Mapping environmental weeds in the Mount Lofty Ranges, South Australia, using high resolution infrared aerial photography

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Summary This paper presents the methodologies and findings of a collaborative research project between Flinders University and the City of Mitcham Local Government Authority. The aim was to map the key woody environmental weeds on the western slopes of the Mount Lofty Ranges within the City of Mitcham. This region comprises 5350 ha and contains many competing land-uses such as undeveloped woodland reserves, conservation and recreation reserves, rural, urban and transport routes. The region is under enormous pressure from environmental weeds and contains significant stands of the poorly conserved remnant grey box (*Eucalyptus microcarpa* Maiden) woodlands. The region also contains blue gum (*Eucalyptus leucoxylon*. ssp. *leucoxylon* F.Muell.) and river red gum (*Eucalyptus camaldulensis* Dehnh.) associations.

Supervised classification of high resolution (~0.3 m) 1:10 000 ortho-rectified infrared aerial photographs enabled relatively fast mapping of several environmental weeds on all landholdings in the study area. Analyses have separated as accurately as possible the individual canopy reflectance signal of blackberry (*Rubus fruticosus* L. agg.), desert ash (*Fraxinus angustifolia* ssp. *angustifolia* Vahl), European olive (*Olea europaea* ssp. *europaea* L.), hawthorn (*Crataegus monogyna* Jacq.), Montpellier broom (*Genista monspessulana* (L.) L.A.S.Johnson) and *Pinus* spp. Initial fieldwork involved the collection of locations of the key weed species using a GPS. This information acted as the training dataset to determine the extent of each weed. Field verification tested the accuracy of the outputs, with accuracy's of over 90% obtained for several classifications.

Keywords Accuracy assessment, environmental weeds, infrared aerial photography, remote sensing, weed mapping.

INTRODUCTION

Environmental weeds are a serious threat to native vegetation in South Australia. They can completely alter the structure and function of native vegetation, out-compete native flora, and in the worse case, cause species extinction. The 5350 ha study area is situated on the western slopes of the Mount Lofty Ranges, approximately 15 km south east of the Adelaide GPO, and is within the City of Mitcham Local Government Authority. It contains grey box (*Eucalyptus microcarpa* Maiden) woodlands which are a priority four (one: most important; eight: least important) vegetation association (Neagle 1995) and are poorly conserved in South Australia. Other significant vegetation associations in the study area include blue gum (*Eucalyptus leucoxylon* ssp. *leucoxylon* F.Muell.) and river red gum (*Eucalyptus camaldulensis* Dehnh.) woodlands. All of these vegetation communities are seriously threatened by environmental weeds. Mapping environmental weeds in these areas is the first step towards a strategic control program. Mapping through remote sensing is the most cost effective and time saving option, given that the majority of land in the study area is under private ownership.

Infrared imagery captures reflectance of vegetation in the near-infrared, red and green spectrums. Up to 50% of infrared light is reflected by the individual leaves of plants, compared to only approximately 10% of visible (red, green, blue) light. Even though reflectance from the canopy is lower at 35% and 3–5% for the near infrared and visible spectra (Campbell 1996), respectively, the greater percentage of reflectance in the near infrared makes infrared imagery more useful for mapping vegetation. Furthermore, differences in reflectivity's of plant species are often more pronounced in the near infrared than in the visible spectra, making it possible to separate vegetation at the species level. For example, Key *et al.* (2001) recently used infrared aerial photography to classify and map individual tree species in a temperate forest in the United States with approximately 76% accuracy. The application of infrared imagery to weed mapping in agricultural settings is relatively common (e.g. Lamb and Weedon 1998, Medlin *et al.* 2000), with accuracy's of 75–85% attainable. However, in an environmental management setting, weed mapping using any form of remote sensing, let alone infrared imagery, is relatively uncommon. Ullah *et al.* (1989) mapped blackberry in south-eastern Victoria using infrared imagery at 2.5 m to 5 m resolution. Recently, Stow *et al.* (2000) briefly reported on the potential of high resolution (0.5 m) infrared imagery to map *Acacia* invasion in the fynbos biome of southern Africa without reporting any quantitative accuracy assessment. Their report did conclude that it would be possible to weakly separate *Acacia* from the indigenous South African vegetation.

This paper describes the methods used to separate key environmental woody weed species from native vegetation and other landscape features using high resolution infrared images. The weeds mapped were blackberry (*Rubus fruticosus* L. agg.), desert ash (*Fraxinus angustifolia* ssp. *angustifolia* Vahl), European olive (*Olea europaea* ssp. *europaea* L.), hawthorn (*Crataegus monogyna* Jacq.), Montpellier broom (*Genista monspessulana* (L.) L.A.S.Johnson) and *Pinus* spp. The results will form a critical component of the City of Mitcham's $481 000 woody weed control program by increasing strategic removal works.

MATERIALS AND METHODS

Infrared images Thirty infrared 1:10 000 aerial photographs were purchased from the South Australian Department for Environment and Heritage. The infrared images were captured on the 18th November 1998 for an unrelated project. Each survey was flown around midday. The dates and times of the survey flights were chosen to minimise impacts of shading. Each image was converted from the original film to digital format using a photogrammetric scanner, at a resolution of 25 microns (approximately 400 pixels per cm). This converts to an on-ground resolution of approx. 0.3 m per pixel. The total cost of the image data was $3300.

Pre-processing All images were orthorectified using approximately 20 ground control points per image. The original infrared images contain considerable within canopy variation due to the differences in reflectance from individual leaves. This variance makes classification more difficult and will increase the level of misclassified pixels within individual canopies. A convolution filter (7 × 7 smoothing matrix) was passed over each image to reduce this within canopy variation. Histogram stretching was then applied to the colour bands of each image to increase variation between canopies. Breakpoints were established at the lower and upper ends of the range of pixel values that represent vegetation in each of the infrared, red and green bands. Data that was not vegetation was removed from the image, with the remaining data stretched across the full range of pixel values.

Classification Supervised classification was used to classify the infrared images. Supervised classification uses pixels of known identity (training data) to classify pixels of unknown identity by applying an algorithm chosen by the user (Campbell 1996). Over 250 sets of training data (signatures) were initially collected in the field. The algorithm used here was the maximum likelihood decision rule (Richards and Jia 1999), which is based on the probability that a pixel belongs to a particular category assuming each band within the signature has a normal distribution. The initial signature sets were evaluated to determine the extent of similarity between signatures and whether normality existed within signatures. Normality was determined from histogram plots of pixels values in each colour band, while similarity was determined using the Transformed Divergence measure of signature separability. Modifications were made accordingly. A total of 201 signatures were used in the final classification process.

Accuracy assessment An error matrix (Congalton and Green 1999) was constructed using individual cell-based site-specific comparisons between the classified data and the reference data sourced from the original infrared images and field verification. The location of pixels chosen for comparison was derived using a stratified random sampling technique. Five hundred random points were 'thrown' over the final classification of the study area, for each of the eight categories being assessed. The categories assessed were *Eucalyptus*, the six weed species, and 'other', representing grass, bare ground, other vegetation, urban features and shadow. Of the 4000 points generated in total, 431 (10.8%) points were checked. Those points nestled deep within private property and large patches of native vegetation were ignored because of their inaccessibility.

RESULTS

Table 1 lists each weed category, its total cover within study area, and its proportion of the study area. The

Table 1. Cover of each weed and *Eucalyptus*.

Classification	Area (ha)	Proportion of study area (%)
Blackberry	53.12	0.99
Montpellier broom	5.37	0.10
Desert ash	18.87	0.35
European olive	228.01	4.26
Hawthorn	0.85	0.02
Pine	78.47	1.46
Eucalyptus	1150.40	21.47
Other	3821.92	71.34
Total area	5357.00	100.00

results for *Eucalyptus* are presented for comparison and to aid discussion. *Eucalyptus* canopy covers the majority of the study area, comprising 21.47%. European olive canopy is the next most extensive (4.26% of the study area), with pine canopy the third most extensive (1.46%). It is important to remember that the figures presented in Table 1 represent direct canopy cover and thus may be considerably less than the real extent of the weed invasion. For example, a weed control practitioner may consider 10–30% European olive cover to be an invasion of serious concern. Thus, while European olive canopy covers only approximately 4% of the study area, the proportion of the study area covered by serious European olive invasion may be between 13% and 40%. If 50% European olive cover was only considered serious then approximately 8% of the study area would be considered as seriously invaded by olives. A slightly different calculation can be applied to weeds that are generally restricted to riparian habitats, e.g. blackberry and desert ash. The proportion of the study area covered by blackberry, for example, is only about 1% (Table 1). However, if riparian habitats comprise 3% of the study area, then approximately one third (30%) of this habitat is invaded by blackberry.

Table 2 presents the error matrix generated from field verification. The overall accuracy is 74.25%, however, if delineating by category and omission/commission, it is evident that accuracy is not consistent between the viewpoint of the producer and consumer. Producer accuracy (PA) measures how accurately data in the original image is classified (errors of omission), whereas consumer accuracy (CA) measures the accuracy of the classified image, i.e. the probability that a classification on the map actually represents that category on the ground (errors of commission). For example, the producer can only be 69% confident that blackberry was correctly classified as blackberry, while the consumer can be 91% confident that when they see blackberry in the final map, it is blackberry (Table 2). On the other hand, the producer can be 83% confident that olive in the study area has been classified correctly as olive, whereas the consumer can only be 63% confident that what the final map tells them is olive is actually olive (Table 2).

DISCUSSION

The main impediment to mapping weeds that have invaded native vegetation is that they are generally found beneath the overstorey canopy due to the nature of their dispersal. Avian dispersal of blackberry, hawthorn and olive ensures that many specimens will be found beneath the canopy of perching trees such as eucalypts. Mapping these weeds from remotely sensed images taken from above the overstorey canopy is extremely difficult, if not impossible. Successful mapping will only be achieved within gaps and on the fringes of the overstorey canopy, or from extensive infestations with limited native overstorey canopy. Given this limitation, it is essential that results produced here be used in conjunction with field based assessment and further spatial analysis. For example, the presence of

Table 2. Error matrix for all classified images. CA, consumer accuracy (commission error); PA, producer accuracy (omission error).

	Reference Data									
Classification	Blackberry	Montpellier broom	Desert ash	European olive	Hawthorn	Pine	Eucalyptus	Other	Totals	CA (%)
Blackberry	53		4					1	58	91.38
Montpellier broom		25						1	26	96.15
Desert ash	20	3	15			3	1	1	43	34.88
European olive	1			59		20	8	6	94	62.77
Hawthorn	1			1	8	1	1	1	13	61.54
Pine				8		46	8	1	63	73.02
Eucalyptus					2		61	2	65	93.85
Other	2			3	1	1	9	53	69	76.81
Totals	77	28	19	71	11	71	88	66	320	
PA (%)	68.83	89.29	78.95	83.1	72.73	64.79	69.32	80.3		74.25

small quantities of European olive canopy amongst a eucalypt woodland, as determined from spatial analysis of the outputs of this research, may suggest that many more olives will be found beneath the overstorey canopy. Field assessment would confirm this. It is also likely that these olives will be seedlings, juveniles and small adults. Similarly, the distribution of Montpellier broom is likely to be underestimated in the final outputs because this weed is commonly found in the shrub layer beneath eucalypt canopy.

Another reason for the mixed success of mapping is that the spectral reflectance of some weed species cannot be separated from the spectral reflectance of other vegetation. The low levels of accuracy in some classifications (Table 2) are an outcome of the similarities in spectral reflectance of some weed species. Reduced accuracy in pine and European olive classification was due to similar reflectance values. Similarly, confusion between blackberry and desert ash, *Eucalyptus* and European olive, and *Eucalyptus* and pine were all as a result of similarities in spectral reflectance values.

CONCLUSION

This research has, for the first time, attempted to map the key environmental weeds found within the City of Mitcham. As far as the authors are aware, this is the first published account in Australia that has used high resolution (sub 1 m) infrared aerial photography to map multiple species of environmental weeds. The outputs will have widespread and valuable applications. Undoubtedly, the two worst environmental weeds in the study area are blackberry and European olive. The distribution of these two invasive species is now known. *Pinus* spp. are also of serious concern along the western slopes of the Mt. Lofty Ranges. The distribution of these species is now known. Montpellier broom is a weed of serious concern in the shrub layer of large tracts of native vegetation in the study area. This species has now been mapped in instances where it is not directly beneath canopy. Furthermore, *Eucalyptus* canopy has been accurately mapped, the results of which have a multitude of uses outside of weed management, e.g. quantitative ecology, fire prevention management, vegetation clearance assessment.

ACKNOWLEDGMENTS

This research was funded by the Native Vegetation Council and City of Mitcham. Thanks to Dr. David Bass and an anonymous referee for comments on a draft version of this manuscript. NDC also thanks Dr. John Virtue and Paul Jupp from the Animal and Plant Control Commission for their continued support.

REFERENCES

Campbell, J.B. (1996). ‘Introduction to Remote Sensing’. (Taylor and Francis, London).

Congalton, R.G. and Green, K. (1999). ‘Assessing the accuracy of remotely sensed data: principles and practices’. (CRC Press, USA).

Key, T., Warner, T.A., McGraw, J.B. and Fajvan, M.A. (2001). A comparison of multispectral and multitemporal information in high spatial resolution imagery for classification of individual tree species in a temperate hardwood forest. *Remote Sensing of Environment* 75, 100-112.

Lamb, D.W. and Weedon, M. (1998). Evaluating the accuracy of mapping weeds in fallow using airborne digital imaging: *Panicum effusum* in oilseed rape stubble. *Weed Research* 38, 443-451.

Medlin, C.R., Shaw, D.R., Gerard, P.D. and LeMastus, F.E. (2000). Using remote sensing to detect weed infestations in *Glycine max*. *Weed Science* 48, 393-398.

Neagle, N. (1995). ‘An update of the conservation status of the major plant associations of South Australia’. (Department of Environment and Planning, Adelaide).

Richards, J.A. and Jia, X. (1999). ‘Remote sensing and digital image analysis’. (Springer-Verlag, Berlin).

Stow, D., Hope, A., Richardson, D., Chen, D., Garrison, C. and Service, D. (2000). Potential of colour-infrared digital camera imagery for inventory and mapping of alien plant invasions in South African shrublands. *International Journal of Remote Sensing* 21, 2965-2970.

Ullah, E., Field, R.P., McLaren, D.A. and Peterson, J.A. (1989). Use of airborne thematic mapper (ATM) to map the distribution of blackberry (*Rubus fruticosus* agg.) (Rosaceae) in the Strzelecki Ranges, south Gippsland, Victoria. *Plant Protection Quarterly* 4, 149-154.