

Terrain Classification in Urban Wetlands with High-spatial Resolution Multi-spectral Imagery

Richard Christopher Olsen^{*a}, Jamada Garner^a, Eric Van Dyke^b

^aPhysics Dept., Naval Postgraduate School, Monterey, CA

ABSTRACT

The Elkhorn Slough area is a major wildlife reserve, and important wetlands area along the central coast of California. As part of the ongoing study of the slough, accurate classifications of the regions in the slough and its watershed are needed. The objective of this work was to use the 4-m spatial resolution, 4-color sensor on the IKONOS satellite. A manually constructed classification map was used to train the spectral classifiers. As the work evolved, a problem emerged due to the relatively high spatial resolution. Regions of interest such as oak woodlands have highly variable spectral elements when observed at high spatial resolution. As a consequence, the refinement of the regions of interest obtained from the original classification map required not only the elimination of erroneous spectral elements; but also required inclusion of a range of spectra, as opposed to the traditional approach of selecting pure exemplars. Modest success was obtained from the classification effort. As a consequence, additional virtual bands were created by constructing texture features from the higher spatial resolution panchromatic band. This enabled spectrally similar classes such as trees and cultivated fields to be distinguished.

Keywords: Terrain Classification, Multi-spectral, texture analysis

I. INTRODUCTION

Terrain Classification (or TERCAT) using multi-spectral imagery (MSI) from space dates to the origins of the remote sensing community, beginning with the Earth Resources Technology Satellite (ERTS) program, and the launch of the satellite which became Landsat 1. The 4-color Multispectral Scanner (MSS) on that mission, with its 80-meter spatial resolution, provided spectral imagery in the visible to near-infrared (VNIR) spectral range. Subsequent additions to the Landsat program included the Thematic Mapper (TM) instrument, which added two short-wave infrared (SWIR) bands, and had 30-meter resolution in the reflective portion of the electromagnetic spectrum. (Avery and Berlin, 1992) Mapping of wetlands areas using MSI data has been done previously by authors such as Jensen et al. (1986)

High spatial resolution MSI from space became available with the advent of the IKONOS satellite, in 1999. Meacham, 1999). The 4-color instrument provides VNIR imagery at 4-meter resolution, and a panchromatic channel with 1-meter resolution. The MSI bands correspond quite closely to the Landsat VNIR bands. (Table 1 lists the spectral response characteristics for IKONOS, in a calibration document provided by Space ImagingTM, Spectral bandwidths are full-width at half-max). A fairly fundamental question that the new data sets provide is a question as to what differences occur when the higher spatial resolution data are used for TERCAT. Gong et al (1992) noted that at least in some regimes, there is not an increase in classification accuracy as spatial resolution increases. A parallel question which emerges is how the very high resolution panchromatic channel can contribute to scene classification.

Texture processing of Landsat data dates to the early work by Haralick et al (1973), but computational constraints have limited the utility of such. Haralick et al (1973), Haralick (1979), and Anys et al (1994) have defined sets of texture measures to use in such analysis. Similar work was done by Irons and Petersen (1981), and Wetzka et al (1976). Analysis of modern Landsat imagery has been conducted by Frohn (2001), in classification of rice fields. SPOT panchromatic and spectral data provided a higher resolution dataset, as shown by Gong and Howarth (1990); Agbu and Nizeyimana (1991); and Briggs and Nellis (1991). Higher resolution imagery has been studied by Bucher & Lehmann (2000), who used 25-cm resolution airborne imagery in combination with lower spatial resolution hyper-spectral imagery.

^{*} olsen@nps.navy.mil; phone 1 831 656 2019; Physics Dept., PH/Os, Naval Postgraduate School, Monterey, CA USA 93943

Table 1 - IKONOS Spectral Band Characteristics

Band	Lower 50% (nm)	Upper 50% (nm)	Bandwidth (nm)	Center (nm)
Pan	525.8	928.5	403	727.1
MS-1 (Blue)	444.7	516.0	71.3	480.3
MS-2 (Green)	506.4	595.0	88.6	550.7
MS-3 (Red)	631.9	697.7	65.8	664.8
MS-4 (VNIR)	757.3	852.7	95.4	805.0

Ref: Brad Peterson , IKONOS Relative Spectral Response and Radiometric Calibration Coefficients, Space Imaging Document Number: SE-REF-016, 4/26/01.

2. OBSERVATIONS AND ANALYSIS

The Elkhorn Slough sits on the central Californian coast about 160 km south of San Francisco (Silberstein and Campbell, 1989). Its waterway is a narrow winding body that measures 200 m wide and 7 to 8 meters in depth at its mouth in the town of Moss Landing. The slough is supplied freshwater from winter rains and salt water by tidal flows from the ocean. Ikonos satellite imagery of the Elkhorn Slough, its surrounding wetlands and adjoining uplands was collected on October 23, 2002. Figure 1 shows the imagery.



Figure 1. IKONOS image of Elkhorn Slough, October 23, 2000. Bands 4 (NIR), 3 (red), and 2 (green) are presented as a false-color infrared image. The image is 10 km x 20 km. North is to the top.

The other data input for this project was a classification map provided by the Elkhorn Slough Foundation (ESF). The vector map defined geo-referenced polygons that were used to define regions of interest for this study. The map was the product of a compilation of information from aerial photos and Global Positioning System (GPS) assisted field observations. The ESF used a 50% thumb rule to qualitatively define each ROI. The rule stated that each region was defined to be the material which comprised at least 50% of it.

Elkhorn Slough Classification Map

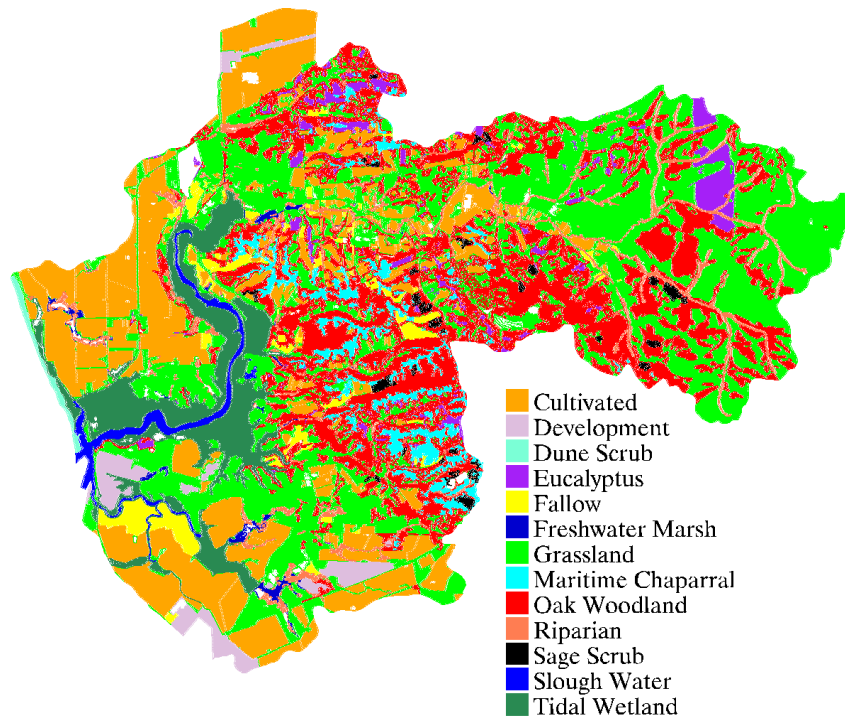


Figure 2. Elkhorn Slough Classification Map. The major classes are shown. Note that the classification map extends further east than the 10km wide Ikonos image.

The classification map was used to define a training set for the October 23 imagery. The objective was to train the classifier, enabling subsequent surveys at considerably less effort. A pair of problems arose. Figure 2 shows a contour distribution of the data points for a prominent category in the scene – Eucalyptus Trees. The data are cast into principal component space, and shown as a scatter plot for principal components 1 and 2. The scatter plot shows a range of brightness values corresponding to the illumination variations in the trees. Also, there is contamination due to errors in the classification map. These include soil regions, and even a small water region ($PC1 \sim -250$, $PC2 \sim -100$). Garner (2002) worked through each of the 17 classes in the classification map, resolving the primary component in each ROI, and in some cases, differentiating several unique spectral classes for that component.

A second, subtler problem arose during this process. It is normal when working with spectral imagery to take the extrema of the point distributions as exemplars, or pure end-members to use in classification processes. Unfortunately, the extrema in distributions such as those shown in Figure 3 are not in fact good end-members for the class. The contour plot shows that the centroid of the distribution is quite a bit lower, due to the substantial contribution of shade to the tree class. The bright extrema actually corresponds better to the bright-cultivated vegetation (strawberry fields).

Garner (2002) went through the scatter plots of the different classes obtained from the ESF classification map, and generated a larger set of spectral classes. That process was repeated for this work, and some 50 unique classes were obtained. A number of ‘pond’ subclasses in particular were obtained which correspond to various holding ponds for agricultural and sewage purposes. These multiple subclasses served to clutter the classification results significantly.

Minimum Distance (MD) and Maximum Likelihood Classifiers were run (Stefanou, 1997). Spectral Angle Mapper (SAM) classification was also run, but gave poor results, which would be expected given the lack of sensitivity to overall brightness in that classifier. Confusion matrices were constructed assuming the original classification map was correct. Results were surprisingly poor, apparently due to the second point noted above. Results will be summarized below.

Figure 4 shows the results of one classifier, with about 55% accuracy compared to the input classifier map. Visually, one of the main problems is the tidal wetland, which classified as slough water here, basically because the tide was up, and those areas showed as water.

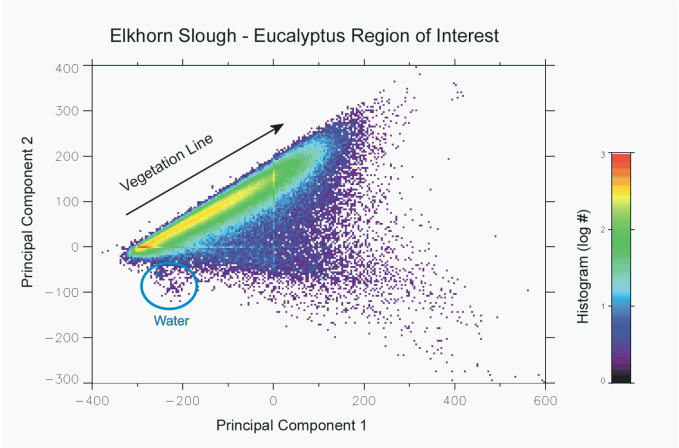


Figure 3. The color contour plot shows a distribution of points. The contour scale is logarithmic, from 1-1000. Vegetation brightness increases to the top right corner. Bright soil regions are to the lower right. Plotting artifacts produce the linear features along PC1=0, and PC2=0.

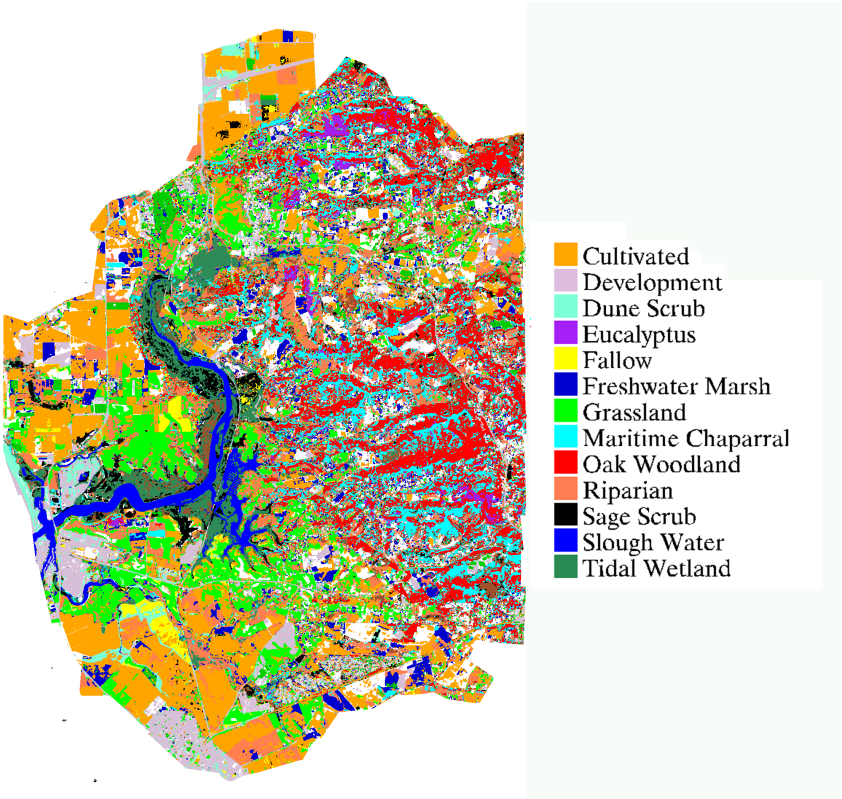


Figure 4. Classifier results from a maximum likelihood classifier applied to MSI data from Ikonos. A 7x7 maximum operator was applied to the classifier results to reduce clutter in the presentation. The color scale is the same as in Figure 2. One additional class is included: Dry Ponds. This is basically a soil class, and is indicated in white in the figure. A few minor classes were set to black.

The relatively poor results motivated the addition of texture information, exploiting the higher-spatial resolution (1-meter) panchromatic band. Four virtual bands were created at the 4-m resolution of the MSI data. Variance filters were run for 4x4 and 16x16 boxes (4-m square and 16-m square), and a correlation filter was run at the same resolution. The latter was run in the horizontal direction, with a spacing equal to the size. (That is, the correlation coefficient was calculated for adjacent 4x4 and 16x16 boxes.) A primary motivation for this was to distinguish the relatively coarse tree regions from the similarly colored cultivated fields, which were very uniform. (Attempts to use the ‘textbook’ filters as shown by Haralick (1979) foundered on problems with the commercial software package being used.) Figure 5 illustrates the range of classes produced from the texture filtering.

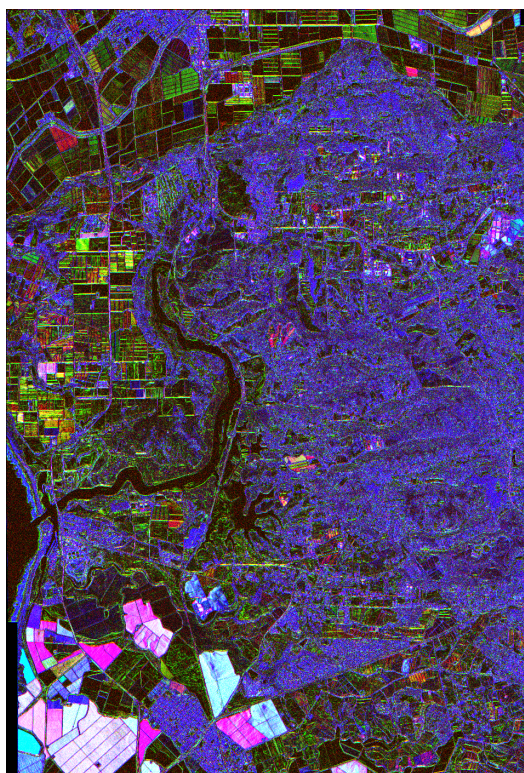


Figure 5. Texture image from panchromatic band. Red is the 4x4 correlation, Green is the 16x16 correlation, and Blue is the 4x4 variance result. The relatively brighter blue regions are the urban area (Watsonville, top left, Castroville, lower left), and forested hillsides on the right hand side of the image. The brightly colored regions in the lower left are cultivated fields.

This information was then included in 8-band ‘virtual’ multispectral data files, and SAM and ML classifiers were run. There was a modest improvement in the classifier results, as shown below. Finally, since part of the point of the study was to consider how the higher spatial resolution improved the performance of the classification process, a second analysis process was run on Ikonos data subsampled down to Landsat resolution (30 m). The same classifiers were run, using a region of interest (ROI) set mapped down to the lower resolution data. Table 2 shows the results from this combination of classification runs.

Table 2: Confusion matrices for Classifier Results

Classifier/Input	4-m resolution	30-m resolution
Maximum Likelihood		
4-bands	50.14 %	37.89 %
8-bands	55.33 %	44.15 %
Minimum Distance		
4-bands	26.76 %	18.60 %
8-bands	8.69 %	13.15 %

As might be expected, higher spatial resolution produces higher accuracy results. For the ML classifier, including the texture information also improves the accuracy, though not by a great deal. Note that the larger relative increase in the 30-m resolution results is something of an artifact, since the textures still come from 1-m resolution data. To be fair, the texturing ought to be done on 7 to 10-meter resolution data to properly compare improvement. Curiously, the MD classifier gets worse. This is probably due to the relatively larger dynamic range in the texture bands, even though they were normalized to have the same means as the MSI bands.

3. DISCUSSION

The results of the classification process to date are somewhat unsatisfying. The classification accuracy does improve with spatial resolution, and the inclusion of texture information improves the classification accuracy. Further work is needed to test other texture processes, and a revised ground truth is needed that matches the fine detail of the Ikonos image data. A subsequent image was taken in October 2001, and a third Ikonos image is scheduled for October 2002. The hope is that once properly trained using the October 2000 image; subsequent evolution of the area can be tracked with a significantly lower level of effort.

4. REFERENCES

1. Agbu, P. A., and E. Nizeyimana, "Comparisons between Spectral Mapping Units Derived from SPOT Image Texture and Field Soil Map Units", *Photogrammetric Engineering and Remote Sensing*, 57, 397-405, 1991.
2. Anys, H, A. Bannari, D. C. He, and D. Morin, "Texture Analysis for the Mapping of Urban Areas Using Airborne MEIS-II Images", *Proceedings of the First International Airborne Remote Sensing Conference and Exhibition*, ERIM, Strasbourg, France, 231-245, 1994.
3. Avery, Thomas Eugene, and Graydon Lennis Berlin, *Fundamentals of Remote Sensing and Airphoto Interpretation*, New York, MacMillan Publishing Company, 5th Edition, 1992.
4. Briggs, J. M., and M. D. Nellis, "Seasonal Variation of Heterogeneity in the Tallgrass Prairie: A Quantitative Measure Using Remote Sensing", *Photogrammetric Engineering and Remote Sensing*, 57, 407-411, 1991.
5. Bucher, T.; F. Lehmann, "Fusion of HYMAP Hyperspectral with HRSC-A multispectral and DEM data for Geoscientific and Environmental Applications", *Geoscience and Remote Sensing Symposium, 2000. Proceedings. IGARSS 2000. IEEE 2000 International*, 7, 3234- 3236, 2000.
6. Frohn, R.C., "Satellite remote sensing of wild rice", *Geoscience and Remote Sensing Symposium, 2001. IGARSS '01. IEEE 2001 International*, Sydney, NSW, Australia , 4, 1634 – 1635, 9-13 July 2001.
7. Garner, J. J, Scene Classification Using High Spatial Resolution Multispectral Data, M. S. Thesis, Naval Postgraduate School, Monterey, CA, June 2002.
8. Gong, P., and P. J. Howarth, "The Use of Structural Information for Improving Land-Cover Classification Accuracies at the Rural-Urban Fringe", *Photogrammetric Engineering and Remote Sensing*, 56, 67-73, 1990.
9. Gong, P, D. J. Marceau, and P. J. Howarth, "A Comparison of Spatial Feature Extraction Algorithms for Land-Use Classification with SPOT HRV Data", *Remote Sensing of Environment*, 40, 137-151, 1992.
10. Haralick, R. M., K. Shanmugam, and I. Dinstein, "Textural Features for Image Classification", *IEEE Transactions on Systems, Man, and Cybernetics*, 3, No. 6, pp. 610-621, 1973.
11. Haralick, R. M., Statistical and Structural Approaches to Texture, *Proceedings of the IEEE*, 67, 786-804, 1979.
12. Irons, J. R., and G. W. Petersen, "Texture Transforms of Remote Sensing Data", *Remote Sensing of Environment*, 11, 359-370, 1981.
13. Jensen, J. R., M. E. Hodgson, E. Christensen, H. E. Mackey, L. R. Tinney, and R. Sharitz, "Remote Sensing Inland Wetlands: A Multispectral Approach", *Photogrammetric Engineering and Remote*, 52,87-100, 1986.
14. Mecham, M., "IKONOS Launch to Open New Earth-Imaging Era", *Aviation Week & Space Technology*, New York, McGraw-Hill, October 4, 1999.
15. Silberstein, M, and E. Campbell, *Elkhorn Slough*, Monterey Bay Aquarium Foundation, Monterey, CA, 1989.
16. Stefanou, M. S., A Signal Processing Perspective of Hyperspectral Imagery Analysis Techniques, M.S. Thesis, Naval Postgraduate School, Monterey, CA, June, 1997.
17. Weszka, J., C. Dyer and A. Rosenfeld, "A Comparative Study of Texture Measures for Terrain Classification", *IEEE Transactions on Systems, Man and Cybernetics*, SMC-6, 269-285, 1976.