

MAPPING THE INVASIVE PLANT *ARUNDO DONAX* AND ASSOCIATED RIPARIAN VEGETATION USING AVIRIS

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1. INTRODUCTION

It is now widely recognized that invasions by non-native plants present a serious ecological threat to the already greatly reduced native ecosystems of California (Barbour et al., 1993; Bossard et al., 2000). In response to the expanding ranges and increasing damage done by harmful non-natives, control of invasive species has become a priority for environmental management and an integral component of many habitat conservation efforts. This is especially true for riparian ecosystems in southern California, where invasive species threaten the last vestiges of remaining native habitat and associated species already reduced to precariously small and fragmented populations (Zemba, 1989). This study focuses on an invasive plant that has proven very destructive to riparian ecosystems, *Arundo donax* (Arundo, giant cane). An aggressive invader, the plant successfully out-competes all surrounding vegetation, completely converting large areas into solid, impenetrable cane fields that deplete water resources, trap sediment, and burn readily (Jackson et al., 1993). Arundo is present in large stands in the study area on the Santa Margarita River on Camp Pendleton Marine Corps Base and has been the target of an ongoing eradication effort since 1996 using a combination of mechanical and herbicide control methods (Omori, 1996).

A key requirement for the effective management of invasive plants is the ability to identify, map, and monitor invasions as well as the invaded plant communities. Hand-mapping in the field or from aerial photos are techniques commonly used in support of eradication efforts, but these methods are labor intensive and limited. Hand-mapping from field observation requires access to the site from the ground, a prospect that is not always practical, safe, or timely, especially on an active military base. Interpretation of aerial photos is extremely time-intensive and often necessitates interpretation of large numbers of photographs (Avery, 1992). In addition, it can be difficult to distinguish the weed species in the photos even with magnification, making the interpretation process highly subjective and likely to differ from one analyst to another. Because of these constraints, weed mapping is usually done on an as-needed basis, and comprehensive maps that would support time-series evaluation are not generally made. There is the need, therefore, to develop repeatable and reliable automated techniques for monitoring the spread of weeds and the effects of eradication efforts as well as changes in the habitats being managed. Imaging spectrometry data offers the spectral resolution necessary to distinguish between plant species or communities using a greater variety of subtle spectral reflectance characteristics, potentially allowing for mapping of the invader and surrounding plant communities which cannot be accomplished using more conventional multi-spectral imagery.

This study tested the suitability of imaging spectrometer data for improved mapping of a native riparian plant community invaded by Arundo. The research included trials in mapping the major vegetation types in the riparian corridor: riparian woodland, scrub, and annual grasslands. The ability to monitor these vegetation types along with the invasive plant is important for tracking habitat required by endangered species being managed at Camp Pendleton. This work will be useful in future decisions about methods for mapping Arundo and associated riparian vegetation in other regions.

2. METHODS

2.1 Study Site

The Camp Pendleton Marine Corps Base is a 49,857 ha area in northern San Diego County, California, used for Marine Corps military maneuver training (Figure 1). The base contains the largest contiguous stretch of unbuilt coastal land in southern California (Steinitz, 1996). Despite sixty years in service as a ground-troops

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training and practice range, Camp Pendleton contains large areas of relatively intact native habitat. Biodiversity in this region is among the highest in the continental United States; vascular plant diversity on the base exceeds 650 species (Zedler et al., 1997). The Base's high biodiversity and location, abutting the San Mateo Wilderness Area and near the Santa Rosa Plateau Ecological Reserve, and that fact that it encompasses the lower reaches of five watersheds, make it a key component in conservation of the region's ecosystems.

The focal area for this study is the Santa Margarita River, the largest river on the base. The lower 16 of the river's 60 miles lie within the boundaries of Camp Pendleton. This stretch of river is one of the few relatively undisturbed riparian corridors remaining in southern California (Zemba, 1989) and is one of the last strongholds of the federal-listed endangered Least Bell's Vireo, a riparian obligate bird once common throughout California's Central and San Joaquin Valleys and Coast Ranges, and the Mojave Desert (Franzreb, 1989).

The Camp Pendleton Marine Corps Base presents several common problems land managers face in monitoring invasive species and improving habitat condition. The land is managed for multiple uses: military use as well as for the conservation of endangered species. Military training causes large scale and repeated disturbance to environmental conditions which in turn reduces the value of the landscape for future training activities and has consequences for natural systems. The types of mechanical disturbance that a military base experiences, from walking, camping, vehicles, wildfires, soil erosion, detonation of explosives, excavation, and the movement of troops and equipment to and from other parts of the world, provide opportunities for transport and establishment of invasive species.

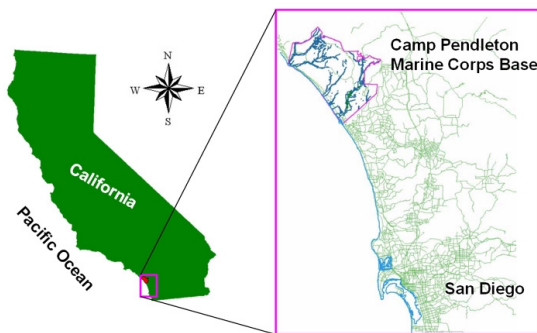


Fig. 1)

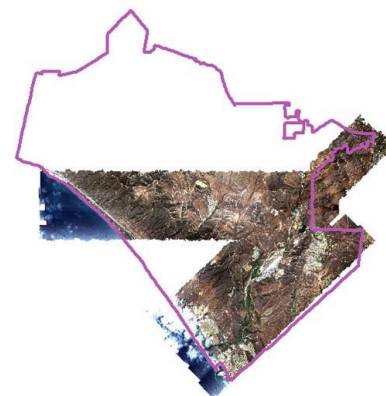


Fig. 2)

Figure 1. Location of Camp Pendleton Marine Corps Base on the southern coast of California.

Figure 2. September 2000 AVIRIS data coverage over Camp Pendleton

2.2 AVIRIS data acquisition and calibration

NASA's low-altitude, high spatial resolution (approximately 4 m x 4 m) Advanced Visible/Infrared Imaging Spectrometer (AVIRIS) data was acquired on 8 September 2000 over portions of Camp Pendleton Marine Base. Eight flightlines composed of 12-14 scenes each were collected (Figure 2) and geometrically corrected by the AVIRIS team at NASA JPL. At the time of the AVIRIS data collection in late summer, deciduous vegetation (such as willow and sycamore) was in full canopy and the giant cane, which becomes senescent during winter months, was near its peak of greenness and active growth. Water to support the riparian vegetation is provided by the baseflow of the Santa Margarita River, largely underground by this time of year, and so it is still in vigorous growth in September despite the late timing in California's summer dry season.

The AVIRIS data was calibrated to surface reflectance using the atmospheric correction program ACORN (Analytical Imaging & Geophysics, Boulder, Colorado) with field calibration spectra for reference. Image analyses were performed using ENVI software (Research Systems, Inc., Boulder, Colorado). The AVIRIS scenes were spectrally subset, georectified, and mosaicked for use in overlays with other geographic data. All analyses were performed on ungeorectified data to avoid error due to changes in pixel spectral properties from warping. A total of 59 noisy bands were removed and a mask was created to select for vegetated areas using a Normalized Difference Vegetation Index (NDVI) of greater than 0.2. The riparian zone was selected using a 100-year flood plain map for Camp Pendleton as the template for a mask. A Minimum Noise Fraction (MNF) transform was performed to

compress and reduce noise in the data and to order the transformed bands by the variability represented in the new bands (Green et al., 1988). MNF bands 1-20 containing 98% of the variance in the dataset were selected for use in the maximum likelihood supervised and spectral angle mapper classification. Reflectance data was also used in spectral angle mapper analysis and in analysis using the continuum removal technique.

2.3 Fieldwork and GPS data collection

This study combined AVIRIS data, aerial photos, field observations, and geographic information systems (GIS) data for the creation of training sets and accuracy assessment polygons. Ancillary data included 1999 1:3,000 aerial photos over selected areas, a riparian vegetation map created in 1997 by drawing field observations onto 1994 aerial photos, recent (2000, 2001) Arundo distribution maps for parts of the river created by the Base to track eradication efforts, and roads, coastline, and base boundary data from the San Diego Association of Governments (SANDAG) and Camp Pendleton's GIS operations office. The 16 aerial photographs provided by the Base were examined under magnification for determination of vegetation existing at the time of the photos.

Forty-four geolocations were recorded during two trips to the study site in September 2000 and September 2001 using a Trimble Pro-XRS (Trimble Navigation, Inc., Sunnyvale, California) global positional system (GPS) receiver providing sub-meter accuracy, and these were associated with notes and hand-drawn maps. Reflectance spectra of several dominant species, Arundo, and calibration targets were collected in the field coincident with the AVIRIS data collection overflight using a GER2600 Spectrometer (Geophysical & Environmental Research, Corp., Millbrook, New York) in continuous 2-11 nm bands across 325-2530 nm. Data were acquired near solar noon and calibrated to reflectance using a Spectralon reference panel (Labsphere, Inc., North Sutton, New Hampshire) for 13 canopy samples with 2-10 replicates each. Locations of the sampling sites were recorded with the GPS. Field spectral readings were compared with reflectance data from atmospherically-corrected AVIRIS data to evaluate the success of the calibration and the validity of the training sets selected (Figure 3). Preliminary classification maps were verified in September 2001 by loading the images onto an iPAQ (Compaq Computer Corp., Houston, Texas) handheld computer connected to the Trimble GPS for direct field validation.

2.4 Classification methods

A 7 km x 1.6 km subset of one flightline over the Santa Margarita River was chosen for its abundance of giant cane (referred to below as Image 1), and pre-processed as described above. Predominant spectral features were evaluated by viewing results from the unsupervised classifications and a display of MNF transform bands 2, 3, and 4. A pixel purity index found few pure pixels, and these were displayed to show spatial arrangement of potential classes in the scene. Seven vegetation types were chosen for classification: Arundo, scrub, riparian woodland, annual grassland, aquatic plants, green lawn, and tamarisk. The Arundo class consists of pure stands of Arundo, with polygons taken from areas of green Arundo as well as stands of more mature, senescent Arundo. The riparian woodland community in this reach of the Santa Margarita River consists primarily of tree willows (*Salix lasiolepis*, *S. laevigata*, and *S. gooddingii*), exotic Eucalyptus, and, to a lesser degree, cottonwoods (*Populus fremontii* and *P. balsamifera* spp. *trichocarpa*), and sycamore (*Platanus racemosa*). The scrub class includes two communities: riparian southern willow scrub dominated by mulefat (*Baccharis salicifolia*) and the shrub-willow *Salix exigua*, with scattered coyote brush (*Baccharis pilularis*), and Diegan coastal sage scrub comprised largely of California sagebrush (*Artemisia californica*) and white sage (*Salvia apiana*). The annual grass vegetation class consists of exotic annual grasses such as ripgut brome (*Bromus diandrus*), slender oat (*Avena barbata*), and wild barley (*Hordeum* spp.) (Hickman, 1993; Zedler et al., 1997). At the time of the image collection in September, annual grassland plants had completed their life cycles and were standing dead biomass. Tamarisk or salt cedar (*Tamarix* spp.) is another harmful invader in riparian areas, and so it was mapped when seen in the field so classifications could be included. The green lawn training set is an area of homogeneous green, irrigated lawn. The aquatic plant class polygons encompass stands of emergent sedges (*Carex* spp.) and rushes (*Juncus* spp.) and mats of microalgae. These last two were selected because they were observed to be confused with Arundo in preliminary, unsupervised classifications.

Regions of interest (ROIs) were created for use as training sets using a combination of field GPS data, field notes and hand-mapped polygons, and 1999 1:3000 aerial photos supplied by the Camp Pendleton Base. ROI polygons were created on an un-georeferenced true-color display of the image data using the GPS coordinates as reference by visually matching features in the un-georeferenced and georeferenced images. Spectral profiles of the vegetation classes, created by averaging values taken from the reflectance image data, are shown in Figure 4. It can

be seen from this comparison that the vegetation types have distinct response patterns across the region of the spectrum sampled by AVIRIS. The tamarisk spectral profile was very close to that of scrub, and was omitted from classifications due to poor results.

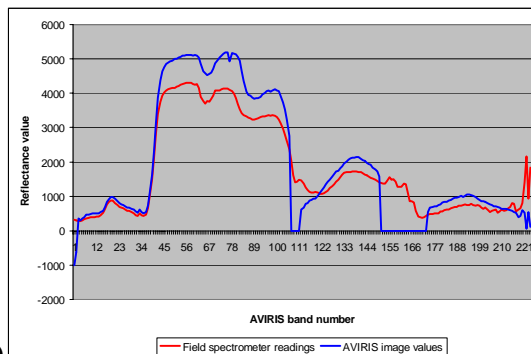


Fig 3)

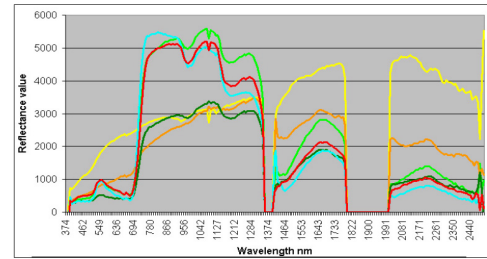


Fig 4)

Figure 3. Comparison of field spectrometer readings and AVIRIS image spectra (averaged values) for Arundo.

Figure 4. Spectral profiles from AVIRIS reflectance data for vegetation training sets (averages of values for all pixels).

Training set ROIs were analyzed for spectral distinctness using the ENVI image processing program's spectral separability calculation, which reports both the Jeffries-Matusita and Transformed Divergence separability measures (Richards, 1994). All were found to have high separability values (close to the highest value of 2.00). Upon examination using the ENVI n-dimensional visualization tool, however, it could be seen that the pixels from the ROIs were not completely unique with regard to the areas in the data space that they occupied. The classes were trimmed using the draw tool in the n-d visualizer, but the use of these spectrally trimmed ROIs did not improve upon classification results.

Polygons for use in validating classification results were digitized over a georectified true-color display of the AVIRIS imagery overlaid with the GPS points, and using the hand-drawn maps and notes from the field, ground photos, 1997 Camp Pendleton riparian vegetation map and 2001 Arundo eradication maps as reference. In total, 209 polygons were created for six vegetation types: Arundo, riparian woodland, scrub, annual grassland, aquatic plants, and tamarisk. The total area covered by these polygons was 68.3 ha, or approximately 15.4% of the 443.9 ha scene being classified. The true-color image, classification results, and validation polygons were co-registered using ground control points taken from a 1:100,000 roads coverage, and the confusion matrix function in ENVI used for quantitative comparison.

Several methods for classifying the image were compared: unsupervised classifications (Isodata and K-means); continuum removal using the water absorption feature at 970 nm with an unsupervised (Isodata) classification; supervised (maximum likelihood) classification using training sets from the image; and spectral angle mapper using training spectra from the image. Analyses were performed on MNF-transformed and reflectance data. Maximum likelihood and spectral angle mapper techniques were also applied to a second image (referred to below as Image 2) using spectra imported from the first image.

3. RESULTS

3.1 Unsupervised classification

Results of unsupervised classifications using K-means and Isodata algorithms with several thresholds provided interesting insights into the spectral and spatial features of the dataset but did not yield results appropriate for use in mapping the desired vegetation types. The results were helpful in the selection of training set ROIs, but comparisons with ground data were too inaccurate to be considered further.

3.2 Continuum removal

The use of the water absorption feature at 970 nm to map the plants in the test image resulted in the identification of giant cane relatively well when it was applied to a scene with only *Arundo* and terrestrial riparian vegetation species. However, presence of other high water content plants in the image, such as the aquatic plants growing at the edges of the reservoir near the upper edge of the image, resulted in confusion and made this a less than optimal procedure for giant cane mapping (see Figure 5a).

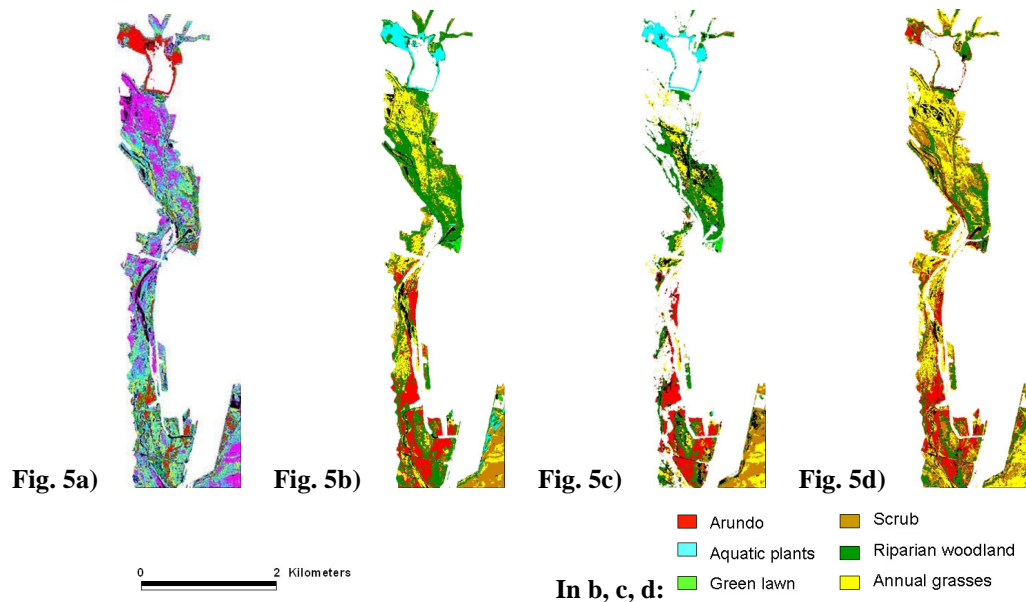


Figure 5. Results from selected classifications of Image 1.

a) continuum removal (5 classes assigned colors from red to blue red=plants with highest water content, blue=plants with lowest water content), b) maximum likelihood on MNF, c) spectral angle mapper on MNF, d) spectral angle mapper on reflectance data.

3.3 Maximum likelihood supervised classification

The maximum likelihood supervised classification performed on MNF transformed data using training sets taken from the same image was very successful in mapping *Arundo*, annual grasses, and riparian woodland, with less success in classifying the scrub vegetation type. Tamarisk results had a high rate of confusion with scrub, so the tamarisk training data was dropped from subsequent classifications. Figure 5b shows the best result, performed with no threshold. *Arundo* classified at a 95.27% overall accuracy rate, and annual grasses and aquatic plants classified correctly in 79.78% and 81.82% of the pixels, respectively. The high percentage of successful classification of *Arundo*, aquatic plants, and annual grassland is to be expected in the classification of the image from which the training sets were taken, as geometric characteristics of the data and the biophysical status of the monotypic *Arundo*, aquatic plant, and grassland stands are likely to be very similar to those in the training set polygons. The result for riparian woodland, 90.73% correct, however, is surprisingly good considering the range of species and canopy cover possible in that vegetation class. Scrub was confused in 45.01% of the pixels with riparian woodland, and 16.41% of the time with annual grass.

3.4 Spectral angle mapper using reference spectra from the same image

The spectral angle mapper technique, when used on calibrated reflectance data, is relatively insensitive to illumination and albedo effects (Kruse et al., 1993), and can be used with spectra imported from other images or stored in spectral libraries. For these reasons it was considered the most likely to provide repeatable results in different images, possibly both over the same spatial area taken in different years and over different spatial areas.

Spectral angle mapper was applied to both reflectance data (165 bands) and MNF transformed data, which yielded markedly different results. When applied to MNF transformed data (and the reference spectra extracted from the MNF data), an angle of 0.10 radians for all classes only classified a small fraction of the image. The classes began to have reasonable spatial distributions only at very large angles, and the best image was created using a 1.2 radian angle for all classes (Figure 5c). Results were as follows: Arundo mapped correctly in 84.89% of the pixels, and riparian woodland, annual grasses, and aquatic plants success rates were 79.76%, 48.02%, and 71.76%, respectively. Again, the classification of scrub yielded the lowest rate of success at 28.56%.

When reflectance data was used with the SAM method, and the reference spectra were extracted from the reflectance data, an angle of 0.10 radians for all vegetation types classified most of the image. In this case there was significant confusion in both directions between the Arundo and aquatic plant vegetation types. Removing the aquatic plant training set from the process increased confusion with the green lawn class. Figure 5d shows the most successful result, using four vegetation classes with angles of 0.15 radians for four classes: Arundo, scrub, riparian woodland, and annual grasses, and success rates of 70.91%, 42.56%, 64.37%, and 64.67%, respectively.

The MNF-transformed data was also rotated back to image space, and SAM performed using ROIs from the inverted MNF data and from the original reflectance data, and with a variety of angle settings for the different classes. Although the classes displayed good spatial patterns, none of these results classified the vegetation types as well as either SAM with the MNF transformed data or SAM with the reflectance data.

3.5 Maximum likelihood supervised classification of a second image, using imported spectra

The maximum likelihood classifier can accept imported spectral data for use as training sets with which to classify an image. Spectra for Arundo, riparian woodland, scrub, and annual grasses were imported from the first image classified and applied to a 500 m x 800 m section of an image (Image 2) over a lower reach of the Santa Margarita River, acquired in the same overflight but in a different flightline. Image 2 was pre-processed separately from Image 1 (from which the reference spectra were taken). For this classification, 165 bands were used, both from the original reflectance data and from the results of an MNF transform inverted back to image space. Training data from both the reflectance and MNF processed data were applied in various combinations and thresholds. Results were variable; none of the results were good for all classes in one image. In some cases, one or two classes looked reasonable and another completely spurious. In order to find a promising arrangement of training data and thresholds to use on the second image, the first image was classified with its own ROIs after MNF transformation and conversion back to image space. These results were also inconsistent (see discussion).

3.6 SAM classification of a second image using imported spectra

A SAM classification of Image 2 using vegetation spectra imported from reflectance data of Image 1 was performed for five classes: Arundo, riparian woodland, scrub, annual grasses, and aquatic plants. Both the reflectance data and the MNF result converted to image space were classified with the imported spectra. These results were evaluated qualitatively, using the 1997 riparian vegetation map and 1999 aerial photos in visual comparison. Figure 6 shows the resulting maps compared to the 1997 riparian vegetation for that area. A 0.15 radian angle was used in both cases for all classes. The technique applied to reflectance data appears to have worked well for riparian woodland and scrub, but the aquatic plants did not classify at the 0.15 radian angle, even though there are marshes in the floodplain within the image. Inspection of aerial photos from 1999 show that the image created from the reflectance data (Figure 6b) was more accurate for current giant cane distribution than the 1997 riparian vegetation map. The large area mapped as solid cane in the 1997 vegetation map (Figure 6a) appears as a 30-50% mosaic of cane and riparian woodland in the 1999 aerial photos. The cane-infested area along the river channel in the lower part of the image is approximately 50-75% Arundo mixed with riparian woodland in the 1999 aerial photo, and so reflects extensive new growth of the weed since the 1997 vegetation map was made. The result of the classification done with MNF transformed data looks more like the vegetation map (Figure 6c), but

comparison to the aerial photos indicates that it did not produce the best result. This method was also less effective at mapping the other vegetation classes.

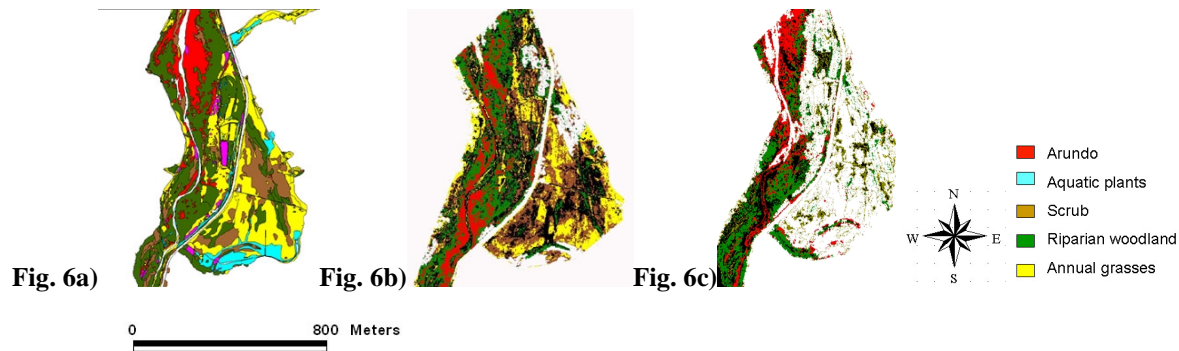


Figure 6. Results of classification of Image 2 using imported spectra.

a) 1997 riparian vegetation map, b) SAM classification of reflectance data using reference spectra of the vegetation types imported from a different image, c) SAM classification of MNF transformed data converted back to image space. The pink polygons in the 1997 riparian vegetation map at left represent tamarisk, but are classified as scrub in image b, as no training data for tamarisk was entered in this analysis.

Results are summarized in Table 1. For the mapping of a single image with training sets from the same image, the maximum likelihood supervised classification gave the best results for all classes. When reference data was applied from one image to the mapping of another, however, the SAM technique performed on reflectance data gave the best results.

Table 1. Summary of Results

IMAGE	METHOD	DATA	TRAINING SETS FROM	RESULTS
Image 1	Maximum Likelihood	MNF	Image 1 MNF	<u>Good</u> : Overall Accuracy= 75.7% Arundo Accuracy= 95.3% Kappa coefficient= 0.69
	SAM	MNF	Image 1 MNF	<u>Good</u> : Overall Accuracy= 61.5% Arundo Accuracy= 84.9% Kappa coefficient= 0.54
	SAM	Reflectance	Image 1 Reflectance	<u>Good</u> : Overall Accuracy=60.2% Arundo Accuracy= 70.9% Kappa coefficient= 0.48
	Maximum Likelihood and SAM	Reversed MNF	Image 1 Reflectance	<u>Poor</u>
Image 2	SAM	Reflectance	Image 1 Reflectance	<u>Good</u>
	SAM	Reversed MNF	Image 1 Reflectance	<u>Poor</u>
	Maximum Likelihood	Reflectance	Image 1 Reflectance	<u>Poor</u>
	Maximum Likelihood	Reversed MNF	Image 1 Reflectance	<u>Poor</u>

4. DISCUSSION

A maximum likelihood classification using training sets from the same image provides an excellent method for mapping vegetation classes, once training sets have been selected and all possible sources of confusion are included as ROIs. The limitation with this method, however, becomes apparent when a map for a larger region comprised of multiple images and flightlines is needed, or for images acquired in different years. The analyst is faced with either needing training sets from every scene or mosaicking the scenes together before any processing occurs. The first option is not likely to be feasible and even defeats the purpose of using a remote sensing approach. The other, that of mosaicking the images, was not practical due to large file sizes and the computing resources necessary to process them together as a single file. In many situations, available images are not contiguous or are collected at different times. A method is needed to classify multiple images for the same classes using training sets imported from one image, or using data from a spectral library. While this is a common practice for geological mapping, mapping vegetation presents challenges in that the spectral response is highly subjective to changes in environmental, climatic, and seasonal parameters.

The spectral angle mapper technique, although less successful than the maximum likelihood classification in mapping Image 1, looks more promising for use with imported reference spectra. The data must be in image space for the use of imported spectra. The use of the MNF transform is helpful for compressing the image data, but presents the challenge of transforming each image differently due to different ranges of variability in the images, thereby making the resulting MNF-transformed data impossible to compare with reference spectra from other images. Converting the data back to image space solves this problem, but there are apparently changes in the data that affect the clustering algorithms. Classifications performed directly on reflectance data provided better results than those performed on MNF transformed data that was converted to image space. This is possibly due to small but important differences in the average spectral responses of different vegetation classes being smoothed out of the data in the MNF noise reduction process, resulting in classes that are less distinct.

The scrub vegetation class presented a challenge with all methods, which confused it most often with riparian woodland. The greatest contributor to this error is probably the inherent variability within the classes in their species compositions and cover densities. It can be seen by examining the spectral response of class pixels using the n-dimensional visualizer that there is some overlap between riparian woodland and scrub, with the riparian woodland class having pixels that respond similarly to those of scrub. It may be possible to improve upon these results by refining the woodland class. Tamarisk classification was poor due to the fact that the canopy was green and neither senescent or flowering at the time of the image, and so failed to provide a significantly distinct enough spectral response to distinguish it as a separate class.

In order to gain insight into the factors contributing to variability in the dataset, statistical information from the MNF transform process was compared to the spectral properties of the vegetation classes to infer the physiochemical characteristics being used to distinguish the classes. During the MNF transform, original bands are first noise-whitened and then transformed to new bands by identifying the principal component vector (Green, 1988). The resulting eigenvectors are then ordered by their information content (i.e., proportion of variance represented) and the contribution of the original bands to these new bands is recorded as an eigenvalue number between 1 and -1 (Research Systems Inc., 1995). Contribution toward the variability in the transform bands is expressed in assigned weightings from zero in either the positive or negative direction. MNF band 1 showed weightings that were evenly distributed across the spectrum, which indicates a heavy contribution of albedo effects in the image rather than from differences in physical or chemical characteristics of the vegetation. MNF bands 2 and 3 are composed of information that is more heavily weighted in the 490-700 nm range than in any other region of the spectrum, indicating strong variability in the spectrally active areas of chlorophyll and other pigments. Also contributing to much of the variability in the data is the near-infrared region. Lower-order bands, such as band 5, show weightings more equally distributed across the spectrum, with contributions in the SWIR becoming more prominent. This is an intuitive result given the absorption properties of various plant and mineral constituents. Unlike broader-band, multispectral data, hyperspectral data provides the spectral resolution to take advantage of these characteristics.

5. CONCLUSIONS

This study shows that the invasive plant *Arundo donax* and associated riparian vegetation types can successfully be mapped using AVIRIS data and with standard imaging spectrometry techniques. However, adequate ground data for part of the area is necessary for development of training set and refinement of the mapping technique, which can then be applied to the larger region. Once selected and refined, training spectra from one image can then be applied to separate images in the same region and for the same year using the spectral angle mapper technique with the angles that gave good results in the original image. The use of the MNF transform may in some cases remove distinguishing features from spectral data and make classification of spectrally similar features less successful.

Despite the need for site-specific information, these techniques show promise as useful tools for evaluating the status of important habitats and the advance (or eradication) of an invasive weed. This is especially applicable in the management of riparian systems because constituent habitat types can change significantly in their spatial extents and distribution in just a few years. More work is needed to discover if spectra can be used in images from different years for the same region for development of a sequence of maps that would allow change analysis, since variations from year to year in the timing of plant phenological stages will certainly be a factor.

6. ACKNOWLEDGEMENTS

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7. LITERATURE CITED

- Avery, T. E. and Berlin, G. L., 1992. Fundamentals of Remote Sensing and Airphoto Interpretation. Macmillan Publishing Co., New York.
- Barbour, M., Pavlik, B., Drysdale, F. and Lindstrom, S., 1993. California's Changing Landscapes. California Native Plant Society, Sacramento, California.
- Bossard, C., Randall, J. M., Hoshovsky, M. C., 2000. Invasive Plants of California's Wildlands. University of California Press, Berkeley, California.
- Franzreb, K. E., 1989. Ecology and Conservation of the Endangered Least Bell's Vireo. 1st edition. U.S. Fish and Wildlife Service, Sacramento, California.
- Green, A. A., Berman, M., Switzer, P. and Craig, M. D., 1988. A transformation for ordering multispectral data in terms of image quality with implication for noise removal. IEEE Transactions on Geoscience and Remote Sensing, vol. 26, no. 1, pp. 65-74.
- Hickman, J., ed., 1993. The Jepson Manual: Higher Plants of California. University of California Press, Berkeley, California.
- Jackson, N. E., Frandsen, P., Douthit, S., (eds.), 1993. *Arundo donax* workshop proceedings. Ontario, California.
- Kruse, F. A., Lefkoff, A. B., Boardman, A. B., Heidebracht, K. B., Shapiro, A. T., Barloon, P. J. and Goetz, A. F. H., 1993. The Spectral Image Processing System (SIPS) - interactive visualization and analysis of imaging spectrometer data. Remote Sensing of Environment, vol. 44, no. pp. 145-163.

Omori, G., 1996. Eradicating the giant reed (*Arundo donax*) in riparian areas of Marine Corps Base, Camp Pendleton. California. Agri Chemical & Supply, Inc., Oceanside, California.

Research Systems Inc., 1995. ENVI User's Guide, The Environment for Visualizing Images, Version 3.4. Research Systems, Inc., Boulder, Colorado.

Richards, J. A., 1994. Remote Sensing Digital Image Analysis. Springer-Verlag, Berlin.

Steinitz, C., (ed.), 1996. Biodiversity and Landscape Planning: Alternative Futures for the Region of Camp Pendleton, California. Cambridge.

Zedler, P., DeSimone, S., Giessow, J., Lawson, D., Else, J., Bliss, S., 1997. The Plant Communities of Camp Pendleton Marine Corps Base, California. San Diego State University, San Diego.

Zemba, R., 1989. Riparian Habitat and Breeding Birds Along the Santa Margarita and Santa Ana Rivers of Southern California. *In*: A.A. Schoenherr (ed.), Endangered Plant Communities of Southern California, 15th Annual Symposium, Schoenherr, pp. 98-114. Southern California Botanists, Special Publ. No. 3, Fullerton, California.