MAPPING SUBMERGED MACROPHYTES: USING MULTI-RANGE SPECTRAL FEATURE FITTING TO MAP SUBMERGED EELGRASS IN A TURBID ESTUARY

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ABSTRACT

Classification of submerged aquatic vegetation (SAV) is difficult due to the attenuation of light in water. The purpose of this study was to develop a site specific hyperspectral image classification technique to identify deep eelgrass beds using portions of the spectrum least affected by light attenuation. Using multi-range spectral feature fitting, this study classified eelgrass by targeting spectral response in the blue-green portion of the spectrum through five distinct ranges between 476nm to 589nm. Mapping via spectral feature fitting improved discrimination between eelgrass and non-eelgrass areas compared to a separate spectral angle mapping classification. This technique allowed researchers to map eelgrass at a greater depth than other classification methods. Total accuracy for presence/absence was 81%.

INTRODUCTION

Along the coast of California and the Pacific Northwest, submerged vegetation such as kelp, eelgrass and algae provides critical habitat for many aquatic species and is fundamental both for environmental and economic health. However, managing these vast vegetation beds requires knowledge of their location and health. Water adds an unwanted complexity for mapping vegetation, and many of these aquatic resources, particularly in the turbid estuaries of the Pacific Northwest, remain unmapped.

Water attenuates light. Classification algorithms work based on the statistical separation of reflectance values between different targets. In aquatic environments, this relationship becomes complex as light is attenuated and statistically, targets appear more similar. This is also a function of water depth. As a target is found deeper within the water column, more light is attenuated and the more difficult it is to distinguish it from its surroundings. This relation is reflected in the below adaptation of Lambert-Beer's Law:

$$L(z, \lambda) = L(0,\lambda)^{-kz} \qquad (1)$$

where z is depth, k is an attenuation coefficient, λ is a wavelength and L is radiance. In turbid waters, the attenuation coefficient is greater, resulting in less water leaving radiance and more difficulty in mapping submerged features. However, water leaving radiance, as illustrated above, also differs depending on wavelength. The red-infrared range of the spectrum is more rapidly attenuated than blue and green range wavelengths (Bukata et al., 1995).

Hyperspectral sensors can best approach the cohesiveness of information of a field spectrometer. Like traditional sensors, they passively collect reflectance data, but at much shorter wavelength intervals. The result being that when the bands are viewed together, they create a quasi-continuous spectral curve for each pixel. Past eelgrass mapping projects in Humboldt Bay have relied on delineation of aquatic beds using aerial photography. However, additional problems have been seen with this type of image classification. Difficulties in mapping submerged species and inability to discriminate between algae and eelgrass have hindered the classification efforts.

In October 2004, a hyperspectral sensor acquired imagery over Humboldt Bay during high tide, when all eelgrass was submerged. The amount of water over the eelgrass beds was calculated to be 1.5-3.5m. As tidal cycling is different for the bays, lower water levels were seen in South Bay, while increased water depths were seen in North Bay. Eelgrass was mapped with good success in South Bay by spatial subsetting the image and using a spectral angle mapping (SAM) classification. However, when water depth was greater than 2.2m, distinguishing eelgrass from non-eelgrass areas became problematic (Judd, 2006). The same technique applied to the North Bay was not successful, with many false negatives in deeper water.

Throughout the classification of eelgrass in South Bay, we noticed certain characteristics of the submerged eelgrass spectral curve in South Bay. Other researchers have used a spectral feature fitting (SFF) algorithm to enhance these characteristics of the spectral curve for aquatic vegetation (Williams et al., 2003). The purpose of this study is to evaluate whether a spectral feature fitting algorithm would be able to classify deep submerged eelgrass in areas in areas where other classification schemes have failed.

METHODS

Study Area

Humboldt Bay is located in northern California, sixty miles south of the Oregon border. It is a shallow estuary with dredged channels for vessel passage. It is considered to have of the most important eelgrass habitat areas in the Pacific Northwest (Phillips, 1984). California Sea Grant along with other state, federal, and local agencies have carried out monitoring efforts for eelgrass in Humboldt Bay. The specific study area is located in North Bay, the largest of three bays which make up Humboldt Bay (Fig. 1). The area covered two flight lines where water depth was an estimated 2.2m-3.5m at the time of data acquisition.

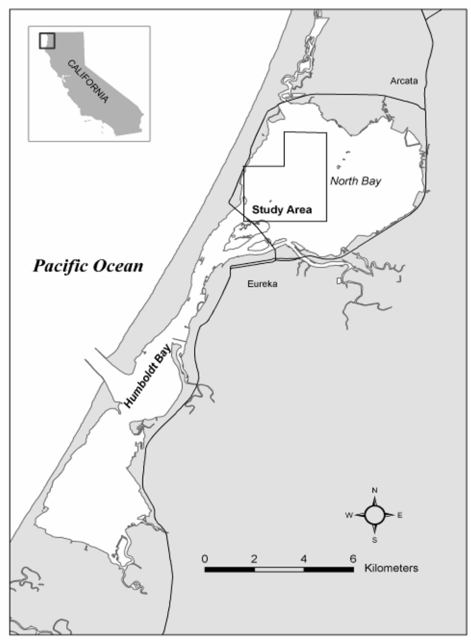

Figure 1. Study area is located in Humboldt Bay

Data sources

Navy Research Laboratory Portable Hyperspectral Imager for Low Light Spectroscopy II (PHILLS II) sensor (Davis et al., 2002) acquired imagery at high tide. The image has 122 bands ranging from 421nm to 966nm, each approximately 4.5nm in width. Florida Environmental Research Institute (FERI) carried out the flight and image preprocessing.

A bathymetric data fusion product developed by CICORE-Moss Landing combined Topographic LIDAR (EarthData, 2002), multibeam sonar (CICORE, 2006), and single beam sonar (USACE, 2005) into one GIS raster which was used to model water depth.

Data Preparation

Imagery was subset by flight line, and for each image subset, an inverse minimum noise fraction algorithm was executed. Using the CICORE bathymetric product, areas in which the elevation was too high (>.67m MLLW) or too low (<-1.5m MLLW) for eelgrass growth were masked out and excluded from the analysis.

Determining water depth. Using NOAA CCAP tidal stations, water depth was calculated at each station for the time of each flight line. In ArcGIS 9.1 (ESRI, Redlands, CA 2006), tidal height was modeled over the entire bay using inverse distance weighting from the entrance to the extent of each bay. Map algebra allowed the combination of this raster with the bathymetry fusion to calculate water depth for each 5m grid cell. The image was spatially subset into two water depth classes 2-3m and 3-4m. Four separate classifications were carried out, one for each of the two flight lines and one for each of the two spatial depth subsets.

Eelgrass spectral curve definition. Within each image subset, a single region of interest (ROI) was created in ENVI where dense eelgrass was known to exist. The mean value from this ROI was imported into ENVI's endmember collection file to be used as a reference spectrum.

Classification

ENVI's multi-range spectral feature fitting (MSFF) (Clark et al., 1991; Clark and Swayze, 1995) algorithm was used to select consecutive regions of the spectrum ranging from 476 nm to 589 nm. The five ranges selected were from 477nm to each consecutive peak (477, 500, 519, 533, 565, and 589).

In MSFF, each pixel is evaluated separately, and each represents a “test” spectrum. A least squares algorithm is used to calculate the fit between the test and reference curves by comparing the difference in feature depth in the reference curve and the depth in the test curve. Higher values correspond with test curves that are more like the reference curve for a certain spectral range. These spectral ranges are evaluated separately and a cumulated rules image corresponding to goodness of fit to the reference spectrum is generated. The calculated raster was imported into ArcGIS, where comparison with known areas of eelgrass presence and absence to determine cut-off points. Our knowledge of eelgrass presence and absence came from previous field work surveys for eelgrass along with previous eelgrass classifications. The cut-off points were not statistically derived, rather from visually assessing the image. Statistical ranges were reclassified as eelgrass present or eelgrass absent.

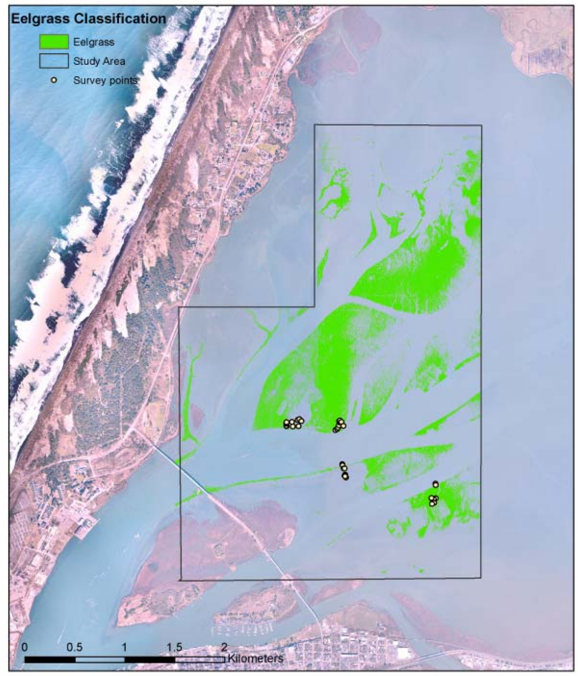

Figure 2. Eelgrass classified as present in MSFF study area

Accuracy Assessment

Prior field eelgrass surveys were used for assessing the accuracy of the image. Selected surveys were conducted within a year of image acquisition to minimize the difference in eelgrass distribution. In Humboldt Bay, eelgrass is always present, though plant biomass may change throughout the seasons. Therefore, presence/absence of species should be spatially consistent with the exception of plants that were uprooted during winter storms. Surveys were evaluated against mapped distribution from MSFF classification. In addition, they were compared with a separate spectral angle mapping classification attempt. The spectral angle mapping (SAM) classification only was done in one of the two flight lines, so fewer ground truth points were available for the comparison.

RESULTS AND DISCUSSION

Classification Results

A total of 1.9 km^2 of eelgrass was classified in the study area (Fig. 2), with an estimated 81.25% accuracy to field surveys (Table 1). Comparison with the spectral angle mapping (Fig. 3, 4) output shows an improvement of the classification product in deep water (Table 2).

Discussion

Ability to map features at deeper water depths. The most promising result is improved classification of SAV in optically deeper waters (whether they actually are deep in the water column or whether light attenuation is rapid), through targeting portions of the spectrum which are unique and are less rapidly attenuated. As far as the MSFF technique, there are two key differences with the SAM classification. First, classification was limited to the blue and green ranges of the visible spectrum, and second, the SFF algorithm was used instead of the SAM algorithm.

Table 1: MSFF Classification Accuracy

Classified Eelgrass Distribution	**Observed Eelgrass Distribution**			
	Eelgrass Present	Eelgrass Absent	Producer’s Accuracy	
Eelgrass Present	14	2	87.5%	
Eelgrass Absent	4	12	75%	
User’s Accuracy	77.8%	85.7%		
		Total Accuracy		81.25%

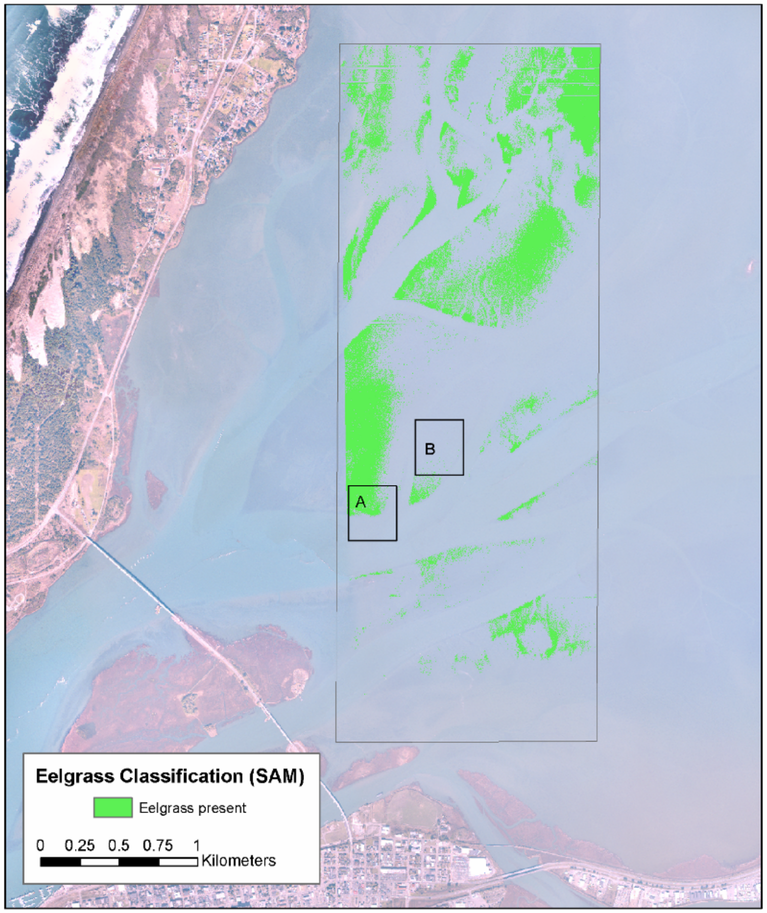

Figure 3. The technique used to map eelgrass presence in South Bay, Spectral Angle Mapping and image subset by water depth has problems classifying eelgrass in deep water, where separability is difficult. In South Bay, poor classification was seen below 7.5ft of water. In North Bay, some areas like in box A are over classified, while other areas, as in box B, are underclassified. Water depth ranges from 7.5 to 11 feet over the eelgrass beds in this study area.

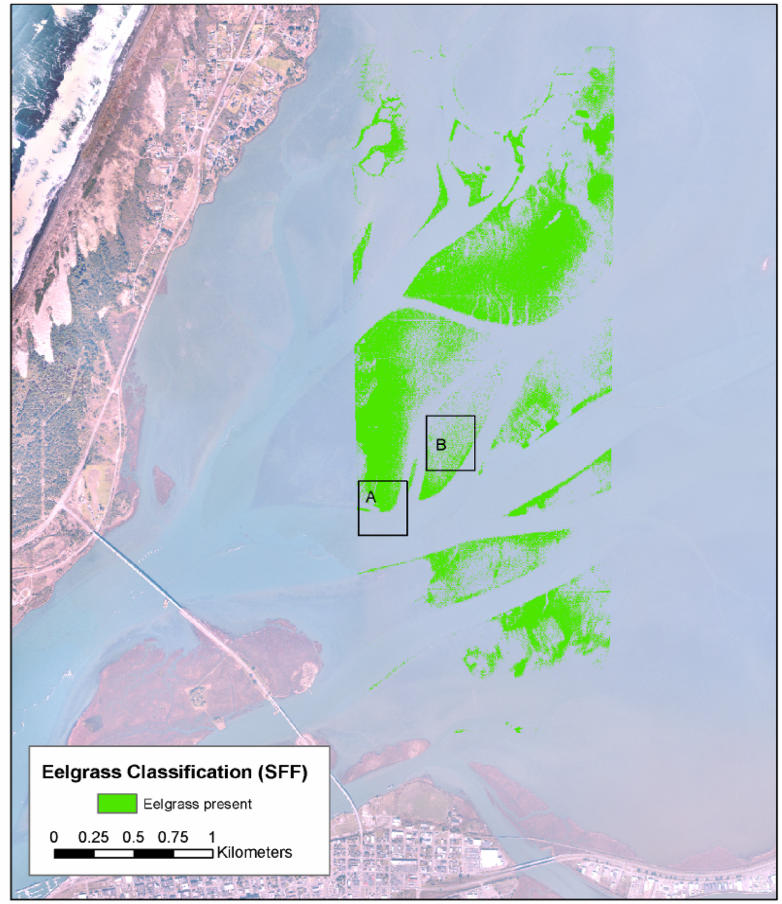

Figure 4. Multi range spectral feature fitting algorithm for the same area. By looking at only a portion of the spectral curve, improved discrimination was achieved in both (A) and (B).

In most classification schemes, features are mapped by statistical distance. In the marine environment, as optical depth increases, total variance within the image dataset decreases. Different wavelengths have different extinction coefficients, and the total variance within the red/infra-red range will diminish quicker than in the blue green range. If the entire spectral curve is considered in the classification scheme, as with the Spectral Angle Mapping attempt, poorer classification results will occur as depth increases. Disparate targets will be statistically close to one another in that range of the spectrum, though they may not be so close in the slower attenuated blue/green range and will be classified in one group. By focusing on ranges that are least effected by attenuation, an improved classification was attained.

Although classification accuracy improved in deep waters over the SAM classification (83% to 54% in select area), at shallower depths (>2m of water) the SAM classification had better accuracy (Judd, 2006). By using only portions of the spectral curve, in the MSFF algorithm, it is likely that valuable information for classification was eliminated. One example in this classification are the areas of line cultivation for oysters, seen in the lower right of the image as square barren boxes. In these oyster cultivation areas little eelgrass grows, but algae covers the oyster lines. It is possible that the two false eelgrass present classifications seen in the MSFF algorithm mistakenly classified algae as eelgrass.

Table 2: Comparative Classification Accuracy

Classification Type	**Classified Eelgrass Distribution**	**Observed Eelgrass Distribution**	
		Eelgrass Present (15 samples)	Eelgrass Absent (9 samples)
MSFF	Eelgrass Present	13	2
	Eelgrass Absent	2	7
		Total Accuracy	83.3%
SAM	Eelgrass Present	5	1
	Eelgrass Absent	10	8
		Total Accuracy	54.2%

Sources for potential error and improvement

As bathymetric data was initially used with both subsets to limit the analysis to the short vertical range that eelgrass is found, some areas of the image that had been misclassified as eelgrass by other classification techniques was eliminated. Two sample points were taken in areas which were estimated to be elevationally too high for eelgrass growth. Of course, the field work in both cases found algae rather than eelgrass there. We did include those two data points in our accuracy assessment, correctly predicting eelgrass absence when indeed absent. It was our thinking that since the elevation modeling was part of this technique, the improvements that were seen from the bathymetric fusion product should also be included. Excluding these points would yield an accuracy of 81% for MSFF and 50% for SAM. It is probable that more sample points in more spatially diverse areas would improve this accuracy estimate. The sample points were taken in easily accessible areas for another eelgrass biomass survey. These areas also are where the interface between eelgrass and non-eelgrass occurs.

CONCLUSION

Multi range spectral feature fitting provides a promising classification technique for vegetation in deep or optically deeper water. By focusing on ranges of the visible spectrum least affected by light attenuation, improved discrimination of bottom types was seen. However, in shallower water depths, SAM classification was more accurate.

In this study, the specific ranges for the SFF classification were chosen by noting visually which ranges appeared unique for eelgrass. However, these ranges were not chosen statistically. It is possible even probable that by evaluating potential ranges for separability, improved classification could be reached. In addition, the cut-off points for classifying the statistic SFF image as eelgrass/noneelgrass areas was also done by visually evaluating the results. By using a formal statistical analysis to derive cut-off points, an improved classification accuracy may be seen. Future studies which investigate or incorporate an algorithm to select the best spectral ranges may increase accuracy.

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