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Mapping eelgrass (*Zostera marina*) in the Gulf Islands National Park Reserve of Canada using high spatial resolution satellite and airborne imagery

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ABSTRACT

Eelgrass is a sentinel species that can indicate the overall health of a coastal ecosystem. An effective coastal management strategy should therefore map and actively monitor the distribution of this sentinel for any significant changes. While manual transect methods are commonly employed to map eelgrass, the analysis of remote imagery has been proposed as an efficient alternative; a remote sensor can capture large and inaccessible areas cost- and time-effectively, nearly instantly, and with high frequency. The purpose of this study was to explore and compare the efficacy of high spatial resolution airborne (AISA) and satellite (IKONOS) imagery for mapping eelgrass distribution at Sidney Spit, Gulf Islands National Park Reserve of Canada (GINPRC). The primary objective was to determine the optimal spectral resolution, spatial resolution and image processing effort for resolving bed location. A two-meter resolution hyperspectral AISA image and a four-meter resolution multispectral IKONOS image were acquired over Sidney Spit in August 2008. Concurrently collected were in situ above-water hyperspectral remote sensing reflectance, underwater videography, and water samples for optical constituent analysis. The images were subjected to varying combinations of 1) image processing steps: atmospheric correction, surface glint correction, deep water masking, and water column removal; 2) image classifiers: with differing user effort and data input requirements; and 3) spectral resolution: >200-band AISA versus a reduced resolution AISA image (AISA(r)) of only four key bands unique to eelgrass – slope 500–530 nm, first derivatives of 556 nm, 580 nm, and 602 nm (O'Neill et al. (2011)) – versus four-band IKONOS. The highest classification accuracies were achieved with atmospheric correction, glint correction, deep water masking, and maximum likelihood (ML) classification of the AISA(r) image and IKONOS full resolution image. AISA(r) achieved eelgrass producer and user accuracies of 85% in water less than 3 m deep, and 93% in deeper areas. IKONOS achieved 79% for water less than 3 m deep and 91% in deeper areas. Most confusion occurred between eelgrass and green algae, and between exposed eelgrass and other exposed vegetation. The most automated combination of methods yielded poor accuracies but could be greatly improved by refining atmospheric correction input parameters and building on the endmember spectral library. This study resulted in recommendations for remote eelgrass mapping and monitoring within the GINPRC.

1. Introduction

Eelgrass, *Zostera marina*, is a fundamental component of coastal ecosystem health. It functions as a shoreline baffle against wave and current action (Fonseca & Cahalan, 1992), a sediment stabilizer (Mateo et al., 2003), and a major determinant of oxygen, carbon, nitrogen and phosphorous balance within the ecosystem (Apostolaki et al., 2010; Hemminga & Duarte, 2000). It also serves as a nursery ground and food source for many marine organisms including out migrating juvenile salmon (*Onchorhynchus* spp.), Pacific herring (*Clupea harengus*), Dungeness crab (*Cancer magister*), rare invertebrate species, and black Brant geese (*Branta bernicla*) (Borg et al., 2006; Mazzella et al., 1989; Sewell et al., 2001). Accordingly, eelgrass is a resource of great importance to sustainable commercial fisheries (Adams, 1976) and has been used worldwide as an indicator of coastal ecosystem health (Sewell et al., 2001).

Despite its far-ranging importance, eelgrass has experienced worldwide decline. The loss has been in response to increasing sea surface temperature and the light restricting nature of increasing sedimentation and eutrophication brought about by anthropogenic activities (den Hartog, 1994; Giesen et al., 1990; Short & Wyllie-Echeverria, 1996). Understanding and mitigating these impacts requires that a baseline eelgrass distribution be established and continually monitored in concert with physical and biological environmental variables. Because the issue of eelgrass decline is time sensitive, the monitoring must be done cost- and time-effectively.

At present, the majority of eelgrass mapping is conducted manually via intertidal and subtidal transects. Though the strategy is effective, it is labor-intensive, requires large investments of time, and is limited by accuracy levels that are highly variable and difficult to define (Environment Canada, 2002; Roelfsema et al., 2009). A proposed alternative is the

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analysis of optical remote imagery, which can capture large and inaccessible areas cost- and time-effectively, nearly instantly, and with high frequency, with the added potential for automation. The ease of an accurate routine optical remote mapping procedure could improve the spatial and temporal coverage of coastal monitoring programs that are aimed at conserving eelgrass communities and investigating their role in the larger coastal ecosystem (Werdell & Roesler, 2003).

A remote optical sensor's ability to identify a benthic substrate, such as eelgrass, relies on the substrate having a unique optical signature among its surrounding substrates. The detail of the signature must also be detectable at the spectral resolution and sensitivity of the sensor. The optical puzzle is complicated by the attenuating effects of the atmosphere, water surface, water column, and its constituents (Kirk, 1994). Image processing techniques such as atmospheric, surface glint and water column correction must be applied to compensate for these effects prior to classification (Guzzi et al., 1987; Hedley et al., 2005; Lyzenga, 1978; Maritorena et al., 1994).

Many researchers have succeeded in mapping seagrasses (Dekker et al., 2005; Pasqualini et al., 2005; Peneva et al., 2008; Roelfsema et al., 2009), macroalgae (Andrefouet et al., 2003; Gower et al., 2006; Kutser et al., 2006; Vahtmae et al., 2006) and corals (Andrefouet et al., 2001; Lobitz et al., 2008; Mishra et al., 2007; Mumby et al., 1997, 1998; Phinn et al., 2005) with varying levels of remote image processing effort. However the vast majority of these studies take place in open ocean and tropical Case 1 waters, which, being void of constituents other than phytoplankton, are relatively transparent. Mapping remains a challenge in the more complex Case 2 waters of temperate coastal regions. In the temperate coastal waters of British Columbia, specifically off the east coast of Vancouver Island, varied constituents (colored dissolved organic material (CDOM), suspended organic/inorganic particles, and phytoplankton) cause complex and varied attenuation of light in the water column (Komick et al., 2009; Loos & Costa, 2010; O'Neill et al., 2011). As a result, the optical signal of the benthic substrate is likely obscured (Phinn et al., 2005; Vahtmae et al., 2006).

The majority of benthic mapping studies have been conducted with multispectral sensors (e.g., Andrefouet et al., 2002; Fornes et al., 2006; Mishra et al, 2006; Purkis, 2005; Su et al., 2006). Although hyperspectral sensors can now characterize spectral signatures in fuller detail and lead to greater benthic classification accuracy (Dierssen et al., 2003; Mumby et al., 1997), the cost is still orders of magnitude greater than multispectral satellite imagery of comparable spatial resolution. Considering this, the ideal sensor for eelgrass mapping would be multispectral, with bands placed at key wavelengths where eelgrass exhibits unique spectral characteristics (Fyfe, 2003).

To explore the cost–benefit gains associated with spectral resolution, this study compared the capacity of three different high spatial resolution sensors for mapping eelgrass distribution in the temperate waters of Sidney Spit, Gulf Islands National Park of Canada (GINPRC): (1) the >200-band airborne hyperspectral sensor AISA (Airborne Imaging Spectrometer for Applications)(Spectral Imaging, 2008), (2) the four-band multispectral satellite sensor IKONOS (Geoeye, 2006), and (3) a theoretically ideal multispectral sensor simulated by convolving the AISA image into five unique eelgrass detecting bands derived previously by O'Neill et al. (2011). Specifically, this study evaluated classification results of the images at varying stages of the following correction process: atmospheric correction, surface glint correction, water attenuation correction, optically deep water masking, and different classification algorithms. Accuracy of eelgrass classification was defined according to ground truth samples.

2. Methodology

2.1. Study area

The research took place at Sidney Spit, a 1.78 km^2 marine protected area on the northeastern extreme of Sidney Island, British Columbia, Canada, protected within the Gulf Islands National Park Reserve of Canada (GINPRC) (Fig. 1). Sidney Spit consists of a 1.8 km long sand spit and sheltered lagoon with shallow sloping sandy substrate. Submerged vegetation present on site during sampling time were fringing eelgrass and eelgrass meadows (*Z. marina*, intertidal and subtidal), green algae (*Ulva fenestrata*, *Enteromorpha* spp., and filamentous green algae), and brown algae (*Fucus* spp., *Sargassum muticum*, and *Laminaria saccharin*, at very low coverage in patches of less than 1 m^2). Sea asparagus (*Salicornia virginica*) was found in large homogeneous stands at southern margins of the lagoon and remained exposed throughout the majority of the tidal cycle. Previous assessment by Parks Canada reported the following average metrics for eelgrass in the lagoon: density = 300 shoots/m^2, biomass = 198.8 g m^{-2}, and total eelgrass meadow extent estimated from orthophotos = 183,000 m^2 (Robinson & Martel, 2007).

At the time of imagery acquisition, the water was characterized by temperature, salinity, total suspended material (TSM), chlorophyll-*a* (Chl-*a*), absorption by chromophoric dissolved organic material (aCDOM), and downwelling diffuse attenuation coefficients, K_d (O'Neill et al., 2011) (Table 1), indicating a case 2 water type. The relative magnitudes of the diffuse downwelling attenuation coefficients, K_d, were related to the distribution of the water constituents. Water's exponential attenuation toward the NIR spectral region resulted in rapid K_d increase beyond 710 nm, while the characteristic blue absorption by CDOM, blue and red absorption by Chl-*a* and red scattering by TSM (Liedtk et al., 1995) resulted in higher K_d values in those spectral ranges. The lowest K_d values occurred between 500 and 600 nm due to lowest attenuation by pigments and other water constituents in this spectral range (Kirk, 1994).

2.2. Field survey and spectral measurements

A benthic ground-truthing survey was carried out at Sidney Spit from July 30 to August 3, 2008. Care was taken to survey all substrates present at the greatest depth range possible, however, additional sites were visited on July 7, 2010 to increase the sample size of deep (>3 m) substrates. Being a very sheltered area, an assumption was made that benthic substrate distribution remained approximately similar since field collection in 2008.

Initial reconnaissance defined six major benthic classes present at the study site: eelgrass *Z. marina* (E); *U. fenestrata*, *Enteromorpha* spp., and filamentous green algae (Ag); sand (S); brown algae (Ab) (present in very small amounts); sea asparagus (Asp); and optically deep (>30 m) water (dW). Polygons marking known locations of each benthic class were delineated on an August 2006 AISA image and split by depth: less than 3 m (shallow substrate, hereforth denoted *s*) and greater than 3 m (deep substrate, hereforth denoted *d*). The 3 m depth stratification was introduced as a means of improving classification of substrates found in a wide depth range and therefore having a large above-water spectral range (Pasqualini et al., 1997). The 3 m threshold was defined based on previous field data (2006, 2008, *not published*) that showed clear spectral shape and magnitude differences above and below 3 m depth, and is in agreement with previous in situ measurements and radiative transfer models (Roelfsema et al., 2006) as well as image analyses (Brando & Dekker, 2003; Phinn et al., 2005; Pasqualini et al., 2005), and was later corroborated by in situ K_d and substrate detection thresholds (O'Neill et al., 2011).

A stratified random sampling method was used to define a total of 507 field sites among the pre-defined polygons (Green et al., 2000). At each site, the percent cover of each benthic substrate was estimated within a randomly placed 0.5 m × 0.5 m quadrat. Deep benthic classes were identified using random video transects with a drop camera. The breakdown of sites surveyed is presented in Table 2.

To evaluate the efficacy of eventual atmospheric and water-column image corrections, spectral ground-truthing of submerged and exposed benthic substrates were required, respectively. In situ total water