ASSESSING THE UTILITY OF MULTISPECTRAL REMOTE SENSING FOR HABITAT MANAGEMENT: LESSONS LEARNED FROM HIGH RESOLUTION NEARSHORE VEGETATION MAPPING IN WASHINGTON STATE

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Introduction

A centerpiece of restoring and protecting coastal ecosystems lies in determining how best to inventory resources and monitor trends. Multispectral remote sensing is often considered for mapping vegetation and other habitat characteristics because it provides a synoptic snapshot that can be classified according to spectral properties. Remote sensing technologies has been applied extensively in forested and agricultural environments. However, the coastal fringe poses a unique set of environmental and technical considerations.

Environmental considerations such as tidal height, cloud cover and vegetation patch size often limit the utility of conventional satellite-based sensors such as LANDSAT TM and SPOT. Additionally, satellite sensor bandsets are not optimized for differentiating marine vegetation. In contrast, airborne sensors can capture high resolution data at times of low tide and minimal cloud cover. The Compact Airborne Spectrographic Imager (CASI) sensor has been identified through marine mapping projects as a preferred method for marine vegetation census (e.g., Mumby et al. 1997). CASI can be deployed from a small plane, and its bandset can be programmed to differentiate features of interest. It has been used primarily in small study areas. While many studies differentiate vegetation types, other research suggests that it is difficult to consistently distinguish the spectra of different species.

This project reviewed research to date and identified the optimal multispectral methods for mapping marine vegetation over hundreds of miles in a temperate environment. We then applied the methods to map shoreline vegetation in Puget Sound. In contrast to previous research, this project focused on management applications of multispectral remote sensing. It tested the ability of the methods to produce an inventory of multiple vegetation types over a large area.

Methods

The Nearshore Habitat Group used CASI sensor data to classify 340 miles of shoreline vegetation during two successive inventory projects in 1995 and 1996. This paper summarizes methods and results for the 1996 data set. For a full discussion of methods and results, see Berry & Ritter (1997) and Ritter and Berry (1999).

Classification Categories

Eight nearshore vegetation types were identified for multispectral classification: eelgrass, brown algae, kelp, green algae, mixed algae, salt marsh, spit and berm vegetation, and red algae. These vegetation types encompass most common macroscopic vegetation found along Puget Sound=s shorelines. The vegetation types were selected largely by spectral discrimination considerations (Aitken *et al.*, February 1995).

Resource management priorities led to the selection of some vegetation classes despite discrimination difficulties (e.g., Washington Administrative Code (WAC) 220-110-250; WAC 365-190-080; DNR POL-0300; Wyllie-Echeverria et al., 1994). Kelp and other brown algae have similar dominant pigments and often a similar spectral signature. However, the inventory needed to differentiate kelp from other brown algae because of its recognized ecological function (e.g., Dayton, 1985; Wheeler, 1990). Although both green algae and eelgrass contain chlorophyll *a* and *b* and have a similar spectral profile, the functional importance of eelgrass habitat required that they be differentiated (e.g., Phillips, 1984). Green algae can be an indicator of other processes such as eutrophication. Salt marsh and spit or berm communities are often narrow and obscured by overhanging vegetation, making discrimination difficult. Despite spectral and spatial discrimination challenges, the salt marsh, and spit or berm categories were included due to the recognized functional importance of wetlands (e.g., Seliskar & Gallager, 1983), and because habitats at the land-water interface tend to be impacted highly by development.

Field Data Collection
Field data were collected for two purposes: (1) to guide the image classification process, or (2) to assess classification accuracy. Field data were collected throughout the study area when tides were below +1.0 mean lower low water (MLLW), between June and September in 1996 and 1997. The minimum mapping unit (MMU) was approximately 13 feet (4 meters).

Field data were collected by boat or on foot. Field sites that had a total vegetation cover greater than 25 percent were recorded as vegetated sites. Vegetation class assignments were based on the dominant vegetation category at a site, i.e., the vegetation class comprising 75 percent or more of the vegetated area. Information on vegetated sites were located by either differentially corrected Global Position System, or annotated aerial photographs with transparent overlays. Sites were represented as points, lines, or polygons depending on patch shape and location.

Imagery Acquisition
Digital CASI imagery and simultaneously collected color infrared photography (at 1:11,000 scale) were acquired by Borstad Associates. The instrument was operating in spatial mode, programmed with a custom, 11-channel bandset optimized to differentiate nearshore temperate vegetation (Borstad, 1996).

The CASI system was mounted in a Cessna T210 aircraft. All flight lines were flown at a 10,800' altitude, from south to north, with 50% sidelap between adjacent flight lines. Flying in a consistent direction reduced radiometric discrepancies due to sun angle and sensor viewing angle. Image acquisition dates were selected based on maximum intertidal exposure (minus 1.0 foot mean lower low water or below), and times when sun angle would reduce sun-glint. Imagery was acquired at an approximately 169 square feet (16 square meters) spatial resolution on July 14, 15, and 30, 1996 during low tides.

Image Processing and Analysis
Imagery was adjusted to surface radiance by applying an atmosphere correction, corrected for roll, pitch and yaw and projected into geographic coordinates using DGPS data to yield 169 square feet (16 square meters) pixels (Borstad, 1997). The resulting imagery was warped to fit DNR's orthophotos and coastline vectors. The rectified flight lines were mosaicked into eight, non-

overlapping blocks, requiring 1174.1 MB of disk space.

The imagery was classified using Imagine 8.3 software (ERDAS, Inc., Atlanta, GA) on a Sun workstation (Sun Microsystems, Inc., Mountain View, CA). Classified files were produced using an iterative, hybrid approach to classification, combining unsupervised and supervised methods. The supervised processing relied on the field data (e.g., DGPS-located sites and annotated photography) to develop training signature sets.

Classification Accuracy Assessment

Classification accuracy was assessed by comparing the classified image to a set of field sites (reference data) that had not been available to the image analysts during classification. Approximately one-third of all field sites were assigned as reference data for accuracy assessment. Reference data were chosen so they were a representative subset of all field sites, spread throughout the study area. Because assessment sites included line and polygon features composed of multiple pixels, establishing 'correctness' was not always a >all or none= decision. Sites that were 34%-66% correctly classified received partial credit.

Generalization & Conversion

The classified raster image was converted to vector format to facilitate use in ArcView. Data generalization was used to reduce the number of features and vertices in the coverage to a manageable number. The objective of the generalization was to simplify the coverage while maintaining the salient characteristics of vegetation features at an appropriate scale. A series of evaluation criteria were applied to significantly decrease the number of features and vertices, while minimizing associated changes in total acreage and in the visual appearance of the data.

Results and Discussion

A total of 230 miles of shoreline were mapped in 1996.The imagery was rectified to within +/-3 pixels (approximately 40 feet) in most parts of the imagery. Eelgrass was the most common type of vegetation by acreage. The majority of eelgrass is found in two extensive shallow embayments, Padilla Bay and Samish Bay. Green algae was the second most common vegetation type, followed by salt marsh, brown algae, kelp, spit or berm vegetation, and red algae.

Classification Accuracy

Overall accuracy for the classified image was 86.4%. Classification accuracy for each land cover type was analyzed using producers and user=s accuracy estimates (Table 1). Producer's accuracy is the probability of a reference site being correctly classified, i.e., a measure of omission error. It is the number of sites correctly classified as a land cover divided by the total number of reference sites for that land cover. User's accuracy indicates reliability, or the probability that a site classified on the image is really that land cover type on the ground. It is the number of sites correctly classified as a land cover divided by the total number of sites classified in that category (Congalton, 1991).

Table 1. Producer's and User's Classification Accuracy Percentages by Land Cover Type for the Skagit County Study Area.

	Classification Accuracy	
Land Cover	**Producer's %**	**User's %**
brown algae	78	87
green algae	75	87
kelp	96	95
mixed algae	83	79
eelgrass	84	91
salt marsh	96	94
spit or berm	74	99
unvegetated	100	72

Accuracy rates for individual vegetation types are encouraging with respect to prospective data set uses. Eelgrass, kelp and salt marsh vegetation, which are important to land-use related decision making, had generally high accuracy rates. For most of the vegetation types, the User's Accuracy was higher than the Producer's Accuracy, pointing to a trend of omitting a vegetation feature from the classification (an omission error), rather than confusing it with something else (a commission error). Multiple factors may have contributed to the pattern of higher omission error. The analyst=s training signatures used in the statistically-based classifier may not have represented the population. The percent cover threshold for a vegetated site (25 percent or greater) may have been too low at the lower limit for consistent detection. Temporal changes in vegetation could have occurred between the time at which the field data were collected and the time at which the multispectral imagery was collected.

Some accuracy rates reflect weaknesses in the methodology with respect to specific land cover types. Unvegetated areas had the highest Producer=s Accuracy and the lowest User=s Accuracy rates. We attributed the high Producer=s Accuracy to the capability of the method to correctly identify the completely unvegetated field sites. The low User=s Accuracy rate results from the frequent classification of portions of vegetated field sites that are transitional or have low densities of vegetation as unvegetated.

Spit or berm vegetation had the highest User=s Accuracy and the lowest Producer=s Accuracy rates. This vegetation type was most often incorrectly classified as unvegetated, and also mis-classified as other various vegetation types. This result reflects the inherent weakness of current methods to detect spit or berm vegetation. Spit or berm vegetation is commonly a narrow linear feature with low vegetative density, and often obscured by overhanging vegetation. Other vegetation types were rarely classified as spit or berm vegetation, leading to a high user=s accuracy.

Mixed algae had relatively low Producer=s and User=s Accuracy rates. Confusion between mixed algae and other vegetation types was expected, given that mixed algae is a combination of multiple vegetation types. Mis-classification could have been due to differences in the relative contribution of vegetation types to the overall spectral signature or to temporal changes in species composition. Despite these discrimination difficulties, the mixed algae category is important to describe the common phenomenon of varying species composition in a manner that keeps the number of classification categories tractable.

Green algae had a low Producer=s Accuracy rate. We attribute this to the relatively ephemeral character of green algae in comparison to the other vegetation types. Green algae commonly grows intermixed with eelgrass, in these cases the areas were classified as eelgrass because eelgrass is the more persistent vegetation and is protected by regulation.

Salt marsh and spit and berm vegetation communities are separable from the macroalgae and eelgrass mainly because they contain emergent vegetation and the spectral signatures more closely resemble terrestrial vegetation (Aitken *et al.*, June 1995). Intertidal zonation is another important spatial cue, since these vegetation types occur in the upper intertidal and supratidal zones. To differentiate salt marsh and spit and berm communities from other terrestrial vegetation, the upland areas of non-interest were masked.

Detecting submerged vegetation was difficult. Spectral discrimination of submerged vegetation is influenced by a number of environmental conditions such as, water depth, surface roughness, water clarity and bottom type. Water attenuates the spectral response of submerged features. The longer wavelengths, e.g., near infrared, are absorbed in a few tenths of a meter of water (Lillesand and Kiefer, 1994). The water clarity and surface conditions of Puget Sound further hampers identification. Although the submerged feature is apparently vegetation, the vegetation type is not evident.

Field Data

Approximately 1,500 field data sites were collected during 30 days of field work. We found the photo annotation to be the preferred method because it was the most rapid to collect, and it was robust to positional accuracy issues in the imagery. Some field sites had to be disqualified because they did not meet the minimum mapping unit, the vegetation was obscurred, or seasonal changes in vegetation type were possible given the date of field data collection.

Data Generalization and Conversion

A variety of data generalization techniques were evaluated. After considering the impacts of different alternatives on total acreage and on visual appearance, features with an area fewer than four pixels (approximately 680 square feet) were eliminated. The elimination changed the total area by less than 5 percent, and decreased the total number of features by 58%. In determining the size of features to eliminate, the effect of elimination on visual appearance turned out to be more important than the effect on total vegetation area because the size distribution of vegetation features was weighted towards the small class sizes. While the generalization did not significantly affect the areal extent of vegetation, it changed the frequency distribution of size classes. As a result, the visual appearance of the coverage could change markedly without a corresponding change in area. The narrow, linear vegetation features were most affected by area elimination thresholds.

Conclusions

Our program completed the first large area temperate vegetation mapping project that we know of using high resolution remote sensing methods. Through designing an operational program, we learned much about the strengths and limitations of this methodology in Northwest shoreline environments. Fundamental lessons include:

1. The research question needs to drive the selection of methods. We had two questions: What is

the abundance, distribution and character of vegetation types?; and How are they changing over time? CASI was successful at answering the first question. The multispectral data set provides highly detailed information on resource abundance and distribution, higher than comparable photo-interpreted inventories. It differentiated vegetation types in intertidal and shallow subtidal areas with good patch detail. The total project costs impacted our use of the technology. We have confined the use of multispectral technology to priority areas. For synoptic mapping, we adopted less detailed, helicopter-based survey techniques.

We concluded that multispectral data would be less successful at addressing our second question, change detection, because many of our vegetation types of interest extend into the subtidal zone beyond the water penetration capability of CASI. We are using underwater technology to capture temporal trends in vegetation beds that extend into the subtidal zone. While underwater remote sensing methods capture the subtidal extent of beds, upper intertidal vegetation is difficult to measure and total area covered may be smaller.

2. Integrated expertise is essential to program success. Environmental considerations and technical complexities made it essential for marine scientists, remote sensing specialists, and GIS staff to work together closely. This integrated group was able to evaluate the technical issues and their ramifications on the project as a whole. We encountered technical issues and made trade offs during each phase of the project.

3. Data distribution is important, and problematic. In order to streamline distribution, data and supporting information were made available on CD-ROM in multiple digital formats. Regardless, many potential users lacked the necessary equipment or training. Distributing paper maps proved to be essential in order for many people to be able to use the information in land use planning. We are now planning a Web-based map server, this technology may provide the optimal distribution method for our program data to non-technical users.

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NOTICE

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