Assessment of Estuarine and Nearshore Habitats for Threatened Salmon Stocks in the Hood Canal and Eastern Strait of Juan de Fuca, Washington State: Focal Areas 1-4

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Introduction

To better manage estuarine resources, it is important to develop a detailed understanding of the ecological processes and interactions that control and regulate populations of organisms, such as anadromous salmon (*Oncorhynchus* spp.) of the Pacific Northwest (PNW), that depend at some point in their life history upon the integrity of estuarine habitats. In Hood Canal and the Strait of Juan de Fuca, there is considerable evidence (Ames *et al.*, 2000) that juvenile summer chum salmon (*O. keta*) rely on "natural beaches, eelgrass beds and unimpacted drift cells to provide productive, protected migratory corridors" as they transition from river delta rearing areas to open-water (Simenstad, 2000). Eelgrass beds form a nearly "continuous band" around the lower intertidal and sub tidal regions of Hood Canal from depths of about +1.8 m to –6.6 m (Phillips, 1984). Many factors can affect the quantity and structure of Hood Canal's eelgrass beds and beaches including: filling, excavation, jetty construction, shoreline development (e.g., bulkhead and dock construction), vegetation destruction (Simenstad, 2000), and eutrophication. In turn, these factors can also affect the fitness of migrating salmon at multiple, interacting spatial and temporal scales (Cracknell, 1999; Simenstad and Cordell, 2000; Simenstad *et al.*, 2000) making it difficult to predict the consequences of these perturbations. Fortunately, emerging remote sensing and geographic information system (GIS) technology provide new analytical and visualization tools that allow fisheries scientists/managers to integrate multiple spatial data sets over large geographic areas, thereby achieving a landscape perspective appropriate to managing fish habitat. Perhaps for the first time, it is possible to develop spatial data sets for relative large areas based on

remotely sensed data which describe eelgrass habitat structure at the spatial scales over which salmon respond (~ 1 to 5 m).

Limitations of Remotely Sensed Data

There are limitations, however, in using remote sensing data to tackle important ecological questions in coastal ecosystems. Despite the relatively widespread availability of remote sensing data, it has been used less successfully in coastal areas than for ocean or land applications (Cracknell, 1999). Until recently, projects that relied on space-borne remote sensing were limited to relatively coarse spatial resolutions (i.e., Landsat-MSS, 80 m; Landsat-TM, 30 m; SPOT, 20 m) and infrequent return intervals (16 days for MSS and TM, from 1-5 days on SPOT due to pointing capability). Frequent cloud cover, coastal fog, and tides also limit the use of remote sensing at the land-sea margin. Limitations affecting precise timing of image acquisition is particularly restraining when assessing estuarine and marine intertidal habitats because they are only detectable during the restricted period of extreme low tide exposure.

The limited spectral resolution of widely available sensors represent yet another challenge to mapping seagrasses. Spectral band sets available in space-borne and many airborne sensors do not provide the spectral resolution necessary to discriminate between co-occurring plant species. In assessing the quality of eelgrass beds as salmon habitat, it is important to distinguish between eelgrass and other submergent vascular plants or algae; for example, spectrally similar, and often co-occurring green algae may be indicative of excessive nutrient loading and poor habitat (Alberotanza *et al.*, 1999).

Use of Remotely Sensed Data to Assess PNW Estuaries

In spite of the difficulties in using remotely sensed data to assess coastal environments, satellite imagery has been used to map estuarine land cover in PNW estuaries with some success. For example, Landsat-TM imagery (and other available data) were used by NOAA to map 14 landcover classes along the Columbia River and Willapa Bay as part of the Coastal Change Analysis Program (C-CAP) program (1997). C-CAP is the first national program to place a priority on submerged aquatic vegetation (Ferguson *et al.*, 1995). Although C-CAP typically achieved minimal mapping units of ~1 ha, some of the coastal cover classes were not readily separated with the Landsat-TM bands (Ferguson *et al.*, 1995; Spell *et al.*, 1995; Klemas, 2001). Ward *et al.* (1997) also used Landsat-TM to map eelgrass (*Zostera marina*) meadows in Izembek Lagoon, Alaska, although they too could not discriminate between two co-occurring habitat cover types, i.e., eelgrass and green algae. While useful in creating broad-brush descriptions of coastal vegetation and substrates, better spectral and spatial resolution are necessary to resolve many fine-scale ecological patterns believed to be important to PNW salmon (e.g., use of eelgrass beds for food, cover and migration).

Previous studies have used airborne multi- and hyperspectral sensors to develop GIS coverages describing patterns in the abundance (density) and distribution of eelgrass in PNW estuaries. Strittholt and Frost (1996) used an airborne, 3-band prototype sensor to map eelgrass in Tillamook Bay, OR. They collected 181 images at 1-m spatial resolution from intertidal and shallow subtidal habitats during a summer low tide series. They successfully geocorrected and mosaicked images; however, they were unable to

discriminate between two species of eelgrass and between eelgrass and green algae because the 3-band imagery lacked the necessary spectral resolution. More recently, Washington DNR used 11-band Compact Airborne Spectrographic Imager (CASI) imagery along 547km of Puget Sound to map eelgrass beds and seven other habitat types at a spatial resolution of 4m (Ritter *et al.*, 1996; Berry and Ritter, 1997). Overall classification accuracies were 76% for the 1996 study and 86% for the 1997 study. Eelgrass cover (defined by the authors as *Z. marina*, *Z. japonica*, *Phyllospadix* spp. and *Ruppia maritima*) in the Puget Sound study was correctly classified 82%-91% of the time. Like the study by Ward *et al.* (1997) in Izembek Lagoon, eelgrass was not distinguished from co-occurring species in the WADNR studies.

The Nearshore Habitat Program, Washington Department of Natural Resources used airborne videography to map saltwater shoreline habitats in Washington State from 1994-2000 (Berry *et al.*, 2001). Videography was collected during low tides from a helicopter and the video image was spatially referenced with GPS. Unlike the projects described above, spatial shoreline data sets were not constructed through direct image analysis. Rather, spatial data sets were created through interpretation of the images, the accompanying commentary (recorded by experts onboard the aircraft during image acquisition), and follow up site visits. Nearshore habitats were then mapped to geomorphologically defined units. The average unit length in the Shorezone Inventory data set for Hood Canal was 2,255 m (min 64.5 m and max 22,969.5 m) and most (>60%) were between 1000-2000 m.

Goals of the Current Study

Recognizing the important ecological role that long, relatively thin (~1-5 m) eelgrass corridors play in juvenile summer chum salmon (*Oncorhynchus* spp.) migration in Hood Canal, and the limitations of space-borne remote sensing platforms, we initiated this study to determine (1) if it is feasible to develop eelgrass habitat coverages at a spatial scale of 1-2 m using a CASI sensor; and (2) if we could differentiate between spectrally similar, co-occurring vegetation (i.e., eelgrass and green macroalgae). The broader purpose of this study is to relate the landscape structure of the intertidal eelgrass to shoreline modifications as a quantitative index of essential habitat quality for migrating juvenile summer chum salmon. In this respect, the fine grain resolution was necessary in order to relate the intertidal landscape structure to the behavior and ecology of these small fish. Since we planned to incorporate resulting data into GIS, we were also interested in determining if the CASI imagery (a two-dimensional, charge couple device, array based push broom imaging spectrograph) could be geometrically corrected to approximately the same spatial scale as the image resolution. (~5- 10 m).

Materials & Methods

We collected 19-band CASI imagery (Table 1) along the shoreline of Hood Canal during (+/- 3 hr) a spring low tide series from 29 June to 5 July 2000. Generally, CASI was set to record spectral bands 10 nm wide except for two bands: band 1 was set to a width of 30 nm, and band 19, which was 20 nm wide, to increase sensitivity. The CASI sensor, operated by Hyperspectral Data International, Inc. (HDI), was mounted in a factory

installed camera port on a DeHavilland Beaver, operated by Ecotrust; all imagery was collected in spatial mode. By flying the aircraft at an altitude of 1,140 m Above Ground Level (AGL) at approximately 176-183 km hr^{-1}, we achieved a pixel size of 1.5-m and a ground track of approximately 768 m. Effects of downwelling light were removed from the CASI data by HDI using measurements from the incident light sensor; HDI also geometrically corrected the CASI data using filtered attitude data. CASI data were supplied to Earth Design Consultants, Inc. in ERDAS® LAN format.

Table 1. Band settings for CASI hyperspectral sensor used to map intertidal cover of Hood Canal, Washington, shoreline in June/July 2000. Band settings were based, in part, on measurements made with a hand-held radiometer (see text). Bands were selected to maximize separation of spectrally similar vegetation.

CASI Band	Upper (nm)	Lower (nm)		CASI Band	Upper (nm)	Lower (nm)
1	460	490		10	650	660
2	520	530		11	690	700
3	530	540		12	700	710
4	540	550		13	720	730
5	550	560		14	730	740
6	560	570		15	755	765
7	620	630		16	765	775
8	630	640		17	775	785
9	640	650		18	785	795
				19	800	820

Ground Control Points & Training Data

Field teams placed 3-m X 3-m plastic tarps, visible in the CASI imagery, along the shoreline (Figs. 1a, b). Position of each tarp was measured with a Trimble® Pathfinder ProXR real-time differential Global Positioning System (GPS). On-ground reflectance spectra from selected, monotypic habitat strata were measured at the time of CASI flight at 8 nm intervals from 380 nm to 780 nm using a Photo Research, Inc.® PR-650 hand-held

radiometer (Fig. 2). Five replicate measurements were made from each habitat stratum under ambient light conditions. A spectral library was constructed and used to select CASI band combinations for supervised classification (Table 1).

We selected representative intertidal habitat types as training sites from large, relatively monotypic patches representing varying proportions of eelgrass or other habitat types. We collected cover data from 147 training sites located throughout Hood Canal[1]. In order to precisely locate training sites in the imagery, field teams placed training sites within 10-100 m of ground control point (GCP) tarps and measured the center and corners of each tarp with GPS. At the time of sampling, training sites were assigned one of ten cover classes: (1) dense eelgrass [32[2]], (2) sparse eelgrass [15], (3) green algae [27], (4) mixed algae [7], (5) subtidal brown algae [5], (6) sand flat [18], (7) gravel beach [10], (8) mudflat [11], (9) mixed sand/gravel [21], and (10) drift material [1][3]. Percent cover by eelgrass and other vegetation/substrate classes was estimated both visually using a sample grid (Fig. 3) and, at a later time, from projected digital camera images from within five randomly selected 2.25m^2 (1.5-m X 1.5-m) quadrats from within a 6-m X 6-m (16 cell) sampling grid. We collected real-time differentially corrected GPS data (+/- 0.5 m) at the corners of each grid. Grid cell digital photographs were analyzed by the Wetland Ecosystem Team (WET) at the University of Washington by superimposing a 100-point grid on the image and then counting the intertidal habitat types intersecting each point.

[1] Not all training sites were located within the flightlines processed. Training sites located within each focal area were used directly in that focal area's classification; however, we did use spectral signatures from the other training sites for comparison.
[2] Number of training sites for which data were collected are shown in [ ].
[3] These classes were subsequently revised.

Data on eelgrass shoot density (shoots per 0.1-m quadrat) was also collected from each of the five randomly selected quadrat plots and analyzed by WET.

Geometric Correction

Although HDI geometrically corrected the CASI data, we were interested in improving upon spatial accuracy, if possible. In addition to the GCP tarps, we also located conspicuous, permanent features (i.e., building corners, piers, road crossings, etc.) from digital orthoquads (DOQs). For flightlines in one focal area, teams returned to the field with the CASI imagery to measure locations of additional control points visible in the imagery. We used ERDAS® Imagine to geometrically correct the CASI imagery by fitting the imagery to the control points using a 1st order polynomial model. Root mean square error (RMSE) was measured using seven to twenty-two GCPs for each flightline.

Image Classification

For our analysis, we selected for classification 19 flightlines in four focal areas, representing varying degrees of shoreline development and geomorphology along the shorelines of central Hood Canal (Fig 4). We classified the CASI imagery using a combination of unsupervised-supervised classification. Initially, we performed an unsupervised classification (ISODATA, 12 iterations, 95% convergence, 100 classes) on the 19-band, georeferenced imagery using ERDAS® Imagine® software, which resulted in 100 spectral categories. Following the collection of signatures in ISODATA, the 100 spectral classes were subjected to a Maximum Likelihood Classification. During a 1999 pilot study (Garono *et al.*, 2000), we found that we could only use a maximum of four

CASI bands in a supervised classification when extracting spectral signatures from 5-m X 5-m training site grids. Limitations of the classification algorithm made the use of only four bands necessary. The use of more than four bands would have resulted in a classification that was unsatisfactory due to the training grid (5-m X 5-m) size relative to our 1.5-m pixels. Based on the pilot study, we concluded that we needed to have more and slightly larger training site grids. Therefore, the supervised classification in the current study was performed on spectral signatures extracted from 6-m X 6-m training site grids (Fig. 3) for four CASI bands (2, 8, 16, and 18: Table 1). We selected these bands based, in part, on information collected with the hand-held radiometer to maximize the separation of *Z. marina* from other habitat classes. In order to avoid positional error inherent in long flightlines, we selected small subsets of the images around targets and training sites from the flightlines and aligned them exactly to the recorded GPS location of the associated target (Fig. 1b). Signatures were extracted from these subsets and then applied to the full flightline images from which the subsets were cut. In most cases, training sites were situated between 10-100 m of GCP tarps; therefore, we were relatively certain of their position relative to the visible marker in the imagery. We excluded deepwater and upland areas from the classification and produced a new set of spectral signatures for eelgrass and other habitat types. Maximum Likelihood was used with the resulting signatures to group pixels that shared spectral characteristics.

Although we used trained volunteers to collect habitat cover data, WET found in a number of cases a discrepancy between the assigned habitat class and the cover data, and between the recorded cover data and the analysis of the digital photograph. In these cases, they used the results from the analysis of the digital photographs for the supervised

classification. Since field teams focused on sampling eelgrass, well over half (>63%) of the training data sets were collected at eelgrass sites in the flightlines analyzed. The relatively low number of training sites collected from non-eelgrass sites ultimately limited the number of habitat classes that could be resolved in our classification; however, mapping eelgrass was the primary goal of this project. Therefore, we expected the classification accuracy to be highest for the eelgrass habitat cover classes. Based on review of available training site data, we aggregated the 10 original cover classes into ten classes. These classes were 1) dense eelgrass, 2) sparse eelgrass, 3) green algae, 4) sparse green algae, 5) brown algae, 6) sand, 7) mixed sand/gravel, 8) gravel/cobble[4], 9) mixed algae, and 10) oysters[5].

Classification Accuracy

We assessed classification accuracy by revisiting areas from all flightlines and using our knowledge of the area. We tried two different approaches to quantify classification accuracy: one approach relied on field observations made at discrete points and the other relied on observations made along linear features. We returned to the field in May 2001 with the classified imagery from the first three focal areas and GPS units in order to record the identity of relatively large habitat classes visible in the imagery at discrete points. In May 2002, field crews used differentially corrected GPS to record the identity of cover classes along habitat boundaries (~50-100 m in length) identified in the Focal Area 4 imagery. We were careful to assess only those habitat classes that were not expected to have changed over the intervening time.

[4] The 'gravel/cobble' class was defined differently for FA4, than it was for FA1-3.
[5] Oysters were only mapped in FA1-3.

For a small area around the Hood Canal Bridge, we were able to quantitatively assess the accuracy of our eelgrass classification on a point-by-point basis using an independently-derived data set collected using a towed underwater video system (Woodruff *et al.*, 2002).

Results

We collected 145 overlapping flightlines ranging in length from approximately 0.9 to 20.0 km along most (~70%) of the shoreline (Fig. 4). Each pixel represented an area of 2.25 m^2 on the ground. Here we present results from the initial processing of 19 flightlines in four non-contiguous focal areas, covering approximately 84.3 km of Hood Canal shoreline.

Geocorrection

Though all flightlines were geometrically corrected using tarp GCPs and DOQs, we thought that GCPs collected by field teams using features visible in the CASI imagery could be used to further improve geocorrection. We found that although spatial error (RMSE) was reduced following geometric correction using additional GCPs, it was not improved sufficiently to warrant the additional expense of collecting additional field data (Table 2). Therefore, flightline geocorrection was accomplished using the initial set of GCPs for the remaining flightlines.

Table 2. Shown are length (m) and spatial error (m) following 1st order polynomial correction associated with 19 CASI flightlines from Hood Canal, Washington, June/July 2000. Control points derived initially from plastic tarp GCPs & DOQs. Several flightlines were geometrically corrected using GCPs taken directly from features visible in CASI image during subsequent fieldwork. Note: due to overlap of flightlines the total length of shoreline covered by all processed flightlines was ~84 km.

Focal Area	Flightline	Length (km)	RMSE (m) relative to target and DOQ GCPs	RMSE (m) using additional GCPs collected during subsequent fieldwork
1	2July26	2.5	5.0	2.1
	2July28	1.7	4.8	4.6
	4July29a	11.6	13.7	10.7
	4July29b	10.3	14.0	13.7
2	30June2	15.3	17.3	---
	4July23	15.8	23.5	---
	4July24	3.6	10.4	---
	4July25	2.23	7.5	---

3	5July42	2.8	9.5	---
	5July45	3.9	6.3	---
	5July46	7.4	9.8	---
4	2July08	4.4	4.3	---
	2July09	3.0	14.9	---
	2July10	5.0	7.7	---
	2July12	3.2	7.2	---
	2July13	2.7	3.0	---
	2July14	2.3	13.9	---
	2July17	2.1	11.2	---
	5July18	3.5	8.0	---

Classification

We found that the inter- and subtidal areas of the 19 flightlines were dominated by the dense eelgrass and sand habitat classes (Fig. 5a-e). Subsequent field checks generally showed that there was good agreement between classified eelgrass polygons and existing eelgrass beds. For the most of the other habitat classes, there was also good agreement except for the oyster bed cover class (Focal Areas 1-3) and the Brown Algae class (Focal

Area 4). Our inability to correctly separate oyster beds from wet sand/gravel/cobble and brown algae was most likely due to the relatively low number of training sites. In addition, ‘’sand’ and ‘mixed sand/gravel’ classes, separated in Focal Area 4, were combined in Focal Areas 1-3 primarily due to differing degrees of wetness. We did not pursue improving the classification of non-eelgrass habitat types since they were not the primary objective of this study.

We found that collecting data along 50-100 m boundary lines between adjacent habitat cover types generally worked better for accuracy assessment than collecting single GPS points from the middle of habitat patches. We attributed our success in using linear features over point features to the small spatial error inherent in the imagery: the lines were easier to place on the image than the points. Comparisons made along forty-one, 50-100 m lines in Focal Area 4 resulted in 83% of the habitat classes being correctly identified in the classified imagery.

Table 3. Area (m^2) of intertidal habitat cover classes from 19 CASI flightlines covering approximately 84 km of the shoreline of Hood Canal, Washington, June/July 2000. Note: the habitat cover classes were slightly revised for Focal Area 4.

Habitat Class	FA 1 Area (m^2)	FA 2 Area (m^2)	FA 3 Area (m^2)	FA 4 Area (m^2)
Dense Eelgrass	807,908	353,475	264,310	433,267
Sparse Eelgrass	87,318	309,758	21,314	162,704
Green Algae	90,675	67,100	85,597	79,700

Habitat Class	FA 1 Area (m^2)	FA 2 Area (m^2)	FA 3 Area (m^2)	FA 4 Area (m^2)
Sparse Green Algae	201,132	181,874	47,583	97,673
Brown Algae	8,501	140,882	0	61,301
Sand	542,484	845,640	369,279	717,732
Gravel/ Cobble	206,179	391,518	214,403	---
Mixed Sand/ Gravel	---	---	---	248911
Oyster	45,410	129,220	59,643	---
Gravel/ Cobble[6]	---	---	---	63,608
Mixed Algae	---	---	---	---

Due to the coincidence of an independent investigation of eelgrass in a shallow subtidal segment of our study area, we were able to compare results from this study and results from the independent eelgrass mapping study (Woodruff *et al.*, 2002). This study, conducted in January 2001, produced a GIS coverage of eelgrass beds using an underwater, towed video camera over a 2km length of shoreline. For the area where the two data sets overlapped, we compared the video trackline data to the classified CASI imagery by creating a 1.5m X 1.5m grid from ~1,950 video points. Although we expected

[6] Definitions of the 'gravel/cobble' class differed slightly between FA1-3 and FA 4. We plan to re-evaluate this class once the final focal areas are completed.

seasonal differences and differences in the position of the eelgrass blades (flat at low tide *vs*. upright in the water column at high tide) at the time of each survey, we found very good agreement (>90% of the points common to both data sets were identified as eelgrass) in the eelgrass classification where the two studies overlapped. Results from this comparison were consistent with what we observed using field data collected in YR2001/2002.

Discussion

Phillips (1984) reported that eelgrass beds formed a "nearly continuous band around canal [with] some very large meadows" based on his work done in the 1970's. Thom and Hallum (1991) summarized results from more recent field observations concluding that approximately 32% of the 295km Hood Canal shoreline had eelgrass present. Observational estimates of eelgrass presence may not entirely capture the consequences of eelgrass bed loss because as the beds become fragmented ecological processes in smaller, isolated patches may differ from those in larger patches (Hovel and Lipcius, 2001), especially when the behavior of juvenile summer chum salmon are considered (see Simenstad in (Ames *et al.*, 2000) and (Simenstad and Cordell, 2000). Describing eelgrass bed fragmentation patterns, at a scale appropriate for juvenile chum salmon, was not possible with the data that existed prior to this study. Without high resolution, spatially explicit data, it is difficult to quantitatively assess the change in the

extent and distribution of eelgrass in Hood Canal. Results from this study will make a more rigorous detection of change possible in the future.

We acquired CASI hyperspectral imagery for ~70% of the Hood Canal intertidal shoreline during a summer low tide series (Fig. 4). We have classified part of this high spatial resolution imagery to produce GIS layers depicting eelgrass habitat for 84 km of the shoreline. We were primarily interested in determining if we could acquire and geometrically correct remote sensing imagery at a spatial scale appropriate to juvenile summer chum salmon. The spatial data sets produced in this study are a necessary first step in developing an understanding of the current distribution and abundance of important eelgrass habitat. A spatial approach is important because habitat cover data can be combined with other data sets in a GIS to produce spatial models. Spatial models can then be developed that describe (and predict) the relationship between estuarine habitat cover and other estuarine features. For example, results from this study will become the foundation of a broader study to develop a quantitative index of essential habitat quality for migrating juvenile summer chum salmon. Quantitative metrics, based on the spatial distribution (landscape position) of eelgrass beds, describing the quality of estuarine habitat will be developed directly from the imagery. Relationships between these metrics and factors (e.g., shoreline development, geomorphology, etc.) believed to affect estuarine habitat quality can then be explored within GIS.

We have shown that 19-band CASI imagery can be collected at 1.5-m resolution and geometrically corrected to +/- 4.8m to 23.5 m RMSE using GCP targets and DOQ features visible in the imagery. Our results are similar to those of Clark *et al.* (1997) who used 8-band CASI imagery collected at 1-m spatial resolution to map seagrass beds in the

British West Indies. They concluded that 1m spatial resolution was sufficient to visualize and map bare areas ("blow-outs") within seagrass beds, which are indicative of bed dynamics. Mumby *et al.* (1997) also found high resolution, 8-band CASI capable of accurately monitoring seagrass standing crop and small scale (~10 m) beds dynamics; however, they caution that analysis at spatial resolutions on the order of 1m requires good geocorrection. In the PNW, our results were similar to those reported by Berry and Ritter (1997) and Ritter *et al.* (1996); however, we were able to separate *Zostera marina* from co-occurring species at a slightly improved spatial resolution. Undoubtedly, this improvement was due to our attention to intensely gathering eelgrass habitats almost to the exclusion of other estuarine habitat cover types. We have found that a remote sensing approach is not a substitute for fieldwork, rather remote sensing can be used to extrapolate a study-area wide habitat cover map from the relatively limited number of observations and measurements made by ground teams. Indeed, results from this study would have been strengthened by more field data.

Although our eelgrass classification matched up well with our knowledge of the study area and other available data, a more complete and quantitative assessment of classification accuracy could not be completed without additional information. Information contained in remotely sensed imagery is spectral: thematic significance is given to each pixel (or pixel group) through interpretation (Caloz and Collet, 1997). We recommend that both ground and aerial photography be taken at the time of CASI image acquisition. In our study, we found that we relied heavily on ground view digital photographs taken at each training site. As questions arose during image processing, it was possible to 're-visit' each training site using these images. We also found the DOQs

to be very helpful in establishing a landscape context for individual flightlines; however, we recognized that aerial photography or digital videography taken at the time of CASI image acquisition may have been even more useful as a concurrent view. Since the cost of satellite-base remote sensing scenes has decreased from $4,500 to $600 US during recent years (Klemas, 2001), it may be most effective to develop hierarchical linked spatial data sets. That is, relatively inexpensive satellite data could be acquired for larger study areas and used to develop a broad-brush description of land cover. More expensive, but data rich imagery could be acquired wherever more detail was necessary. Remotely sensed data would be incorporated into GIS, combined with other information and linked spatially. In this way, ecologically important patterns could be evaluated over multiple spatial scales and conservation and restoration actions could be planned within a landscape context, i.e., coastal wetlands could be linked with land use patterns in upstream watersheds (Mitsch, 2000).

Since the quality of the intertidal salmon habitat may be directly influenced by the vegetation present, our broader study depended on our ability to distinguish eelgrass from other spectrally similar, co-occurring species. The spectral resolution of the CASI imagery allowed us to discriminate between estuarine habitat types in Hood Canal. We were successful in acquiring and geocorrecting the CASI flightlines at appropriate spatial scales. We learned that other types of imagery collected at the time of the CASI flights would be useful in image processing because intertidal habitats are malleable and have changed over the course of this study. Field observations collected one or two years following image acquisition have limited usefulness.

The image processing component of this study is nearly complete. Classification of 8 additional flightlines (~52 km of shoreline) is underway and expected to be completed by Fall 2002. Analysis of the landscape patterns and the construction of spatial models is just beginning.

Recommendations

- Complete classification of remaining focal areas.
- Complete collection of field data to be used in classification accuracy assessment.
- Complete landscape analysis relating patterns in eelgrass bed distribution with shoreline features.
- Merge classified focal areas into one data layer with consistent habitat classes.
- If additional imagery is to be collected a future date, consider acquisition of videography and/or photography at the time of image acquisition. In addition, consider acquisition of relatively inexpensive satellite scene to provide a landscape context for classified CASI imagery.

Data Availability

All spatial data are available from the Point No Point Treaty Council, 7999 NW Salish Lane, Kingston, WA 98346 (*http://www.pnptc.org/*).

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FIGURES

Figure 1a. Plastic tarps (3 X 3 m), visible in the CASI imagery (see Fig. 1b), were installed in intertidal areas along the Hood Canal, Washington shoreline and their locations measured with differentially corrected GPS.

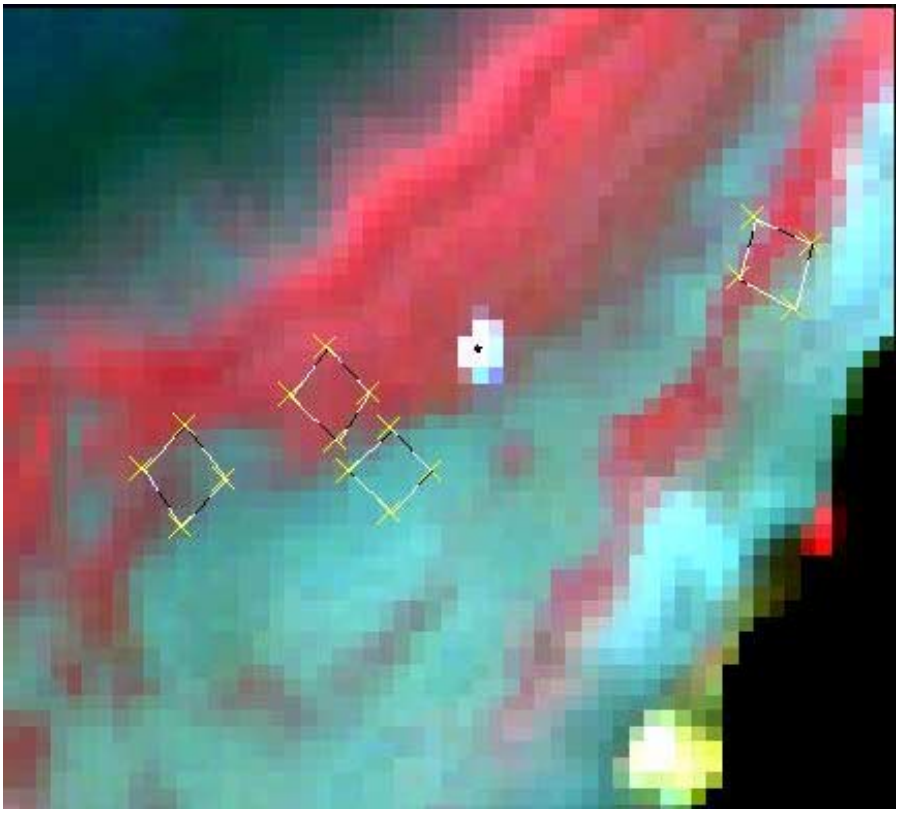

Figure 1b. CASI image showing location of target (white) and four training sites (yellow).

Figure 2. A Photo Research PR-650 hand-held radiometer was used by field teams to construct a spectral library from vegetation throughout the study area.

Figure 3. A field team using a GPS to record the location of the vegetation sampling grid.

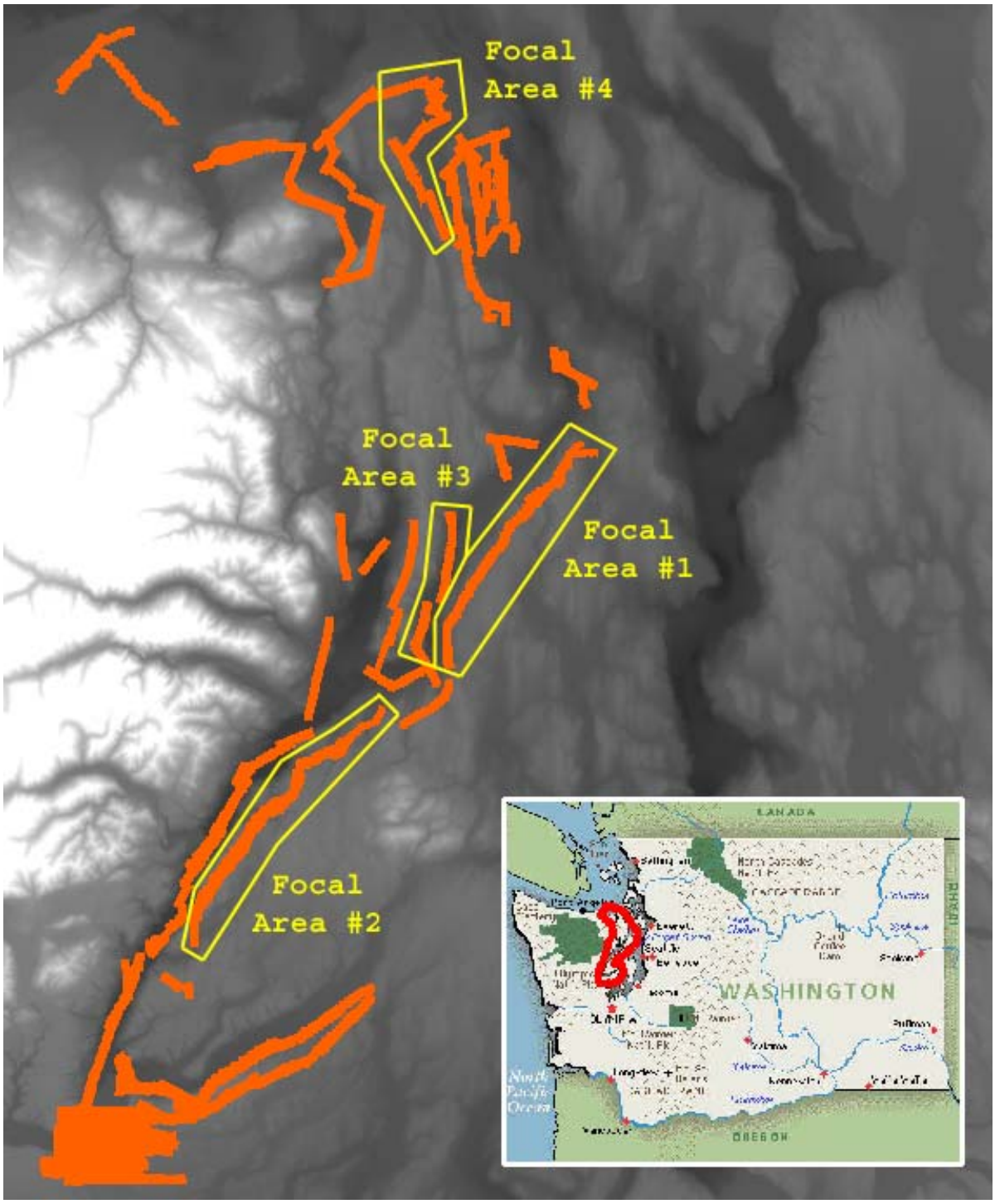

Figure 4. Location of study site and of CASI flightlines collected along the intertidal area of Hood Canal. Yellow boxes are four focal areas.

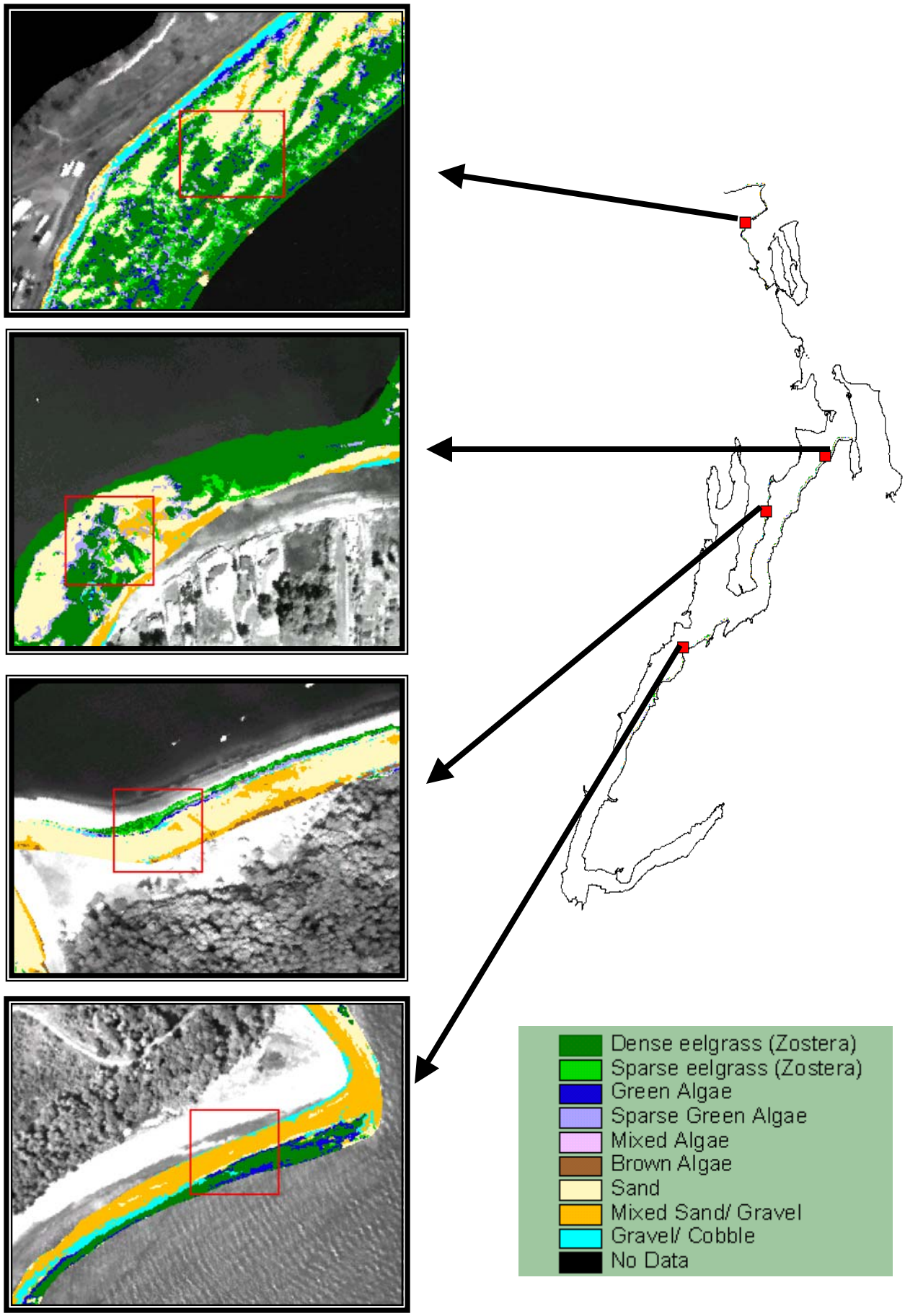

Figure 5a. Examples of classified CASI imagery from each of the four focal areas. 19-band CASI imagery was acquired June/July 2001.

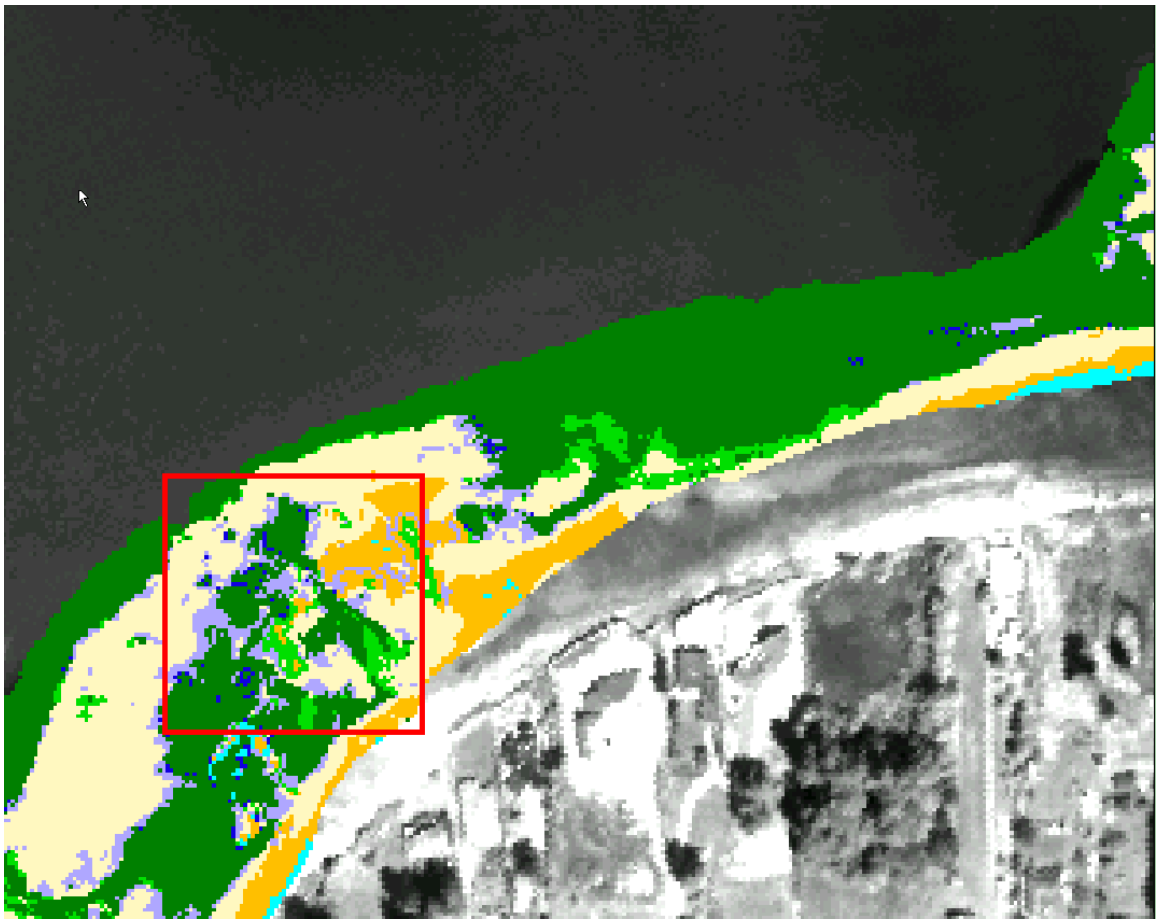

Figure 5b. Example of classified CASI imagery and unclassified band 4 image collected from Focal Area 1 in June/July 2001. Dark green is dense eelgrass and light green is sparse eelgrass (see legend on Fig. 5a for details). Red square is ~ 100m on a side.

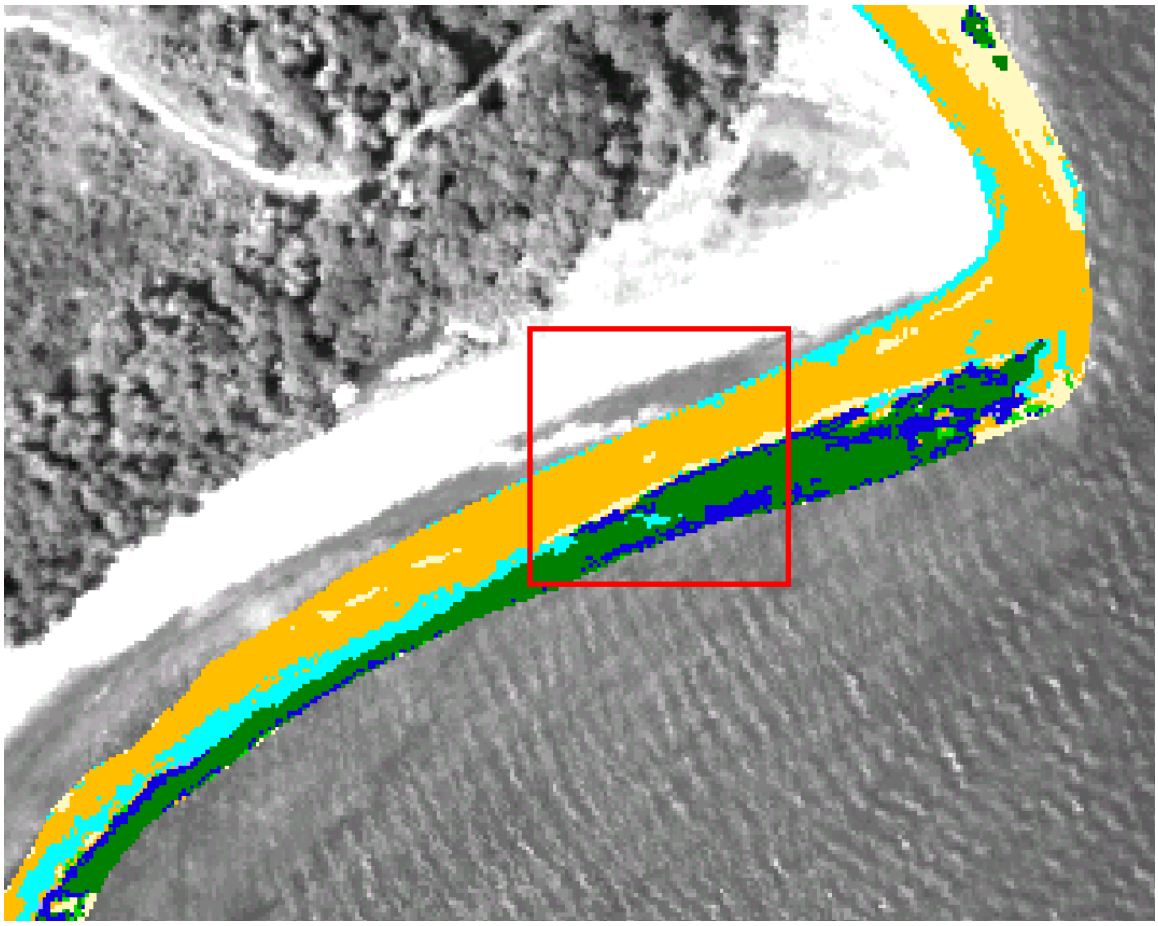

Figure 5c. Example of classified CASI imagery and unclassified band 4 image collected from Focal Area 2 in June/July 2001. Dark green is dense eelgrass and light green is sparse eelgrass (see legend on Fig. 5a for details). Red square is ~ 100m on a side.

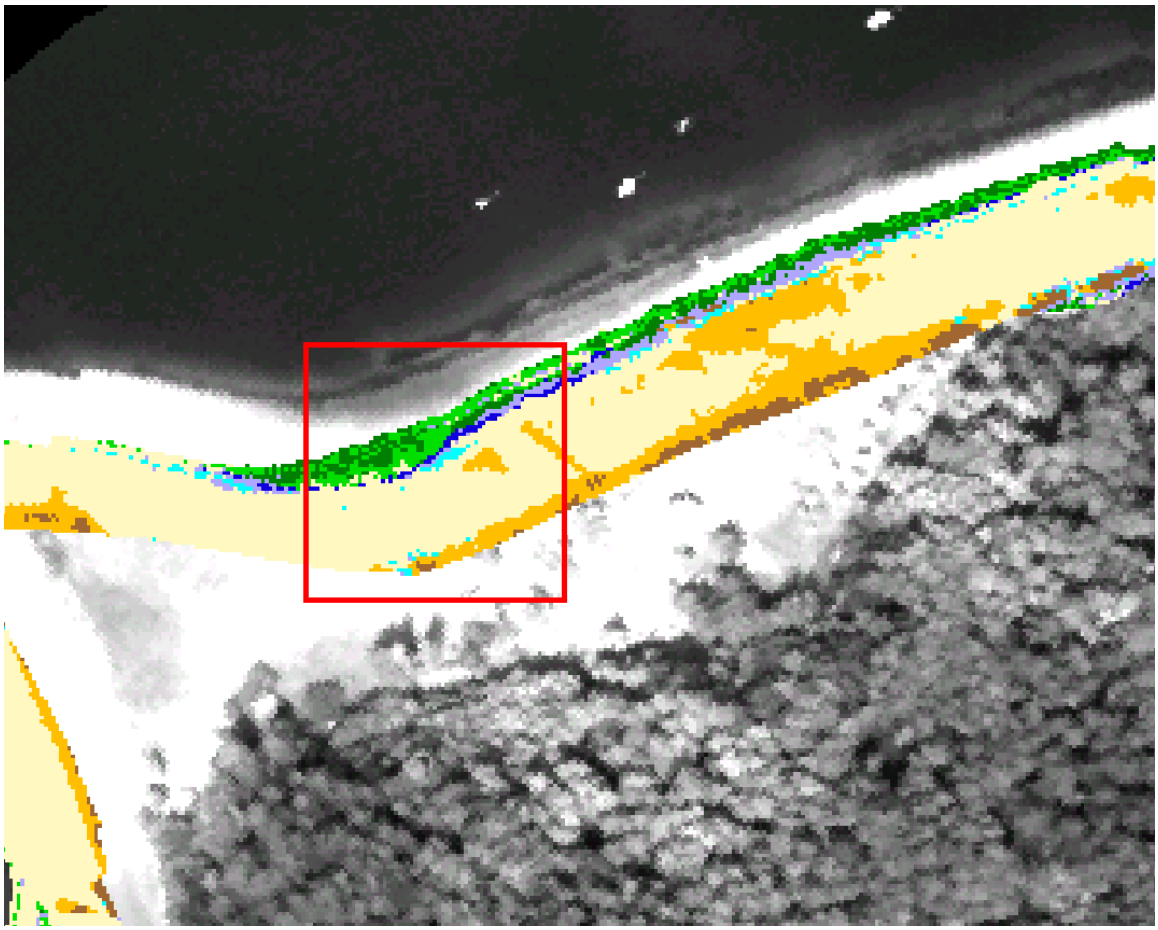

Figure 5d. Example of classified CASI imagery and unclassified band 4 image collected from Focal Area 3 in June/July 2001. Dark green is dense eelgrass and light green is sparse eelgrass (see legend on Fig. 5a for details). Red square is ~ 100m on a side.

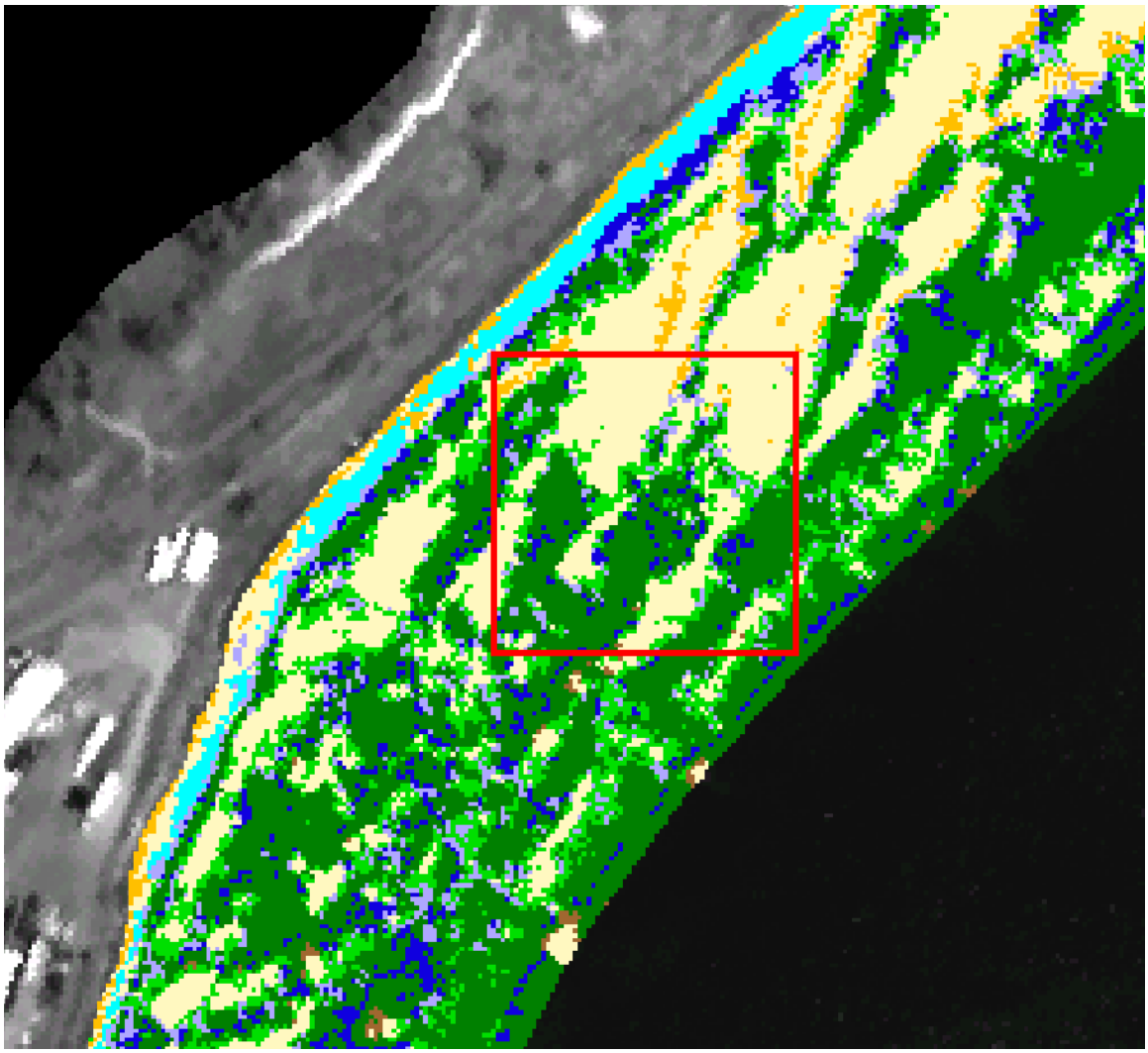

Figure 5e. Example of classified CASI imagery and unclassified band 4 image collected from Focal Area 4 in June/July 2001. Dark green is dense eelgrass and light green is sparse eelgrass (see legend on Fig. 5a for details). Red square is ~ 100m on a side.