.* 2000). For instance, short grass has less shade within its canopy than thick long grass which, in turn, has less than a rainforest. Skidmore and Schmidt (1998) suggest that canopy structure and soil background are two criteria that can alter reflectance.

Remote sensing systems are designed to sample these spectral responses of Earth surfaces in several bands, so that enough information is obtained to distinguish one kind of surface from another (Richards 1993). Common Earth surfaces such as leaves, soil, water, rock, bark and pavements all reflect different parts of the spectrum differently. The reflectance of a surface can be expressed as a ratio or a percentage of the quantity of light incident on that surface. A graph can represent the reflectivity response of a surface by showing percentage of incident light reflected at different wavelengths, as in Figure 2.1.

The reflective properties of minerals and vegetation have been studied in depth. Leaves are interesting in that the reflective properties change with the loss of moisture and variation in pigments such as chlorophyll. Chlorophyll (a) and (b) are important in photosynthesis, they absorb light at particular wavelengths in the red and blue regions of the spectrum (Curran 1985). This selective absorption gives leaves their green colour because comparatively more green light is reflected, as shown in Figure 2.2. Green leaves vary in the thickness of their composite layers leading to further variation in the quantity of light absorbed, transmitted and reflected. The cell walls and numerous air spaces in the mesophyll of a moist green leaf (Curran 1985) are responsible for the high reflectivity in the Near Infra Red (NIR) region of the spectrum (at wavelengths greater than 700nm), which is invisible to the human eye. Dry leaves have lost their moisture and thus the structure responsible for the high NIR reflectivity of green leaves. The NIR end of the spectrum therefore makes a useful diagnostic feature in remotely sensed imagery for maturation or drying out of vegetation.

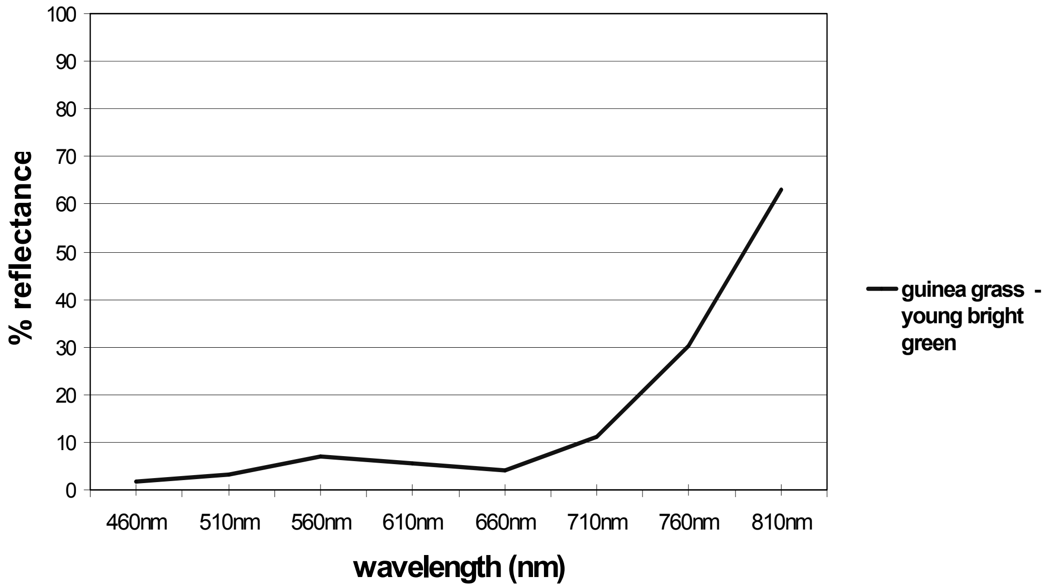


Figure 2.1: An example of typical reflectance of green vegetation, Guinea Grass (*Panicum maximum*).

Finding a way to discriminate plants, or in this case weeds, by their spectral reflectivity response requires dealing with three main issues:

1) Genuine differences between species in their spectral reflectivity response;
2) Genuine variation within a species in its spectral response; and
3) Uncertainty due to the external condition at the time of sampling such as lighting or variation in sampling methodology

Point (1) is a straightforward problem and, given a fine enough resolution, is considered statistically solvable. Several studies have investigated different features of plant spectral response to find the best diagnostic method of differentiating between species. Some of the relevant findings in the literature are summarised below.

Asner and Lobell (2000) suggest that features of plant spectra that are least variable within species but distinct between species are the most desirable for discrimination between plant spectral signatures. Skidmore and Schmidt (1998) found that for eight species of grass there were more pairs of significantly different reflectances in the red region at 650nm (550-680nm) and NIR region at 1300nm than at 800nm in NIR region. Differences were found in the NIR (800 nm) but were not statistically significant because of the greater variances in this region.

Kumar and Skidmore (1998) compared reflectance spectra of ten *Eucalyptus* species in the field. While some species could be differentiated easily over a wide range of wavelengths, others showed differences only at certain positions, and others showed no differences at all. Reflectance values at 550nm, 630nm, 800nm and red edge features seem to be the best locations for discrimination of eucalypts. Nutter *et al.* (2001) also used field methods to correlate soyabean yield and nematode infestation using "Cropscan" reflectance, airphoto images and satellite images (Landsat 7). Percentage reflectance at 810nm had the best relationship with nematode infestation explaining fifty-two percent of the variation in population densities.

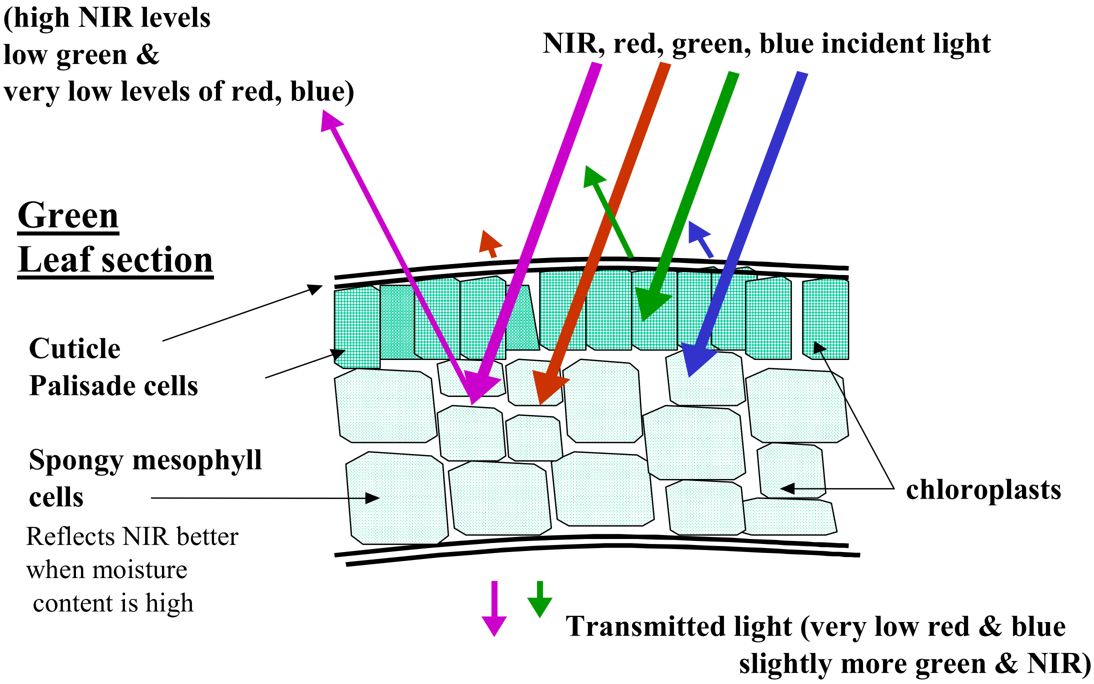


Figure 2.2: Leaf section showing interaction of visible and near infrared light.

The position of the steep rise in reflectance of green leaves in the NIR region is known as the "red edge position". Curran *et al.* (1998) and Datt (2000) found that the position of this 'red edge' correlated with the chlorophyll and carotenoid content of leaves.

Farrand *et al.* (1994) suggest that "apparent" reflectance is dependent not only on the mixture and the composition of surface materials but also on the physical condition of the surface and its orientation to the sun (point c above). Thus while low reflectance may be due to the low reflectance of a surface, it also may be affected by poor orientation or lighting (i.e. shade). Sun angle, sensor angle, topography, aspect and leaf angle (and the change in its orientation during the course of a day) interact in complex geometric ways. All of these factors can influence the amount of shade the sensor "sees" (Curran 1985).

McGowen (1998) highlights how environmental and seasonal variation in weed species can cause their spectral signatures to vary over time (*i.e.* point 2 above). Environmental variation such as in soil moisture status or poor drainage may affect the density of plants and alter the purity of their spectral reflectance. Seasonal differences, such as distinct colouring of flower heads (e.g. molasses grass, *Melinis minutiflora*), may be useful in discriminating a weed from its surrounding vegetation and soil spectra. However, these differences may also be a confounding factor in the Wet Tropics area because altitudinal and climatic gradients affect the timing of events such as flowering and seed set. It may therefore be useful to represent a species by 2, 3 or 4 different signatures (or a mixture of these), which represent distinct stages of growth.

2.3.5 Calibrating an Image

A simple, robust calibration technique that corrects for atmospheric absorption and scatter, called the "empirical line method," has been used successfully in many studies (Roberts *et al.* 1993; Farrand *et al.* 1994; Adams *et al.* 1995; Lewis 1998; Edirisinghe *et al.* 1999 and Sabol *et al.* 2002). It uses a linear regression between field spectral data and the image spectral values to define the relationship between them for each band.

2.3.6 Spectral Component Analysis of the Image

Spectral mixture analysis is a way of identifying which cover classes are present in a pixel and estimating their relative contribution to the mixed pixel (Settle and Drake 1993; Adams *et al.* 1995). The unmixing algorithm is mathematically simple, assuming an additive combination of the spectra of the cover classes.

With an equation for each band of imagery, fractions can be solved simultaneously for up to as many classes as there are bands of imagery. Thus to find the fractions of a large number of signatures, a large number of spectral bands are needed, e.g. Landsat TM covers seven bands. Thus, proportions of up to seven signatures (ideally, seven species) can be "unmixed". Hyperspectral imagery, which covers 128 to 212 bands, has been used in many studies for spectral mixture analysis (eg, Anstee *et al.* 2000; Chewings *et al.*, 2000; Hermann *et al.* 2000; Lewis *et al.* 2000).

The pixel "unmixing" algorithm examines every pixel for the best combination of signatures. It produces a map for each signature showing its proportion in each pixel. From these maps it is theoretically possible to calculate a quantitative measure of the total area occupied by each signature or ground cover type.

From this review of the literature it seems that if spectral component analysis could be successfully applied, two aspects of remotely sensed weed surveys could be addressed simultaneously:

1. The difficulty of obtaining fine scale imagery with high enough resolution to detect individual clumps of a weed species; and
2. A quantitative measure of the proportion of each species could be made with greater accuracy than with standard classifiers.

2.4 RESEARCH QUESTIONS

The research questions investigated in this study are:

1. Can multi-spectral satellite or airborne imagery discriminate individual weed species and if so what spatial resolution is needed?
2. Is it possible to determine the fractional quantity of each weed species at the sub-pixel level using "Spectral Mixture Analysis", and if so what conditions are best for doing this?
3. Which sensor is likely to provide the best overall result for the WTWHA?

2.5 METHODS

2.5.1 Study Sites

The focus of this study is seven sites surrounding towers in the Chalumbin-Woree powerline corridor. The corridor passes through World Heritage listed rainforest, from Bridle Creek (near Davies Creek), to Woree, a suburb of Cairns. Figure 2.3 shows a colour satellite image of the study area. Percentage cover was measured and spectral reflectance data of weed species was collected using a hand-held radiometer. Imagery of the powerline corridor was acquired at two different spatial scales. One source was Ikonos multispectral satellite at four metre resolution and the other was from an Airborne Data Acquisition and Registration (ADAR), system at approximately one metre ground resolution (Figure 2.4).

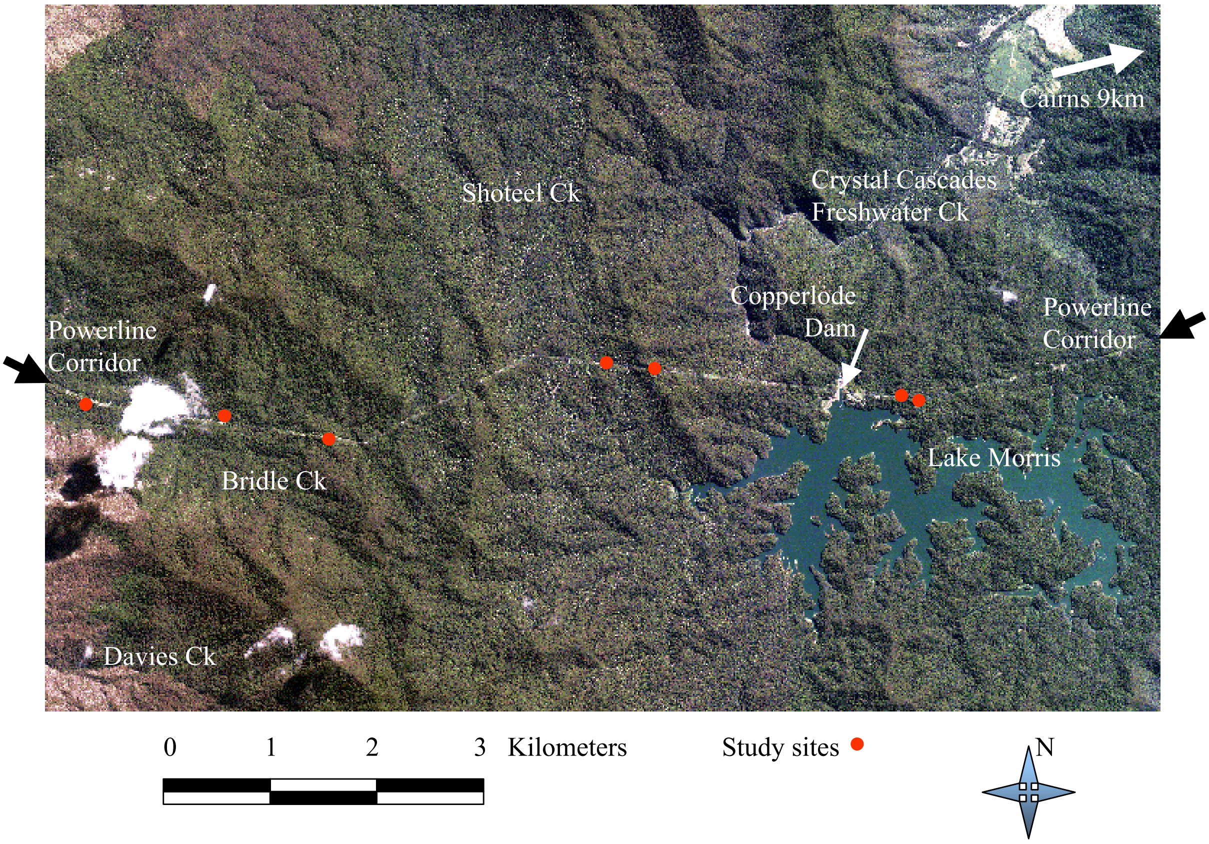


Figure 2.3: Ikonos satellite image of the study area showing the powerline towers within the study sites as red dots.

2.5.2 Floristic Survey Methods

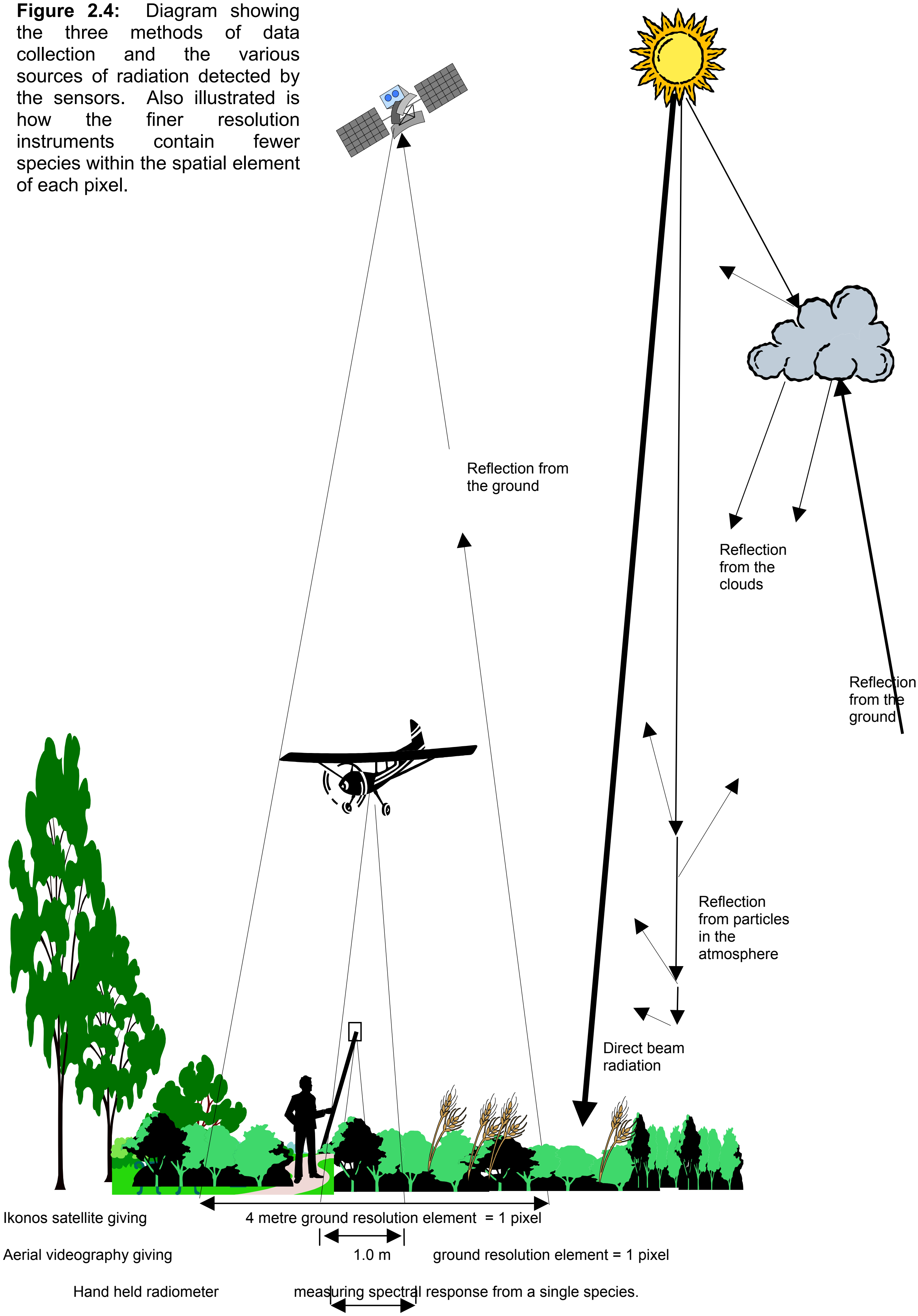
Three sets of field data were collected:

1. Weed and rainforest species present at each site
2. Percentage cover by weed and rainforest species
3. Spectral reflectance recordings of weed species.

Transects

Mr. Robert Jago, a well-respected botanist with many years experience in the Wet Tropics, was employed to identify all plants at each site. Along a sixty metre transect at each site all plants located within five metres each side of the line were identified.

Figure 2.4: Diagram showing the three methods of data collection and the various sources of radiation detected by the sensors. Also illustrated is how the finer resolution instruments contain fewer species within the spatial element of each pixel.



Percentage Cover

Species composition was estimated in several relatively homogeneous areas of the sites. This was used to assess the accuracy of the species identification in the classification of the satellite and airborne imagery (ground truthing). The sites were divided into two or three relatively homogeneous areas assumed to be large enough to be visible from the air. In each area, three to five quadrats, each one square metre, were examined visually for species content. Assessment was based on the percentage of leaf area of each species.

2.5.3 Field Reflectance Measurements

Spectral reflectivity measurements were collected in the field with a hand-held radiometer ("Cropscan" Multispectral Radiometer) and analysed to develop spectral classes to be identified in the imagery. The sensor measures the level of radiation from above and below simultaneously in eight discrete, narrow bandwidths (Figure 2.5).

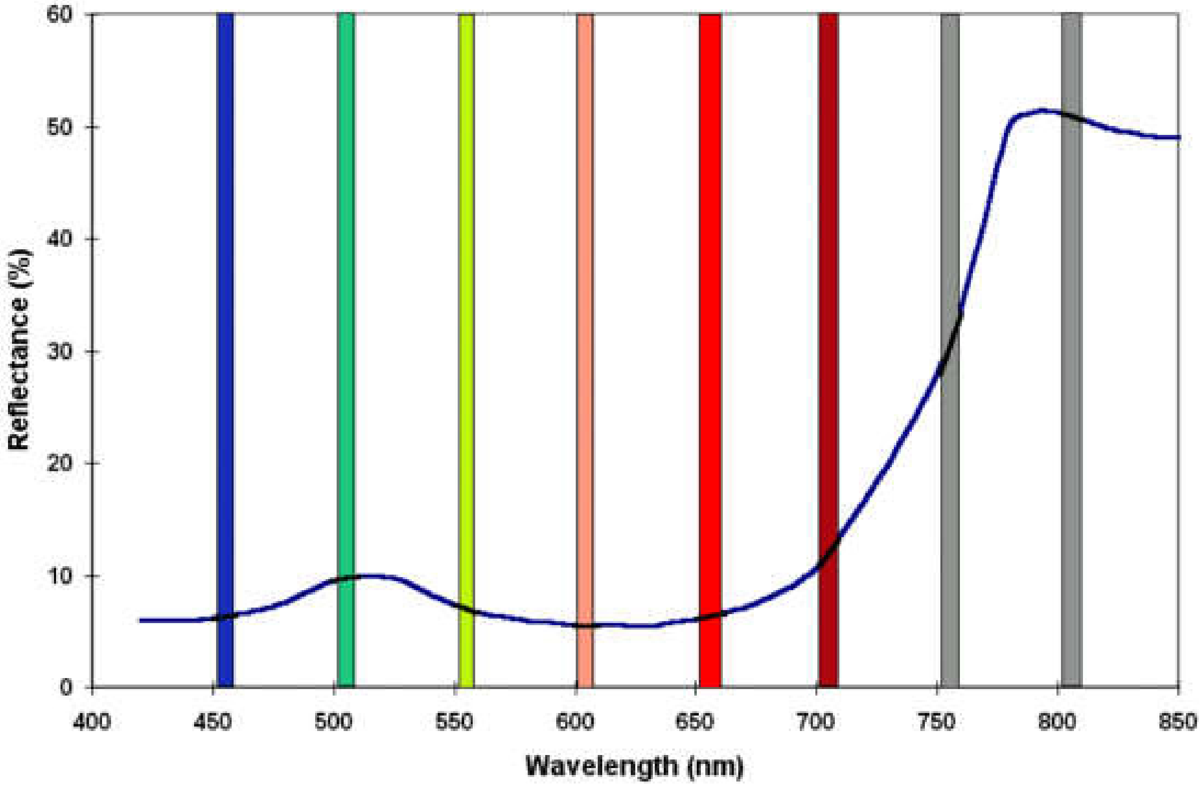


Figure 2.5: "Cropscan" Multi-Spectral Radiometer band positions showing also a typical reflectance curve of green vegetation. Source Cropscan MSR at (http://www.cropscan.com).

2.5.4 Data Analysis

Percentage reflectance for each sample was graphed to gain a visual appreciation of variability of the reflectance curves of different species. Each species showed a wide variation in reflectance that, in most cases, appeared larger than the apparent differences between species. The data was entered into a GIS to organise it into groups of spectral classes (using a cluster analysis). The classes obtained were further subdivided into groups containing samples of a single species. The validity of these groups as distinct spectral classes was tested statistically using discriminant analysis and further refined. "Signatures" for classifying the imagery were made from the resultant spectral classes. The signatures were tested for their separability using a divergence indicator. Both the ADAR and the Ikonos imagery were calibrated and classified using the signatures described.

2.6 RESULTS

2.6.1 Species Present in Transects

Weed species recorded on the transects are compiled in Appendix 1.1. There were two hundred and twenty-seven species identified within the ten metre wide quadrats along the thirty metre transects, but most of these occurred in small numbers. A number of rainforest pioneer tree species were present as well as many shrubs, herbs, ferns and vines. There were forty-four weed species identified and six out of seven sites had one or more weeds as the dominant class of vegetation (Table 2.1).

Table 2.1: Summary of dominant or common weeds found adjacent to transects at sites on Chalumbin-Woree powerline corridor. Weeds were not dominant near the transect at Tower 10108.

Weed Species	Site Tower No.						
	10091	10094	10096	10103	10104	10108	10109
Ageratum conyzoides	x		x	x			x
Axonopus compressus	x		x				x
Axonopus fissifolius					x		
Brachiaria decumbens		x	x	x			
Cyperus aromaticus							x
Hyptis capitata				x			
Lantana camara	x	x	x	x			
Melinis minutiflora	x	x	x	x	x		x
Mimosa pudica	x	x	x	x	x		x
Paspalum paniculatum	x		x	x	x		x
Rubus alceifolius				x	x		
Sporobolus jacquemontii			x		x		x
Stachytarpheta jamaicensis	x	x	x	x	x		x

2.6.2 Percentage Cover Measurements

Despite the large number of species found in the powerline corridors, within the area represented by one pixel in the ADAR imagery (1.0 m^2) there were typically one to three dominant species and generally no more than five species per pixel. No quadrat had more than four species with greater than five percent cover. Therefore the capacity of spectral unmixing techniques to examine the proportion of a weed species in a mixed pixel is not exceeded for three bands of imagery at one metre resolution (i.e. the resolution of the ADAR imagery).

2.6.3 Spectral Reflectivity

The unsupervised classification procedure in IDRISI produced twenty-eight groups of spectral classes from a total of nine hundren and thirty samples. Thirteen groups contained more than four samples of weeds, and the larger groups contained a number of different species. Figure 2.6 provides the mean spectral reflectance curve of the largest twelve groups and Table 2.2 lists the majority of the species in each group.

Signature Clusters

Signatures for each group were created that conformed to the bands used in the ADAR and Ikonos imagery. After creating signatures the separability of every pair was tested with a divergence score. A score of two thousand indicates complete signature separability (obtained in forty-seven percent of signature pairs) while a score between 1200 -1500 suggests separability is less likely, and a score less than one thousand suggests it is unlikely (Stow *et al.* 2000). The majority (seventy-seven percent) of signature pairs earned scores of 1900 or more, and are thus likely to be able to be separately identified when classifying an image.

2.6.4 ADAR Imagery Results

The focus of the study was to investigate the use of field reflectance measurements to classify remotely sensed imagery. The imagery came from an Airborne Data Acquisition and Registration system (ADAR) designed and manufactured by Positive Systems Inc. (http://www.possys.com). The basis of these images is a Kodak digital camera (DCS460) mounted on a small aeroplane and connected to ancillaries such as a controlling terminal, a GPS and a facility to store the digital images as they are captured. Imagery was supplied by the Biophysical Remote Sensing Group at the University of Queensland. The ADAR system is capable of producing high resolution images of the Earth's surface in colour or colour infra red (CIR).

The resolution can be 0.5 - 2.0 metre pixels, depending on the flying height. Each image is 3064 x 2040 pixels. The spectral response for CIR imagery is given in Figure 2.7; note the positions of each band. Instead of recording light levels in the blue region (~450nm) the sensor records the near infra red light, which is highly reflected by green vegetation. Figure 2.7 indicates that the spectral responses of each sensor overlap, allowing a broad range of wavelengths to reach each sensor. Compared to a satellite sensor, the bands of which are well separated in wavelength, the ADAR camera's reduced purity of signal decreases its sensitivity to fine spectral features. This does not matter to the human eye but fine spectral resolution is an important criterion for detecting subtle reflectance features (Anstee *et al.* 2000; Stow *et al.* 2000).

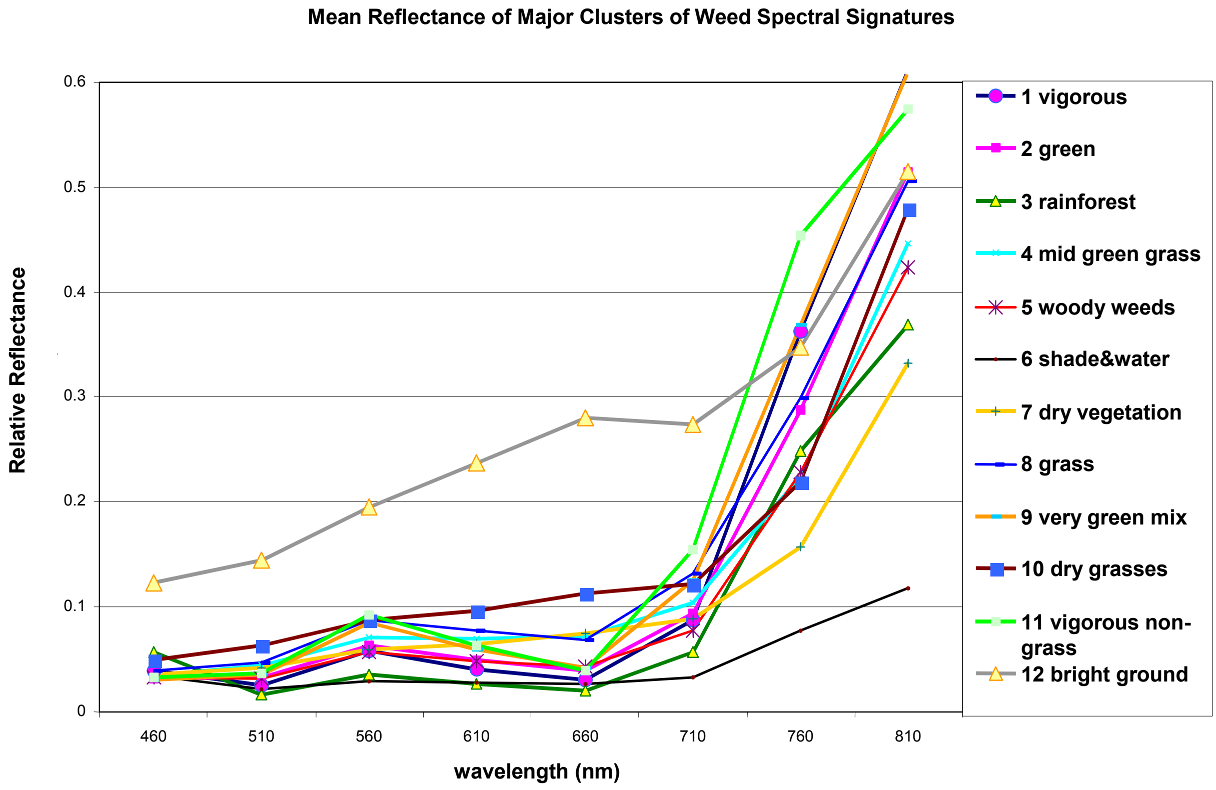


Figure 2.6: Mean reflectance of major spectral clusters of weeds

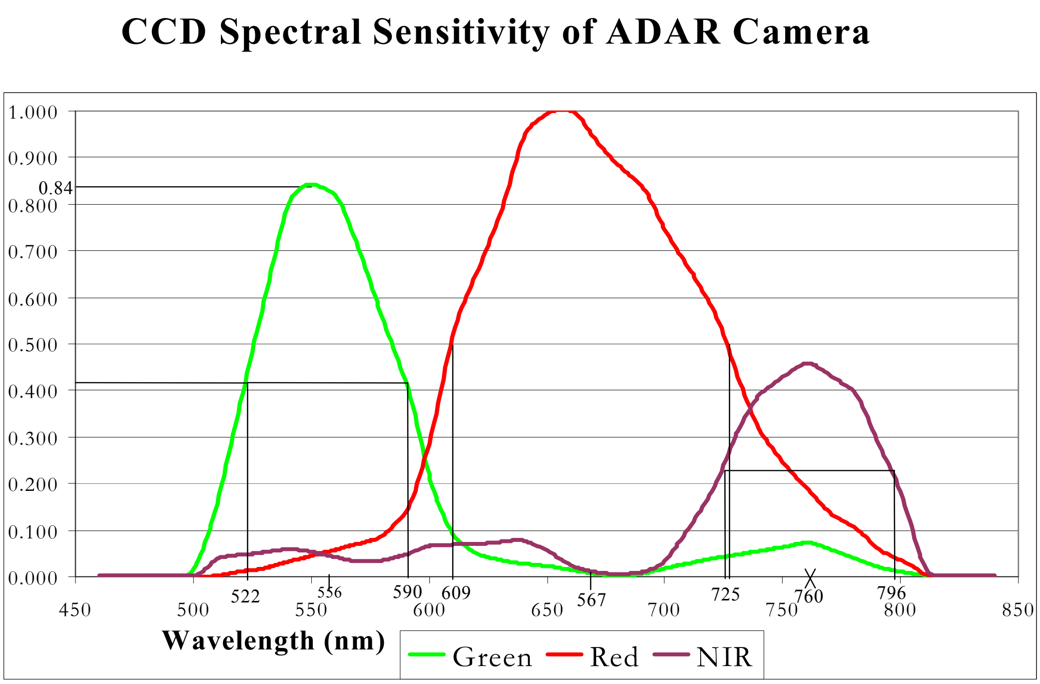


Figure 2.7: CCD spectral sensitivity of ADAR camera. Source: Phinn pers.comm.

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Table 2.2: Summarised species composition represented by each cluster.

Species/Surface Type	No. of samples	Species/Surface Type	No. of Samples	Species/Surface Type	No. of Samples	Species/Surface Type	No. of samples
Cluster 1 – Vigorous	**146**	**Cluster 3 – Rainforest**	**117**	**Cluster 7 – Dry vegetation**	**55**	**Cluster 10 – Dry grass**	**33**
Lantana	41	Rainforest	81	*Themeda triandra,*	10	Blady grass	9
Guinea grass	10	Lantana	22	Dry grass	7	Guinea grass – dry	6
Rainforest	9	Other - 9 types	14	Bare ground	6	Dry grass	4
Rubus spp.	9	**Cluster 4 – Mid-green grass**	**92**	Lycopodiella, mostly dry	6	Small bush	3
Singapore daisy	8	Molasses grass	20	Molasses grass, dry	6	Themeda, dry	3
Solanum spp.	8	Guinea grass	13	Blady grass	**5**	Bare ground	3
Commersonia (flowering)	6	*Lycopodiella cernua*	9	Gahnia sieberiana	4	Other - 3 types	5
Other – 18 types	55	Themeda *spp.*	8	Other - 6 types	11	**Cluster 11 – Vigorous non-grass**	**31**
Cluster 2 – Green	**141**	Dicranopteris -green	5	**Cluster 8 – Grass**	54	Rubus	8
Guinea grass	26	*Paspalum paniculatum*	5	*Paspalum paniculatum*	**13**	*Solanum* spp.	7
Molasses grass	10	Bracken fern	4	Guinea grass	11	Ageratum - no flower, green	4
Paspalum paniculatum	10	*Oplismenus* spp.	4	*Dicranopteris linearis*	8	Ginger,Large	3
Lantana – most flowering	9	Sedge	4	*Gahnia sieberiana*	5	Other - 6 types	9
Omalanthus	8	Other - 11 types	20	Other - 9 types	17	**Cluster 12 – Bare ground (1)**	**14**
Rainforest	8	**Cluster 5 – Woody weeds**	**85**	**Cluster 9 – Very green mix**	**53**	Bare ground/road	14
Ageratum, flowering	7	Guinea grass	25	*Dicranopteris linearis*	9	**Cluster 13 – Water/bitumen, dark surfaces**	**13**
Rubus spp.	7	Blue snakeweed	10	*Rubus* spp	9	**Cluster 14 – Bright Surfaces**	7
Acacia spp.	6	Lantana	10		7	Dicranopteris	5
Melastoma affine	6	Rainforest	5	Ageratum - full flower, no flower	4	Other - 2 types	**2**
Bracken fern	5	Other – 15 types	35	*Solanum* spp	4	**Cluster 15 – Dry Grass**	**6**
Dicranopteris linearis	5	**Cluster 6 – Shade/Water**	**59**	Other – 13 types	20	Dry grass – various	51
Other – 16 types	34	Water, river/dam	22			Bitumen	1
		Shade	19			Cluster 16, 17, 20, 21 – Bare ground	14
		Other – 7 types	18			**Cluster 22, 23, 24, 25 26, 27, Vegetation, various**	8

Calibration

The image (Figure 2.8) must be calibrated in order to use the signatures made from the field reflectance measurements of weed species. The calibration process expresses the imagery values in the same units or terms as the data from the hand held radiometer.

The reflectance measurements of specific locations within the image were regressed against the numerical value (digital number) of their corresponding pixels for each band. The resulting line of best fit was curvilinear and not the linear relationship defined in previous studies (Farrand *et al.* 1994; Edirisinghe *et al.* 1999). Therefore field reflectances were log-transformed to give a linear relationship to the values in the image (Harriss 2002).

Classification

An unsupervised classification indicates the maximum number of classes possible given the spectral space of the image. It does not use any field radiometer data to create these classes. As an example, using unsupervised classification for the site near Powerline Tower no.10103 (Figure 2.9), twenty-two spectral classes were found. However, there is likely to be difficulty in separating some signatures, eg, spectral cluster “2” has membership both on the road and in the forest.

A supervised classification technique using the radiometer field signatures to classify the calibrated image of the same site (Figure 2.10) showed an allocation of only seventeen out of the original sixty-eight classes. The areas of interest to this study, the road verge and the clearing around the tower, belonged to only two classes, shown in pink and blue-green. This suggests two possibilities:

(a) That the calibration of the image did not bring the pixel values, at those locations, within the ranges of most of the signatures; or
(b) That there was insufficient spectral differentiation in the image in those areas of interest.

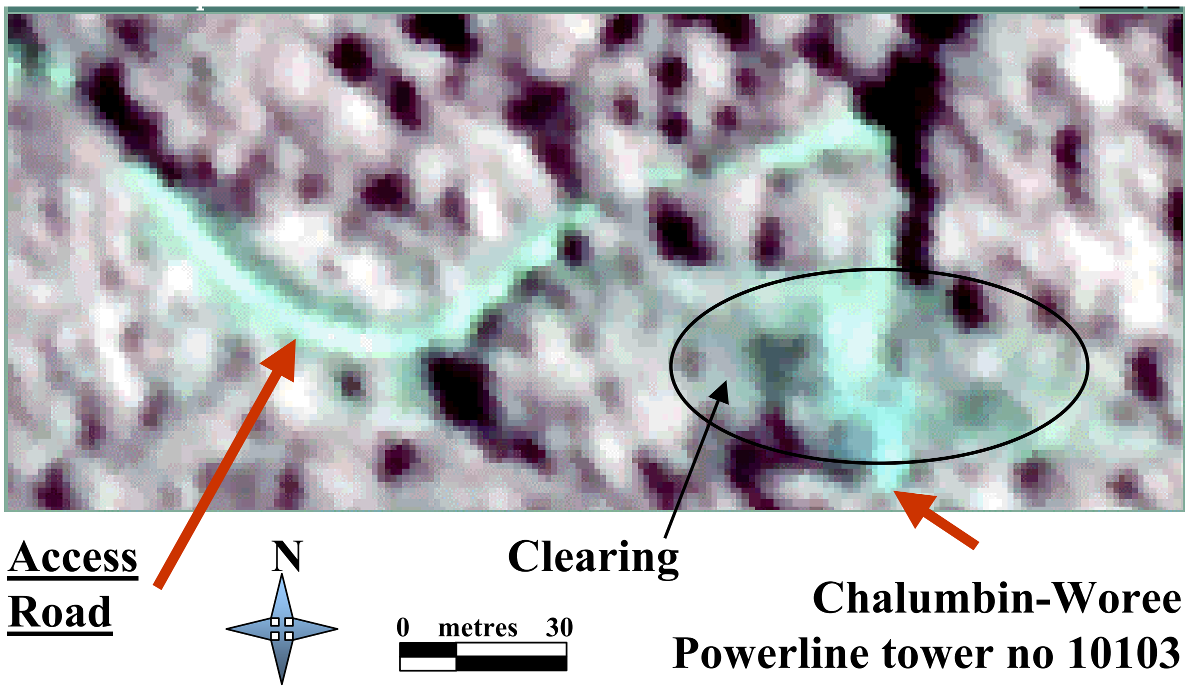

Figure 2.8: ADAR image showing one of the study sites on the Chalumbin-Woree powerline corridor near Powerline Tower no.10103.

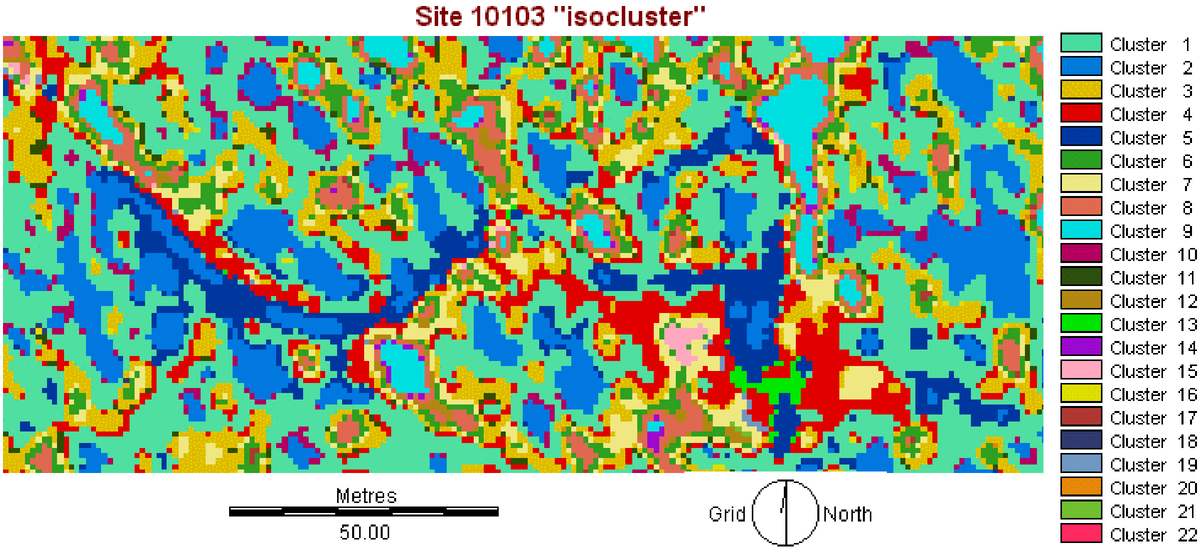

Figure 2.9: Unsupervised classification of the image around powerline tower No. 10103. The spectral class of shade is in light blue, while dark blue is situated on the road and part of the clearing. Red delineates the clearing and the road edge while bright green is possibly the legs of the tower.

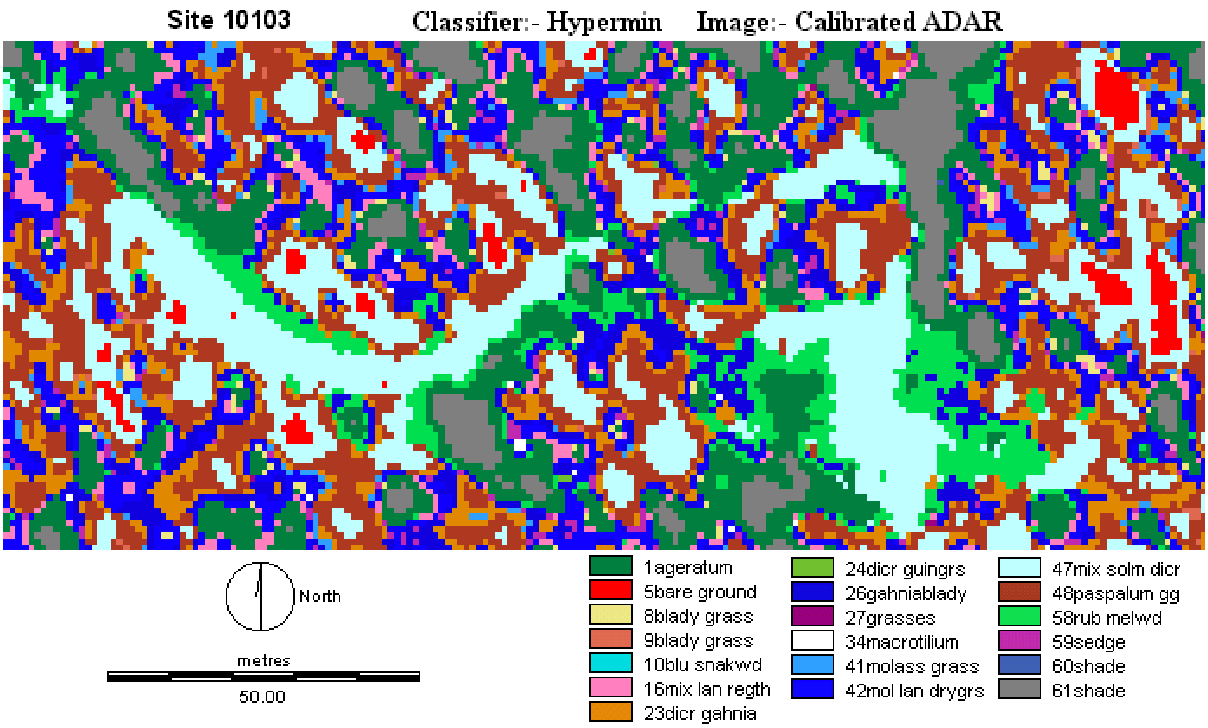

Figure 2.10: A supervised classification with minimum-distance measure using the group of 68 signatures derived from the field data by SPSS discriminant analysis.

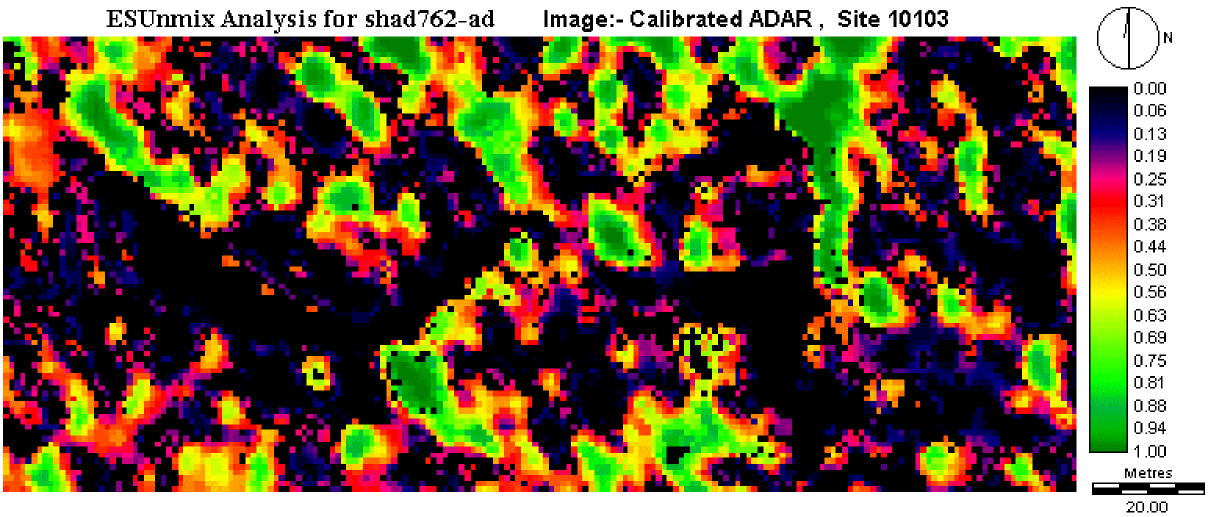

Figure 2.11: Unmixed fractional map of shade class. A pixel coloured dark green in this image indicates an estimated 90% to 100% shade.

Spectral Mixture Analysis

Figure 2.11 shows the fraction of one signature (shade) in each pixel of the image while Figure 2.12 shows the fraction of a signature that is itself a mixture (containing mostly *Rubus*). The members of the mixed group "14" were present along the road to some extent as found in Figure 2.12, but a large number of images generated by this procedure were blank or meaningless. The way each signature represents a spectral class, and the way the spectral components mix to form the overall reflectance of a pixel needs further examination and development of theory.

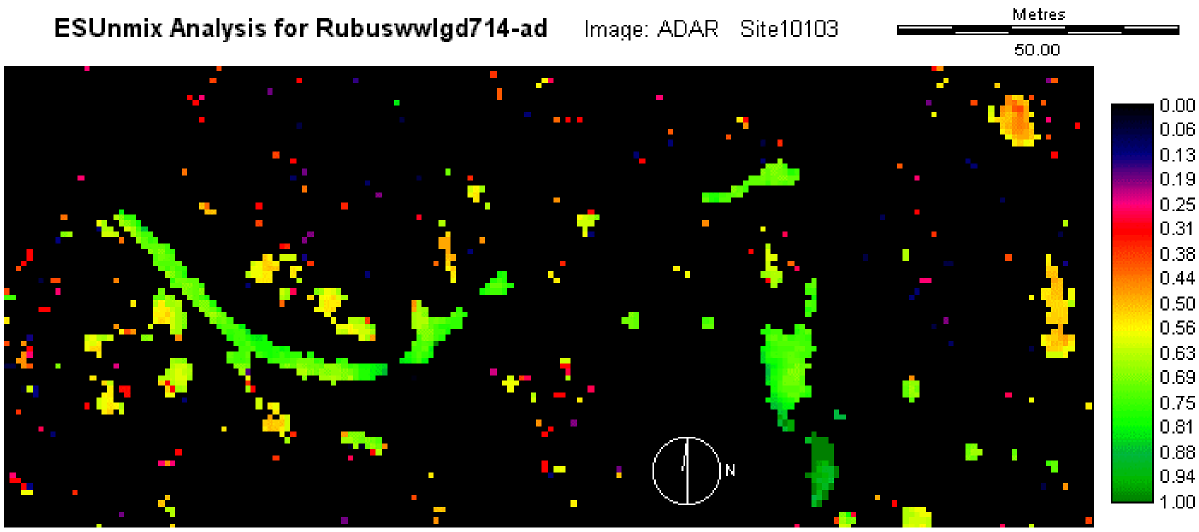

Figure 2.12: Fraction of group 14, which is a mixture of mostly *Rubus, Dicranopteris, Alpinia* spp and *Panicum*.

2.6.5 Ikonos Satellite Imagery Results

A similar set of procedures was undertaken for the Ikonos satellite imagery. The Ikonos satellite was launched in 1999 and provides high resolution imagery in four bands, blue, green, red and near infra-red (Figure 2.13). The ground resolution element, which equates to a pixel, is 4m x 4m, and the instrument sensitivity is high, recording in two thousand and forty-eight grey levels as opposed to the two hundren and fifty-six levels (dn) of the aerial imagery (Lillesand and Kiefer 2000). Its accuracy for mapping purposes is excellent (Fraser 2000). The imagery is expensive at present but is expected to become less so with time and competition from other suppliers such as Orbimage.

Calibration

The imagery was calibrated using the empirical line method, however, unlike the ADAR images, the empirical relationships were linear as expected from the literature.

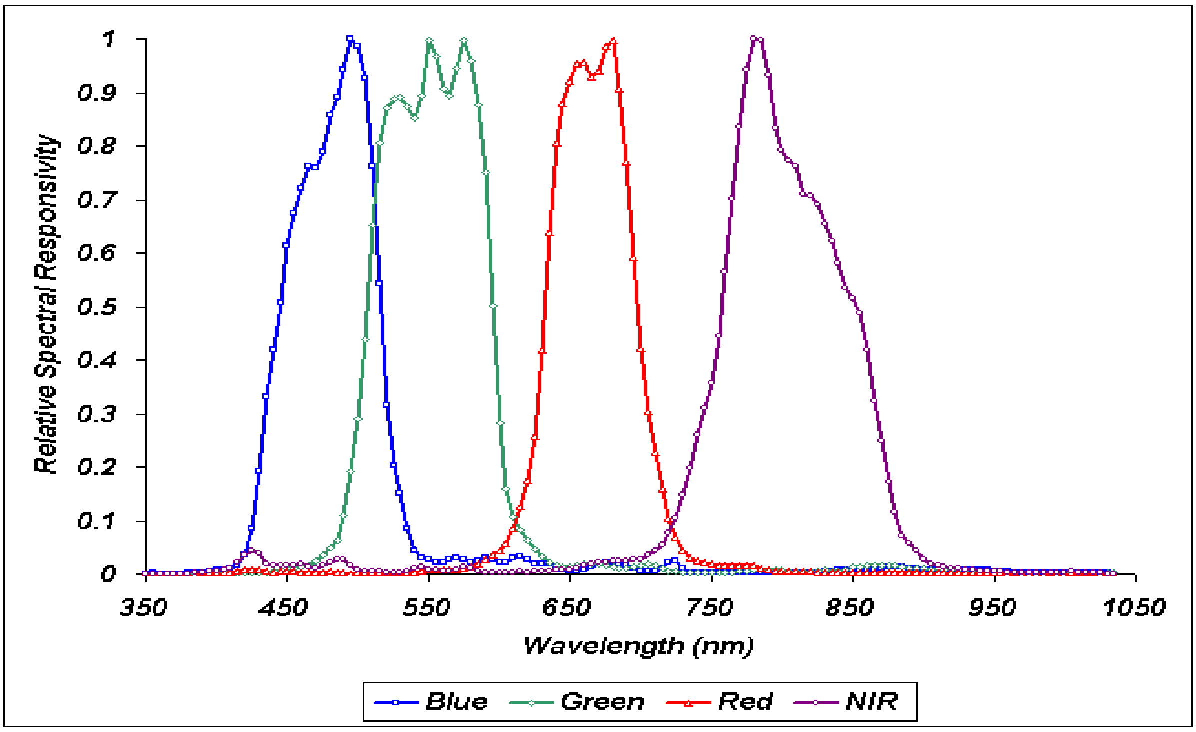

Figure 2.13: Ikonos spectral response for 4m bands: source spaceimaging.com. Note that there is much less overlap between bands compared to the ADAR spectral response and the sensitivity levels are equal across the four bands.

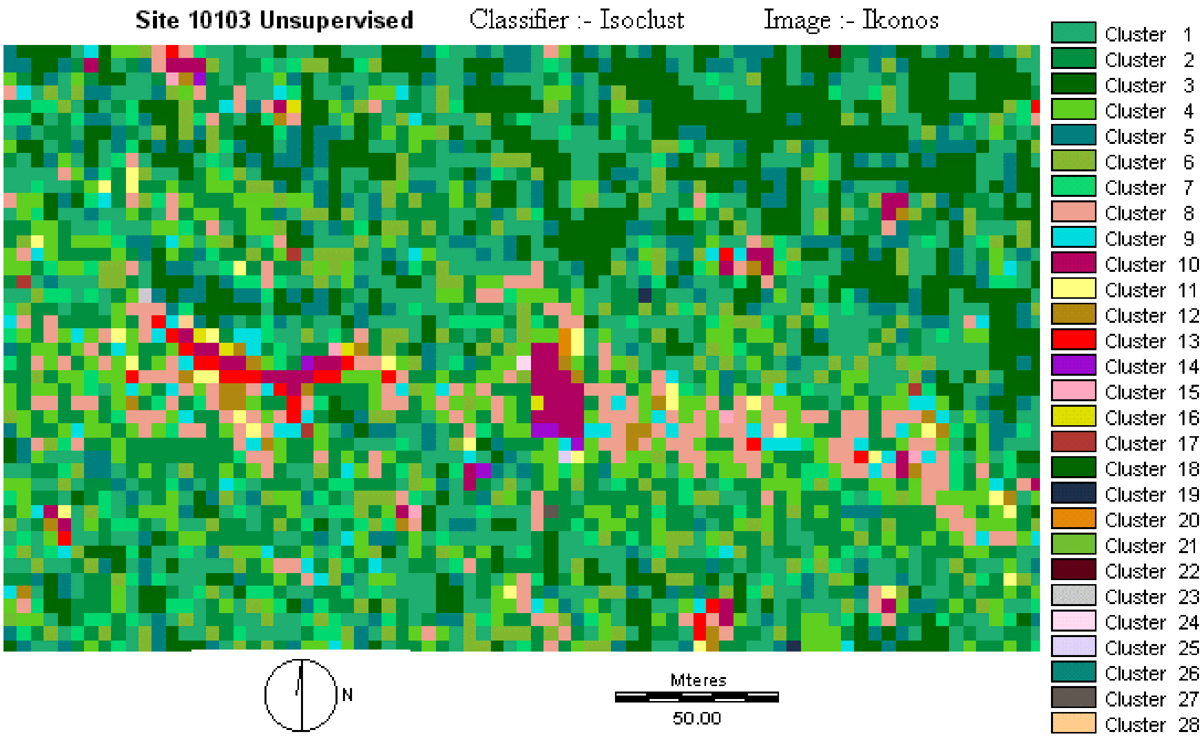

Figure 2.14: Unsupervised classification of the site around tower 10103, showing clusters of pixels with similar values (clusters 1-13 >20 pixels, clusters 14-28 <7 pixels).

Classification and Spectral Mixture Analysis

An unsupervised (clustering) classification of the same site near tower 10103 (Figure 2.14) shows that in the area of interest (the clearing and road verge) many spectral classes can be detected. In fact more spectral classes were discernible in this imagery than in the ADAR imagery, which is surprising given that each pixel covers an area sixteen times larger. It suggests a potential to detect a variety of weed species

Supervised Classification and Spectral Mixture Analysis showed similar results to the ADAR imagery except that in general, more classes were obtained in the Ikonos imagery.

2.7 DISCUSSION

The percentage cover results showed that one to three species dominated an area the same size as the spatial resolution of the aerial imagery. Other species occurred in very low proportions. Although the samples were chosen in reasonably homogeneous areas, this spatial resolution of the field data to one metre matches the spatial resolution of the ADAR imagery. Therefore spectral mixture analysis of the ADAR imagery should be capable of analysing the cover types in at least some areas of the powerline clearing, provided that spectral separation is satisfactory and that variations within species and external conditions can be controlled.

Weeds dominated the powerline corridor in most places, however, the species list from the transects (Appendix 1.1) included only one species found in the categories of serious significance (one or two) of the fifty-seven classified by Werren (2001), out of the five hundred and four exotic plants with self-maintaining populations recognised in the WTWHA (Werren 2001). However, almost four hundred and fifty species remain to be examined by this classification, so other serious weeds may be present. Guinea grass (*Panicum* *maximum*) falls into the second group, mainly due to its aggressive characteristics and potential to impair ecosystem function as a 'transformer species' (Werren 2001). However, Guinea grass was only found commonly in a few subsites of the transects and is not the dominant feature that it is in other powerline and road networks, such as the Palmerston area (see Section 1).

Analysis is required of a number of interactions and effects such as sun / leaf angle, shading etc. on the field spectral responses of weeds to enable full understanding of the variation that is due to species difference alone. There is a wide variation of the spectral response within a species that can overlap the variation seen in other species. For accurate results in classification of imagery, a method that allows for the wide variation in plant reflectivity response must be incorporated. The mean value is clearly inadequate for representing the variance without first trying to define what a representative sample of the species is or its separate stages of growth.

There is adequate power in many statistical processes to be able to separate small differences in spectral signatures but GIS image processing software is limited to a resolution of two hundred and fifty-six levels of information (eight bit) for many processes.

2.7.1 ADAR Imagery

The ADAR imagery showed only a few spectral classes in the cleared areas. This suggests that either the number of spectral classes in the clearing was limited to relatively few or the imagery did not represent the range of reflectances actually present in this area. The brighter areas in the images (the powerline clearing and road) were close to saturation levels for the camera (255 dn) and this could explain the loss of detail, especially when considering the analysis of the camera's performance by Dean *et al.* (2000). Their assessment was that quantitative analysis of colour, or colour infra red imagery (CIR) of vegetation with this camera is not reliable above sixty-seven percent of the maximum range in the green and red bands (*ie.* 170 dn). The ADAR imagery for the seven sites of this study had maximum digital numbers (dn) of 188 to 255 in the red bands. Similarly in the green bands the maximum dn ranged from 236 to 255. This is clearly outside the reliable range for both red and green bands as described by Dean *et al.* (2000).

The camera's unsatisfactory performance can also explain the difficulty found with the calibration of the ADAR imagery, and why the unconventional logarithmic transformation was needed to achieve calibration. Dean *et al.* (2000) found that Kodak`s Active Interpolation (KAI) algorithm (that produces the digital image) includes edge enhancement, increased contrast and spectral response fall-off that varies with wavelength and scene composition. These may be good features for photo-journalism but are undesirable for remote sensing especially for quantitative analysis applications such as extracting reflectance information. The interpolation of colours from neighbouring pixels defeats the purpose of high spatial resolution. Thus successful "unmixing" of the component reflectances of a pixel is compromised.

Accuracy of the calibration process is critical to the success of classifying with field spectral measurements. The image in Figure 2.11 shows a reasonable result for the "shade" class, but the "bare ground" class is positioned where there is rainforest, suggesting either a calibration inaccuracy, or an inadequate separation of the signatures used.

The unmixing algorithm used in this study requires very accurate calibration because it uses only the mean value in signature files to determine the mixture of components in the pixel. The best fit is simply the one with the smallest error. However, it takes no account of the spread in the spectral response pattern of the cover type. This can work well in cases where the surfaces are comprised mostly of non-photosynthetic materials such as in arid areas or for detection of certain chemical absorption phenomena associated with particular minerals (Atkinson *et al.* 1997). But vegetation response patterns are broad and led Asner and Lobell (2000) to say that "broad variations in endmembers often leads to a wide range of plausible cover fraction results". Therefore it is "desirable to establish features of the spectrum that display the least variability while remaining distinct". An alternative classifier such as "Fuzzy C-means" might tolerate high variance in the signature yet still produce a plausible result.

An additional problem with green vegetation is that the NIR wavelengths are highly reflective and the multiple reflections within a canopy amount to non-linear mixing of the spectral components. Bastin (1997) and Small (2001) mention this difficulty and Borel and Gerstl (1994) have actually modelled nonlinear mixing.

2.7.2 Ikonos Satellite Imagery

Many of the above comments apply also to the Ikonos Satellite Imagery. Supervised Classification and Spectral Mixture Analysis showed similar results to the ADAR imagery except that in general, more classes were obtained in the cleared areas with the Ikonos imagery. This improvement could be attributed to having one more band of information available in the Ikonos imagery but it is more likely that it is a reflection of the higher quality of instrument in the satellite. Full exploitation of the greater sensitivity of the Ikonos imagery (requiring improved GIS software) will enable even better discernment of subtle spectral differences in vegetation.

The satellite passes the Equator at 10.30am each day so imagery of North Queensland (shortly before 10.30 am) has some shading due to morning sun angles and effects of undulations in the canopy. Ideally, any imagery used for quantitative assessment should be corrected for illumination effects (McDonald *et al.* 2000; Shepherd and Dymond 2000) due to topographical aspect and sun angle. This procedure was considered beyond the scope of this project and would require a fine scale digital elevation model (DEM), but offers potential for better results.

2.8 CONCLUSION

Technical challenges facing the development of a methodology to use remote sensing and image interpretation in Wet Tropics vegetation monitoring can be summarised as concerns with spatial, spectral and radiometric resolution.

2.8.1 Spatial Resolution

The percentage cover measurements showed that there are mostly one to three, or sometimes four, dominant weed species in a one square metre quadrat on the Chalumbin-Woree powerline corridor. This suggests that a one metre spatial resolution with three bands of imagery would be the minimum necessary to unmix spectral components in homogenous areas. The one metre spatial resolution of the ADAR imagery in three bands is therefore theoretically adequate. The spatial resolution of the Ikonos satellite is much coarser than the patch size of most weeds (except possibly *Lantana, Panicum, Themeda* and *Melinis*). Spectral Mixture Analysis is difficult to apply when there are more spectral classes contributing to a mixed pixel than bands of imagery. Resolution coarser than one to two metres is likely to be inadequate for mapping individual weed species. Thus, Landsat ETM+ imagery (twenty-five metre cells) is unlikely to be productive using this approach except where the patch size of a weed species is greater than 0.1hectare.

2.8.2 Spectral Resolution

To discriminate one species of weed from another requires a feature that is distinct between species, but constant within an individual species. This study has examined the reflectance at eight locations in the light spectrum and found that the ranges within a species are large compared to the differences between species. The solution to this conundrum is to characterise the reflectance of a species across all eight bands simultaneously whilst accounting for or minimising the other variables. Achieving this requires more data than was obtained by this study. However, this study was valuable in highlighting the range of issues involved.

Good spectral reflectance information about weeds may require:

a) Measurement of the full cycles of reflectivity as they change with the seasons (phenological cycles measured around the year at the same sites);
b) Measurement at a consistent time of day, or investigation of time of day and its effect on reflectivity with regards to geometry of sun / leaf / sensor angles and diurnal moisture change in the leaf tissues; and
c) Understanding of instrument variables such as calibration, and performance with respect to light conditions or height above the canopy.

The basis of image calibration is that a relationship, preferably linear, can be found between measurements of field reflectance and the brightness levels measured by airborne or satellite sensors (Niemann *et al.* 2001). This assumption was shown to be incorrect for the ADAR data. The problem was probably due to the adjustment of exposure levels and to the nature of the Charged Coupled Device (CCD) in the camera when it is used in colour mode (gathering data in three colours rather than in monochrome) (Dean *et al.* 2000). However, the satellite data did show a linear relationship to field spectral measurements. Better quality signatures, image calibration and spatial resolution would confirm the linear relationship for the Ikonos satellite.

2.8.3 Radiometric Resolution

The analysis of the field spectral data showed that there is definite potential for developing reliable signatures for spectral classes of weeds from field data. The novel technique of entering the field data into a GIS and image interpretation program is an excellent way to begin the process of finding existing spectral classes. The clustering procedure in IDRISI looks for true clusters (Richards 1993; Eastman 1999) in the data but the statistical resolution was limited by eight-bit data processing (eight bit data has only two hundred and fifty-six values and cannot therefore represent real numbers with greater than three significant figures). Subsequent statistical analysis showed that finer division of spectral classes to near species level was justifiable, and that the real number of signatures developed from these was divergent enough to be separable in ninety-eight percent of pair-wise combinations. Many of the classification routines in IDRISI require eight-bit images and therefore do not take advantage of the high radiometric resolution available with the latest satellite capabilities. This problem of radiometric resolution is shared by many remote sensing and GIS packages at present.

The unmixing routine in IDRISI does, however, use real numbers. This classifier has a fundamental assumption that the spectral response of a surface can be represented by a mean value. It takes no account of the variation of reflectance seen in vegetation. An additional problem with spectral component analysis is the assumption that the reflectance of a pixel is a simple addition of the reflectance of the components within the ground resolution element. Green vegetation is highly reflective in NIR wavelengths and likely to bounce or reflect more than once within a plant canopy thereby losing more energy through absorption and transmission, degrading the distinctive spectral characteristics of particular plants (Borel and Gerstl 1994; Bastin 1997; Small 2001).

The choice of bands in the various sensors is important. Bands that show the features of the plant spectra that are least variable while still distinct are the most desirable (Asner and Lobell, 2000). This study did not examine the advantages and disadvantages of different bands, but the “Cropscan” MSR produced readings at 810nm that were very sensitive to small changes in calibration of the instrument. They were also highly variable, a fact noted in other studies (Skidmore and Schmidt, 1998). There is no doubt that the analysis of many, narrow, more discrete bands (with no overlap), gives the user greater power of spectral discrimination (Curran 1985; Anstee *et al.* 2000; Lillesand and Kiefer 2000). Asner and Lobell (2000) found that moderate bandwidths (20-30nm) were optimal since wider bandwidths confused some classes and smaller bandwidths were subject to high frequency noise.

2.8.4 ADAR (Airborne) Imagery

The performance of the ADAR imagery was disappointing despite its excellent spatial resolution. The overlapping bands and the fact that the colour is produced by interpolation (averaging the dn in each band over ten pixels or so) means that quantitative analysis is imprecise. The response is not linear above sixty-seven percent saturation (ie above 170 dn). These problems can only be overcome by the use of a separate camera or separate image for each band.

2.8.5 Ikonos Satellite Imagery

The high radiometric resolution (11 bit) of the Ikonos satellite produced high quality data. The four discrete bands of Ikonos positioned right across the range of wavelengths expected to be most informative for vegetation studies gave good spectral coverage. However it may be more effective to use field reflectance at 760nm when analysing Ikonos imagery, since it is not as variable as reflectance at 810nm. The imagery should also be corrected for illumination effects using a Digital Elevation Model (DEM).

2.8.6 Hyperspectral Data

Perhaps the ideal imagery for discriminating weeds would be something like Compact Airborne Spectrographic Imagery (CASI) (Lewis 1998) that has eight to twenty bands each 20-40 nm in width but with eleven bit radiometric resolution and one metre spatial resolution. The Multi Spectral Airborne Video System (MAVS) (Edirisinghe *et al.* 1999) that uses four cameras, each with a narrow band pass filter, would be a vast improvement on the ADAR system for quantitative analysis. The Multispectral Airborne Digital Imaging System (MADIS) system operated by Charles Sturt University has similar specifications.

2.9 RECOMMENDATIONS

- The “Cropscan” MSR should be tested under standardised conditions.
- Further work needs to be done to better characterise the spectral responses of weeds.
- To effectively estimate proportions of land cover such as clumps of weeds from imagery requires:
  - Calibrated imagery;
  - Suitable band widths (20 – 30 nm) in the appropriate areas of the spectrum;
  - A high spatial resolution (0.5 – 2 m) that contains few spectral components;

  - Correction for illumination effects; and
  - Processing with classifiers that allow for the variation seen in the spectral response patterns of vegetation.
- Alternative image interpretation software is required with the ability to handle twelve -bit data and real numbers to take advantage of the high dynamic range of the latest satellite data and to be able to discriminate the subtle differences in vegetation signatures. Another feature that would reduce time and effort is signature portability (*i.e.* signatures that can be used on multiple images and in a variety of classifiers).
- Classifiers that allow for variance in a signature should be investigated, e.g. "Fuzzy C-means" or "Artificial Neural Networks" (Atkinson *et al.* 1997) may be more effective at classifying vegetation than Linear Unmixing.
- Large targets such as tarpaulins should be set out whenever imagery is captured for quantitative analysis. Spectral reflectance measurements taken of the targets at the time of flying enables calibration to be carried out accurately, which is important for relating field measurements to the imagery.
- Imagery for quantitative analysis should not be captured with a digital camera unless it is part of a multi-camera array or is fitted with a wheel-filter to enable the camera to be used in monochrome mode (King 1995). It is strongly recommended that an appreciation of these matters is gained before acquiring airborne imagery. The journal articles by King (1995) and Dean *et al.* (2000) should therefore be read.
- Regular usage of airborne imagery will require the ability to "set up and go" quickly due to the lack of cloudless periods in the Wet Tropics that last more than a few days and the inability to safely predict when these will occur. Ultra-light aircraft or drones (computer or radio controlled pilot-less aircraft) may provide a more timely means for the monitoring of environmental weeds. Alternatively use of the Ergon Energy maintenance helicopter to capture imagery may also be a possibility.
- Future work on the spectral response of weeds should be directed at measuring the seasonal variations for each species by establishing permanent plots for regular monitoring. More data is needed for each species. A clustering routine in a GIS that looks for true shoulders or peaks in spectral data should then be used to find spectral groups on a species by species basis.

2.10 MANAGEMENT IMPLICATIONS

Analysis of the ground data showed that identifying weeds to a species level is possible but requires more research and suitable imagery for its application. The ADAR has appropriate spatial resolution of one metre but cannot be recommended for quantitative analysis. A system that has narrow and discrete bandwidths would have vastly improved performance. There is also an unpredictable cost with ADAR imagery of waiting for good weather or being able to fly at short notice when clouds clear.

Ikonos satellite imagery has excellent radiometric resolution, and accurately located cloud free images can be ordered, which is very convenient. However, four metre spatial resolution is probably too coarse for accurate identification of weed infestations. Similar imagery at two metre resolution will be available in three years or so, improving the potential of satellite imagery for this application.

Hyperspectral imagery may be ideal for discriminating weeds. Systems such as Compact Airborne Spectrographic Imagery (CASI) that uses many narrow bands, 11 bit radiometric resolution and one metre spatial resolution may be the best available. Alternatively, the Multi Spectral Airborne Video System (MAVS) that uses four cameras, each with narrow bands, or the Multispectral Airborne Digital Imaging System (MADIS) would offer better spectral resolution than ADAR.