Acoustic and satellite remote sensing of shallow nearshore marine habitats in the Gwaii Haanas National Marine Conservation Area

by

Luba Yvanka Reshitnyk

BSc., University of Ottawa, 2009

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SUPERVISORY COMMITTEE

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(Department of Geography)

Dr. Cliff Robinson, Co-Supervisor
(Department of Geography)

Dr. Maycira Costa, Member
(Department of Geography)

ABSTRACT

Supervisory Committee

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(Department of Geography)

Dr. Cliff Robinson, Co-Supervisor
(Department of Geography)

Dr. Maycira Costa, Member
(Department of Geography)

The ability to map nearshore habitat (i.e. submerged aquatic vegetation) is an integral component of marine conservation. The main goal of this thesis was to examine the ability of high resolution, multispectral satellite imagery and a single-beam acoustic ground discrimination system to map the location of marine habitats in Bag Harbour, found in the Gwaii Haanas National Marine Conservation Area Reserve. To meet this goal, two objectives were addressed: (1) Using the QTC View V sing-beam acoustic ground discrimination system, identify which frequency (50 kHz or 200 kHz) is best suited for mapping marine habitat; (2) evaluate the ability to map nearshore marine habitat using WorldView-2 high resolution, multispectral satellite imagery and compare the results of marine habitat maps derived from the acoustic and satellite datasets. Ground-truth data for both acoustic and satellite data were collected via towed

underwater video camera on June 3rd and 4th, 2012. Acoustic data (50 and 200 kHz) were collected on June 23rd and 24th, 2012, respectively.

The results of this study are organized into two papers. The first paper focuses on objective 1 where the QTC View V single-beam acoustic ground discrimination system was used to map nearshore habitat at a site within the Gwaii Haanas National Marine Conservation Area using two survey frequencies – 50 kHz and 200 kHz. The results show that the 200 kHz data outperformed the 50 kHz data set in both thematic and spatial accuracy. The 200 kHz dataset was able to identify two species of submerged aquatic vegetation, eelgrass (*Zostera marina*) and a red algae (*Chondrocanthus exasperatus*) while the 50 kHz dataset was only able to detect the distribution of eelgrass. The best overall accuracy achieved with the 200 kHz dataset was 86% for a habitat map with three classes (dense eelgrass, dense red algae and unvegetated substrate) compared to the 50 kHz habitat classification with two classes (dense eelgrass and unvegetated substrate) that had an overall accuracy of 70%. Neither dataset was capable if discerning the distribution of green algae (*Ulva* spp.) or brown algae (*Fucus* spp.), also present at the site.

The second paper examines the benthic habitat maps created using WorldView-2 satellite imagery and the QTC View V single-beam acoustic ground discrimination system (AGDS) at 200 kHz (objective 2). Optical and acoustic remote sensing technologies both present unique capabilities of mapping nearshore habitat. Acoustic systems are able to map habitat in subtidal regions outside of the range of optical sensors while optical sensors such as WorldView-2 provide higher spatial and spectral resolution. The results of this study found that the WorldView-2 achieved the highest overall accuracy (75%) for mapping shallow (<3 m) benthic classes (green algae, brown algae, eelgrass and unvegetated substrate). The 200 kHz data were found to perform best in deeper (>3 m) regions and were able to detect the distribution of eelgrass, red algae and unvegetated substrate. A final habitat map was produced composed of these outputs to create a final, comprehensive habitat map of Bag Harbour. These results highlight the benefits and limitations of each remote sensing technology from a conservation management perspective. The main benefits of the WorldView-2 imagery stem from the high resolution (2 x 2 m) pixel resolution, with a single image covering many kilometers of coastline, and ability to discern habitats in the intertidal region that were undetectable by AGDS. However, the main limitation of this technology is the ability to acquire imagery under ideal conditions (low tide and calm seas). In contrast, the QTC View V system requires more hours spent collecting acoustic data in the field, is limited in the number of habitats it is able to detect and creates maps based on interpolated point data (compared to the continuous raster data of the WorldView-2 imagery). If, however, the objectives of the conservation management to create high resolution benthic habitat maps of subtidal habitats (e.g. eelgrass and benthic red algae) at a handful of sites (in contrast to continuous coastal coverage), the QTC View V system is more suitable. Whichever system is used ground-truth data are required to train and validate each dataset.

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To all of my lab mates, many thanks for the chance to discuss ideas and share diverse passions and cooking abilities. With so many experiences to share, you have all inspired me to continue on my road to continue work in conserving the planet and its amazing ecological wonders. Also many thanks to members of other labs, especially in SPAR lab, who were extremely helpful with my many statistics-related questions. A special thanks goes out to Ben Biffard at Neptune Canada - finding him on campus was a turning point in my research. His expertise in acoustic remote sensing was invaluable to this project.

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CO-AUTHORSHIP STATEMENT

This thesis is the combination of two scientific manuscripts for which I am the lead author. The project structure was developed with Dr. Phil Dearden, Dr. Cliff Robinson and Dr. Maycira Costa to map nearshore marine habitats using acoustic and satellite remote sensing technologies. For these two scientific manuscripts, I led all research, data preparation, data analysis, result interpretations and writing. Dr. Dearden, Dr. Robinson and Dr. Costa provided guidance in developing research questions and contextualizing research results. Dr. Costa and Dr. Robinson provided support with research structure and methodological considerations. Dr. Dearden, Dr. Robinson and Dr. Costa supplied editorial comments and suggestions incorporated into the final manuscript.

1.0 INTRODUCTION

1.1 Research Context

Established in June of 2010, the Gwaii Haanas National Marine Conservation Area and Haida Heritage Site (GHNMCA) is Canada's largest and newest NMCA. Located 130 km off the north coast of British Columbia the archipelago boasts a total area of 3,400 km^2 and 1700 km of coastline. The area is extremely remote and is only accessible by boat or float plane. Culturally and economically the area supports many maritime activities including the traditional harvest of marine resources, tourism, as well as commercial and recreational fisheries. These resources are supported by the rich biodiversity of the region. Over 3,500 marine species have been identified around Haida Gwaii, including 30 species of marine birds (Harfenist, Sloan, & Bartier, 2002), 26 species of marine mammal (Heise et al., 2003), 2,503 species of invertebrates (Sloan, Bartier, & Austin, 2001), 348 seaweed species, 4 seagrass species, and 88 marine lichen flora (Sloan & Bartier, 2007). Within the list, 23 species are listed at listed at risk by the Committee on the Status of Endangered Wildlife in Canada (COSEWIC). It is clear that the GHNMCA constitutes an area with a high level of marine biodiversity.

Within the GHNMCA the nearshore (defined herein as coastal region encompassing the intertidal and shallow subtidal zones) has been identified as a crucial conservation component at the transition zone between terrestrial and marine ecosystems (Sloan, 2006). Many important plant-structured communities occur within the nearshore ecosystems of Gwaii Haanas, including kelp, algae and seagrass meadows. These habitats are crucial to the structure and function of the nearshore ecosystems. For example, seagrass provides detritus into coastal food webs (Thistle, Schneider, Gregory, & Wells, 2010), baffles coastlines against wave action (Fonseca & Calahan,

1992) and stabilizes sediments (Mateo, Sanchez-Lizaso, & Romero, 2003). Furthermore, eelgrass contains a high diversity of organisms compared to non-vegetated habitats. For example, Robinson, Yakimishyn, & Dearden (2011) have identified more than 60 species of fish in eelgrass meadows (*Zoster marina*) have found that over 65 species of fish use eelgrass habitat some stage of their life cycle (Yakimishyn & Robinson, 2004).

Conservation mandates within the GHNMCA include the protection, conservation and restoration of marine biodiversity and ecosystems such as eelgrass meadows (Gwaii Haanas National Marine Conservation Area Reserve and Haida Heritage Site: Interim Management Plan and Zoning Plan, 2010). However, several issues have been identified relating to Park's Canada's marine ecosystem mandate in Gwaii Haanas which include: understanding the role of plants in structuring nearshore marine communities; environmental monitoring of threats to, and well-being of, ecosystems; appreciating the role of seagrass meadows in the land-sea linkages in estuaries; and backcountry monitoring of visitor impacts to intertidal habitats, to name a few. These issues are fully outlined by Sloan (2000).

To effectively address issues surrounding marine environments habitat inventories of marine habitat are invaluable. The collection and mapping of reliable, high quality, current and spatially accurate information inventories provides baselines about the current state of marine ecosystems. For example, in British Columbia, both kelp and seagrass have been identified as potential marine environmental indicators of coastal ecosystem health (Rowe, Redhead, & Dobell, 1999) therefore information about the past and present spatial distribution of these habitats is crucial to the understanding of the changes that may be occurring, whether positive or negative.

Within the GHNMCA the inventory of habitats occurring within the nearshore zone is incomplete. To date, mapping of nearshore habitats within Gwaii Haanas has been conducted via two main projects - the ShoreZone project and intermittent field surveys of eelgrass meadows by park wardens (Sloan, 2006), however, these datasets are insufficient in order to address the aforementioned issues with regards to ecological monitoring. For example, the ShoreZone project, while comprehensive in reporting the presence of dominant marine habitats, records the occurrence of these habitats in shore units (a linear measurements) versus polygon data (an aerial measure). Furthermore, this project was limited to the intertidal region and therefore the full extent (in terms of total surface area) of habitats in the nearshore zone is not known. For park wardens, *in situ* data collection for eelgrass mapping using a hand-held GPS aboard a boat to map the peripheries of subtidal meadows introduces spatial inaccuracy and require large investments of time and labour (Ackleson & Klemas, 1987; Dekker et al., 2005).

The 1500 km coastline of the GHNMCA constitutes a vast area for which mapping the extent of nearshore habitats could not be efficiently undertaken using only *in situ* field techniques. Therein lies the need for methods that can efficiently and effectively examine large areas and identify in detail the distribution of important shallow benthic subtidal habitats. A proposed alternative to *in situ* habitat mapping is the creation of habitat maps based on remotely sensed data from that can summarize ecologically meaningful information across large, remote, geographic extents (Mumby & Harborne, 1999). Further benefits of remote sensing include the potential for automation and repeatability, which could improve the spatial and temporal coverage for coastal monitoring of marine ecosystems.

Remote sensing methods of marine habitat include both passive optical sensors and active acoustic sensors. Both techniques and their associated methods of data collection vary with regards to their spatial, temporal and, in the case of optical sensors, spectral resolution and these properties will affect the scale and accuracy of the final habitat map.

Optical sensors are passive remote sensing devices that measure solar electromagnetic radiance reflected off a target substrate (Cracknell & Hayes, 2007). The basis for passive remote sensing for mapping coastal habitats is that these target substrates (e.g. eelgrass) have a unique spectral signature by which they can be discerned from surrounding substrates. However, there are multiple factors attenuating the spectral signal as it travels from the sun, is reflected off the target substrate and is detected by a sensor. In a marine setting, this signature is attenuated by three main interactions: atmospheric, at the air-water surface and in the water column (Kirk, 1994). These interactions will be more significant in coastal waters which have higher concentrations of water constituents (eg. coloured dissolved organic matter, suspended organic and inorganic material) that will increase signal attenuation and make the seafloor more difficult to detect (Phinn et al, 2005).

Of the many optical sensors available for habitat mapping, including aerial photographs (Manson, 2003) and hyperspectral sensors (Brando & Dekker, 2003), satellite-borne multi-spectral sensors have been shown to be cost-effective in mapping nearshore marine habitat (Green, Mumby, Edwards, & Clark, 2000). For example, lower spatial resolution sensors such as Landsat imagery (30 m) can be used to achieve moderately accurate maps (65% to 88%) of benthic habitats (Ferguson & Korfmacher, 1997; Mumby & Edwards, 2002; Wabnitz et al., 2008) but some have been reported as low as 35% (Phinn et al., 2008).

Newer, high spatial resolution multispectral sensors have significantly increased the accuracy with which benthic habitats could be mapped. Sensors such as SPOT (2.5-10 m) and IKONOS (1 or 4 m) have better capabilities at discerning between more habitat classes (Strand et al., 2007). Studies have demonstrated that higher spatial resolution (Capolsini, Andréfouët, Rion, & Payri, 2003) and spectral resolution (Botha et al., 2013) lead to an increase in the spatial accuracy and thematic resolution of habitat maps. However, even with the benefits of multi-temporal high resolution imagery, limitations do exist. For example, all optical sensors are limited in the depth to which they can resolve benthic habitats. Furthermore, purchasing imagery and the necessary imagery-processing software represent significant start-up cost, however, these costs can be justified in comparison to the savings on field work requirements or the acquisition of field-based observations (Mumby, 1999).

Acoustic systems may present a more suitable method for mapping habitats in regions outside of the depth range of optical sensors (Riegl & Purkis, 2005). In contrast to passive optical remote sensing, active acoustic remote sensing involve an echosounder which generate ultrasonic waves which propagate freely underwater, reflect off the seafloor and return to the acoustic sensor (Cracknell & Hayes, 2007). Acoustic remote sensing methods, such multi-beam sonar (Collins & Galloway, 1998), side-scan sonar (Brown et al., 2005), as well as acoustic ground discrimination systems (AGDS) based on single beam echosounders (SBES) (Greenstreet, 1997), have granted more detailed access into describing the characteristics of the seafloor. In particular, single beam echosounders (SBES) present an inexpensive, mobile and non-invasive means of mapping seafloor habitat in coastal areas inaccessible to larger vessels. SBES has been shown to be effective at mapping both sedimentary habitats of the seafloor (e.g. Freitas et al., 2003 and 2006) and, more recently, mapping underwater vegetation (e.g. Quintino et al., 2009).

In comparison to optical sensors, acoustic sensors can achieve greater depth penetration, are unconstrained by optical water properties and can measure seabed structures that may be biologically relevant. Conversely, they cannot map very shallow or exposed regions (<0.5 m), are limited in their spatial resolution and require interpolation between transects and cannot differentiate substrates based on pigmentation (Mumby et al, 2004). It may be possible to overcome the disadvantages present within optical and acoustic remote sensing systems by combining the mapping technologies to produce benthic habitat maps (e.g. Solan, 2003; Bejarano, Mumby, Hedley, & Sotheran, 2010).

1.2 Research Objectives

The goal of this thesis is to examine the applicability of optical and acoustic remote sensing methods for producing maps of nearshore marine habitat for the purpose of conservation management within the Gwaii Haanas National Marine Conservation Area and Haida Heritage Site. The study site of this examination will be Bag Harbour for which two remote sensing datasets are used.

The ability to accurately map benthic habitat using optical and acoustic remote sensing will be evaluated by accomplishing the following objectives:

1. The first objective is to examine the ability of a single-beam acoustic ground discrimination system, QTC View V, to generate habitat maps of submerged aquatic vegetation using two frequencies - 50 kHz and 200 kHz. A hierarchical habitat classification scheme is used to examine the thematic resolution discernible by each frequency. Ground truth data are collected via towed underwater video to validate the accuracy of the habitat maps.

2. The second objective is to compare habitat discrimination from passive optical multispectral imagery and single-beam active acoustic methods. High resolution multispectral WorldView-2 imagery and single-beam acoustic data identified in objective 1 are used to generate habitat maps of submerged aquatic vegetation. The benefits and limitations of each remote sensing system for mapping nearshore habitat within the GHNMCA are assessed.

1.3 Organization of Thesis

The thesis is organized into two individual papers to address the two objectives. The first paper (Chapter 2) looks at the differences in habitat maps produced using a 50 kHz and 200 kHz frequencies with the QTC View system. The second paper (Chapter 3) examines the ability to map nearshore habitat using high resolution satellite imagery and single-beam acoustic techniques and addresses the main overarching goal of this study. Since each paper is meant as an individual publication, there is some overlap between the two papers; e.g., methods and background information. The thesis concludes with a chapter to summarize the key findings and recommendations of this study.

2.0 REMOTE SENSING OF NEARSHORE SUBMERGED MARINE VEGETATION USING THE QTC VIEW V SINGLE-BEAM ACOUSTIC GROUND DISCRIMINATION SYSTEM

2.1 Abstract

The purpose of this study was to map the distribution of submerged aquatic vegetation in Bag Harbour, in the Gwaii Haanas National Marine Conservation Area Reserve and Haida Heritage Site off the northwest coast of British Columbia. A single-beam, acoustic, ground-discrimination system (QTC VIEW Series V) was used to map the distribution of submerged vegetation in a nearshore coastal site, using both 50 and 200 kHz frequencies. Acoustic surveys were conducted independently for each frequency and ground-truth data were collected via towed underwater video transects. The analysis of the video data identified four species of submerged vegetation - eelgrass (*Zostera marina*), red algae (*C. exasperatus*), green algae (*Ulva* spp.) and brown algae (*Fucus* spp.). The acoustic data were processed in the QTC IMPACT software and acoustic classes were interpreted using ground truth video data to create habitat maps at two levels of thematic resolution. Map accuracy were calculated using confusion matrices. Overall, the 200 kHz data were much better at mapping underwater vegetation as the data were able to detect the distribution of both eelgrass and red algae with and overall habitat map accuracy of 81%. Comparatively, the 50 kHz data could only detect the distribution of eelgrass with 63% overall accuracy. Neither frequency was capable of detecting the presence and distribution of brown and green algae.

2.2 Introduction

Submerged vegetation, such as seagrasses and algae, are vital to coastal ecosystem health and resilience. In nearshore environments marine vegetation, such as eelgrass (*Zosterna marina*) and other seagrass species, have been shown to provide crucial ecosystem services such as sediment retention (Mateo, Sanchez-Lizaso & Romero, 2003), baffling against wave and current action (Fonseca & Calahan, 1992) and carbon cycling (Hemming & Duarte, 2000). Furthermore, submerged vegetation has been shown to provide important habitat and food source for a variety of marine organisms including macroinvertebrates (Hovel et al., 2002), and several of fish species including juvenile salmon (*Onchorhynchus* spp.) and Pacific herring (*Clupea harengus*) (Sewell et al., 2001; Borg et al., 2006; Chittaro, Finley & Levin, 2009; Robinson et al., 2011). These vital services highlight the important role of marine habitats and why submerged vegetation is used as a baseline indicator of coastal ecosystem health worldwide (Sewell et al., 2001).

Despite their recognized importance these habitats, and seagrasses in particular, are experiencing global declines and local extinctions (Duarte, 2002; Lotze et al., 2006). These patterns have been attributed to both natural and anthropogenic impacts such as increasing sea surface temperatures and the deterioration in coastal waters due to sedimentation and eutrophication (den Hartog, 1994; Waycott et al, 2009). Furthermore, these habitats suffer from a lack of protection. For example, in Canada, eelgrass is recognized as an ecologically significant species (DFO, 2009), however, no specific legal protection exists to safeguard these habitats and very few are included in marine protected areas (MPAs) (Short & Short, 2003). However, where MPAs do exist it is crucial to establish baselines of eelgrass and algae distribution in a cost- and time-effective manner to contribute to the monitoring and conservation management of coastal ecosystem health.

Traditional mapping techniques of submerged vegetation using divers and field sampling require large investments of time and labour (Ackleson & Klemas, 1987; Dekker et al., 2005). Alternative methods for mapping seabed habitats using optical remote sensing such as satellite imagery (Mumby et al., 1997) and acoustic remote sensing, such multi-beam sonar (Collins & Galloway, 1998), side-scan sonar (Brown et al., 2005), as well as acoustic ground discrimination systems (AGDS) based on single beam echosounders (SBES) (Greenstreet, 1997), have granted new methods for efficiently collecting data for describing the characteristics of the seafloor. However, in coastal waters where optical remote sensing techniques are limited in depth by increased turbidity (ie. Type II vs Type I waters) (Horning et al., 2010) acoustic systems may present a more suitable method for mapping habitats in regions outside of the range of optical sensors (Riegl and Purkis, 2005).

Single beam echosounders (SBES) present an inexpensive, mobile and non-invasive means of mapping seafloor habitat in coastal areas inaccessible to larger vessels. The SBES system used in this study, the QTC VIEW Series V (QTC5) (Quester Tangent Corporation, Sidney, British Columbia), is one such system. It functions on the theory that the first return echo is predominantly influenced by seabed roughness and seabed composition (e.g. sediment porosity and texture) and that statistical analysis of these return echoes can be used to identify habitat types and their spatial distribution (Collins & Galloway, 1998; Collins & Lacroix, 1997; Preston et al., 1999; Preston, 2001; Ellingsen, 2002). This system has been shown to be effective at mapping both sedimentary habitats of the seafloor (e.g. Freitas et al., 2003 and 2006) and, more recently, mapping the distribution of underwater vegetation (e.g. Quintino et al., 2009).

To date only a handful of studies have examined the capability of the QTC5 system to map vegetated habitats (e.g.Moyer et al., 2005; Riegl et al., 2005; Riegl & Purkis, 2005; Preston et al., 2006; Quintino et al., 2009). Table 2.1 provides a short summary of existing literature and study conditions using the QTC5 system to map submerged vegetation. For example, acoustic surveys conducted by Preston et al. (2006) in the Seto Inland Sea, Japan, were able to discriminate between bare seabed and areas covered by two species of seaweed (*Sargassum fulvellum* and *Ecklonia kurome*). Off the coast of Florida, Reigl et al. (2005) used both 50 kHz and 200 kHz frequencies to map the spatial distribution of bare substratum, seagrass and macroalgae. More recently, Quintino et al. (2009) tested the ability of the system to differentiate between bare substratum and submerged vegetation at a site in Mar Menor, Spain. Their results demonstrated that 200 kHz was better at distinguishing between varying benthic algal biomass compared to 50 kHz.

In light of this review, there is still a gap in knowledge in the performance of this system in the unique conditions that exist in temperate marine regions (e.g. Pacific-northwest). Performance, within the context of this study, is quantified through an accuracy assessment of a each habitat map. Of the five studies that have specifically focused on mapping submerged vegetation using the QTC5 system (Table 2.1) only three have assessment the performance of the QTC5 system (Riegl and Purkis, 2005; Moyer et al., 2005; Riegl et al., 2005). Of these three studies, two were conducted in coral reef ecosystems which present different acoustic conditions (ie. consolidated hardground) from seafloor conditions that are typical with the occurrence of submerged vegetation such as seagrass (ie. soft sediments). In the third study working under controlled conditions in Florida, USA, Riegl et al. (2005) reported acoustic classification of seagrass, algae and sand substratum. Notably, the authors found no difference in the overall

Table 2.1 - Studies that have used QTC VIEW V to map submerged vegetation.

Reference	**Location**	**Survey frequency (kHz)**	**Depth range of survey**	**Habitat classes identified**	**Overall habitat map accuracy**
Riegl et al., 2005	Indian River Lagoon, Florida	50 and 200	1- 2 m	dense and sparse macroalgae, seagrass (*Halodule wrightii*, *Syringodium filiforme*, and *Thalassia testudinum*), bare substratum	60%
Riegl and Purkis, 2005	Arabian Gulf, Dubai, UAE	50 and 200	< 8 m	coral, rock, ripples and algae, bare sand	60%
Moyer et al., 2005	Florida, USA	50	3-35 m	sand, rubble, reef	60%
Preston et al., 2006	Seto Inland Sea, Japan	200	not specified	sand, gravel, algae (*Ecklonia kurome*, *Sargassum fulvellum*)	no final habitat map authors reported that only 5% of ground-truth data were misclassified
Quintino et al., 2009	Mar Menor, Spain	50 and 200	1.5 - 2.5 m	sand, mud, algae (*Caulerpa prolifera*) at low, medium and high densities	No final habitat map, but found significant relationship between 200 kHz frequency and algal biomass

accuracy of maps produced using 50 kHz data compared to habitat maps produced using 200 kHz data, which is contrary to the results of Preston et al. (2006) and Quintino et al. (2009). Overall, these results indicate that there is a need to examine the applicability of the QTC5 system in other marine systems.

The present study analyzed the ability of the QTC5 system to generate habitat maps of the distribution of submerged vegetation at a site within the Gwaii Haanas National Marine Conservation Area in British Columbia, Canada. Acoustic data were collected using two frequencies (50 kHz and 200 kHz) and the thematic resolution and spatial accuracy of the resulting maps were compared. This objective of this research is to support conservation management within the GHNMCA by examining suitability of the QTC5 technology for mapping nearshore ecosystems.

2.3 Methods

2.3.1 Study area

Acoustic surveys were conducted in Bag Harbour, a small estuary south of the Burnaby Narrows in Haida Gwaii, British Columbia, Canada. The site is located within the Gwaii Haanas National Marine Conservation Area Reserve and Haida Heritage Site (GHNMCA) (Fig. 2.1). The site is approximately 600 m long and 300 m wide and is largely protected from predominant south-easterly winds by surrounding land masses and mountains.

Since 2004, Bag Harbour has been visited as a part of the GHNMCA eelgrass monitoring survey program which collects data on the water conditions, biological characteristics of eelgrass meadows and fish sampling (via beach seines) (Robinson et al., 2011; Robinson & Yakimishyn,

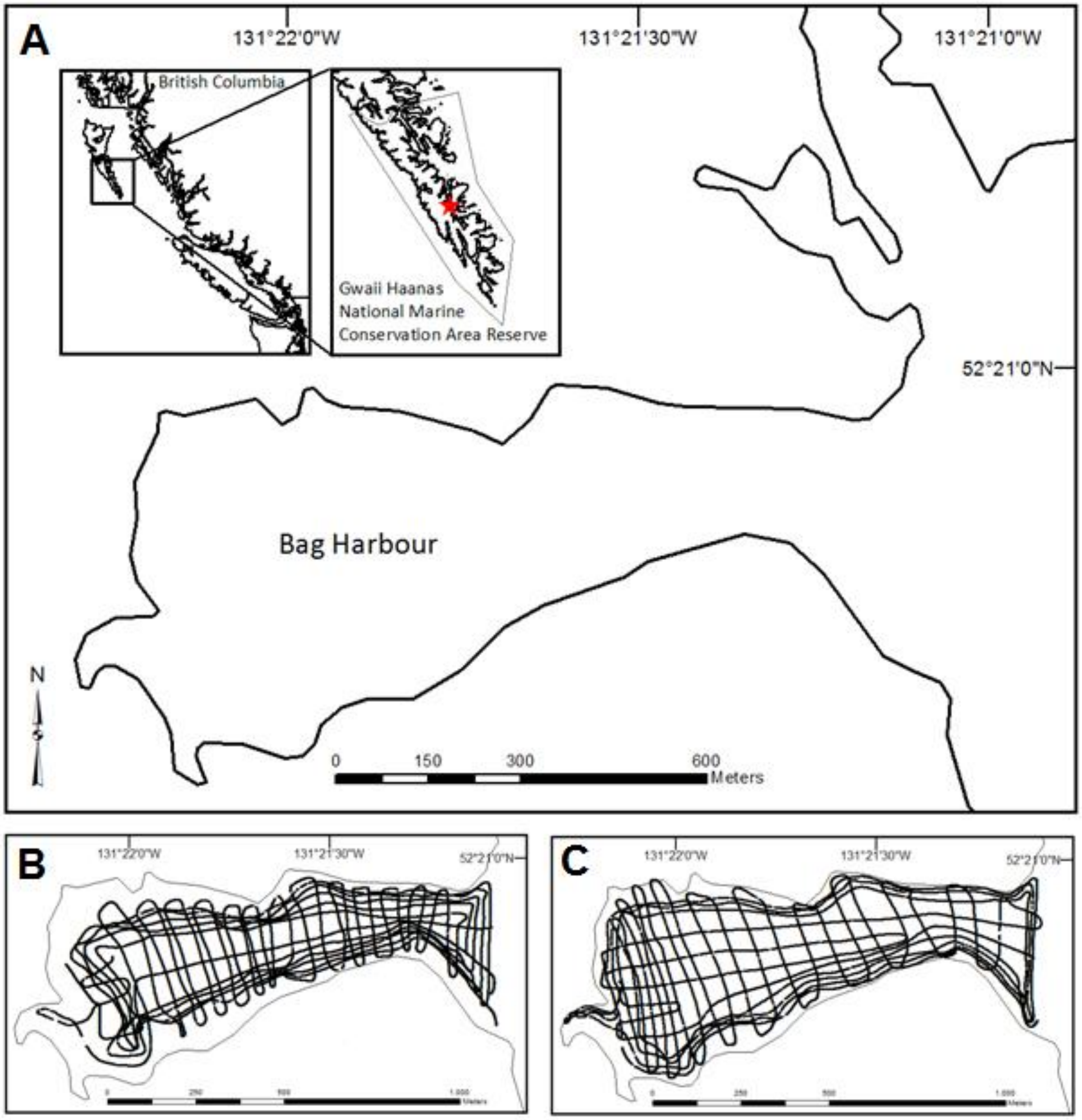


Figure 2.1. (A) Study area Bag Harbour, Gwaii Haanas National Marine Conservation Area Reserve and Haida Heritage Site, Haida Gwaii, British Columbia, Canada. (B) 50 kHz acoustic survey tracks. (C) 200 kHz acoustic survey tracks.

2013). Turbidity data from all eelgrass monitoring sites within the GHNMCA are shown in Table 2.2, with Bag Harbour demonstrating middling turbidity conditions. In 2008, an eelgrass assessment by Parks Canada in Bag Harbour produced the following average metrics for eelgrass: density = 800 shoot m^{-2}, biomass = 937 g m^{-2} which represented a higher mean than the GHNMCA sites' mean of 746 shoot m^{-2} and 698 g m^{-2} for density and biomass, respectively. Leaf area index was 1.76 which is slightly below the GHNMCA sites' mean of 2.8 (Robinson & Yakimyshyn, 2008). At least 20 fish species inhabit the eelgrass meadows, as determined by beach seine (Robinson et al., 2011; Robinson & Yakimishyn, 2013). The total areal extent of inter- and subtidal eelgrass meadows have never been mapped at Bag Harbour. Apart from eelgrass, there are patches of green algae (*Ulva* spp.) and brown algae (*Fucus* spp.) present at the site (Howes et al.,1994).

2.3.2 Sampling

2.3.2.1 Acoustic data

Two acoustic surveys were conducted on June 24th (200 kHz) and 25th (50 kHz), each approximately 4 hours in total survey time. The data were obtained with the acoustic system QTC VIEW Series V (QTC5) connected to a dual frequency (50 kHz and 200 kHz) echosounder (Hondex 7380). The echosounder was mounted to the side of a small vessel (~ 6.7 m long) and was submerged 0.5 m below the water's surface. The base settings of the echosounder were: pulse duration of 300 μs, ping frequency of 7 pings s^{-1} and 28° and 10° beam widths for 50 kHz and 200 kHz, respectively. Survey speed did not exceed 4 knots. A differential Global Positioning System (dGPS) (Ashtech MobileMapper100) acquired positional data (<1m horizontal accuracy) which was logged continuously during each acoustic survey. The QTC5

Table 2.2 - Turbidity measurements of eelgrass monitoring sites within the GHNMCA from July 2004-2011.

Site name	Years sampled	Range of turbidity (NTU)	Mean turbidity (NTU)
Sedgwick	2005-2006, 2008-2010	0.000-0.339	0.072
Murchison	2005-2006, 2008-2010	0.000-0.380	0.088
Kendrick point	2008-2011	0.022-0.325	0.113
Huxley	2006, 2008-2010	0.000-0.712	0.161
Swan Bay	2005-2006, 2008-2010	0.000-0.617	0.164
Bag Harbour	2004-2006, 2008-2011	0.023-0.876	0.196
Balcolm Inlet	2005-2006, 2008-2011	0.000-1.396	0.278
Rose Inlet	2005-2006, 2008-2011	0.010-1.750	0.374
Ikeda	2005, 2008, 2010	0.081-1.166	0.399
Louscoone	2005-2006, 2008-2010	0.001-2.323	0.473
Head of Louscoone Inlet	2005-2006, 2008-2010	0.002-3.095	0.605
Heater Harbour	2005-2006, 2008-2011	0.000-5.941	0.952
Section Cove	2005-2006, 2008-2010	0.002-6.619	1.157

system was run from a field laptop computer that allowed real time data display and storage. The vessel's path for both surveys is shown in Figure 2.1B and 2.1C.

2.3.2.2 Ground truth video data

Video data were collected on June 3rd and 4th, 2012 using a small colour underwater video camera (Deep Blue Pro, Ocean Systems Inc.) mounted to a custom-made aluminum wing. Survey transects are shown in Fig. 2.2A. Live video feed was visible via a field computer and allowed the operator to maintain the camera 1-2 m above the seafloor using an electrical downrigger. This height provided an imagery swath width of approximately 1-2 m. Video transects were run both parallel to shore (approximately 5-10 m apart) and orthogonal to shore (approximately 50 m apart). Video survey tracks are shown in Figure 2.1(panels B and C). Vessel speed was maintained between 1-2 knots during video surveys (greater speeds negatively impacted the quality of the video). A depth logger (Sensus Ultra U-04133, Reefnet Inc.) was attached to the camera and recorded depth every second during deployment. A dGPS was mounted next to the downrigger to maximize positional accuracy and logged positional data each second. Video and dGPS data were recorded directly to a field laptop computer hard drive. Additionally, the extents of exposed eelgrass meadows were mapped by walking the edges with a handheld dGPS during a low tide event (+0.5 m) on June 2nd, 2012.

2.3.3 Video data analysis

A hierarchical classification scheme was used to identify habitats in the video data, where "habitat" refers to the presence of submerged vegetation on the seafloor (or lack thereof). While it is possible to map substrate characteristics of the seafloor using the QTC5 system (Frietas et al, 2008) it was outside of the scope of this study. A two-tiered hierarchical classification scheme based on the framework outlined by Allee et al. (2000) was developed in order to test different

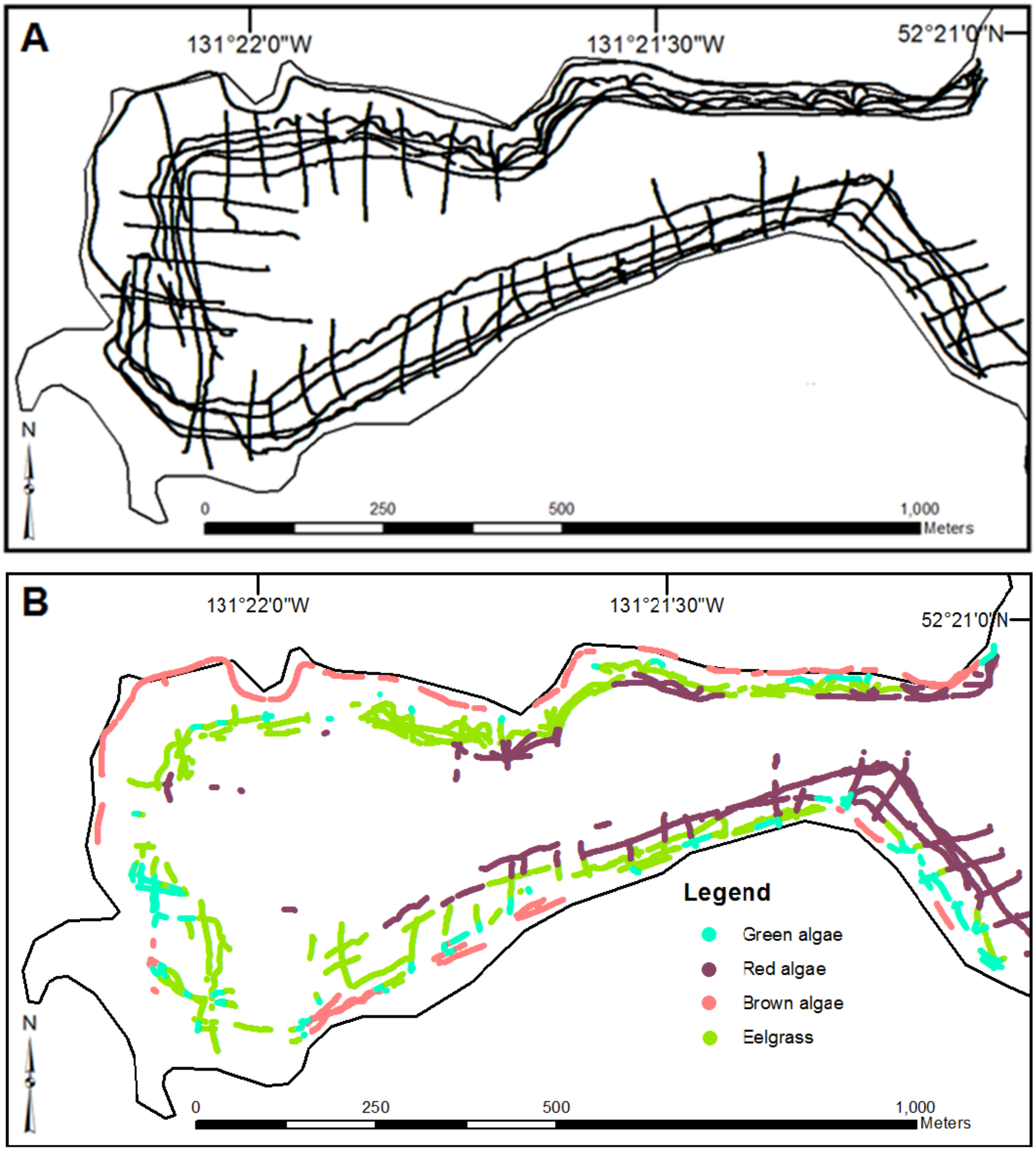


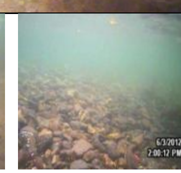
Figure 2.2. Study area showing (A) survey tracklines for towed underwater video data collected on June 3rd and 4th 2012 and (B) study area showing classified video track lines for four main vegetated habitats: brown algae (*Fucus* spp.), green algae (*Ulva* spp.), eelgrass and red algae (*C. exasperatus*).

levels of thematic resolution. The first level of the habitat scheme (hereafter referred to as Level 1) included all species of submerged aquatic vegetation present in the video. The second level of the habitat classification scheme (hereafter referred to as Level 2) further differentiated each habitat class identified in Level 1 based on that habitat's density on the seafloor. In this study density was defined by a semi-quantitative visual assessment of vegetation cover on the seafloor within a video frame. "Dense" cover was noted where substratum was not visible due to vegetation cover. Sparse cover was recorded where substratum and vegetation were both present. Unvegetated cover was recorded where no submerged vegetation was present. The habitat classification scheme is shown in Table 2.3 and includes a description and photo of each habitat class. Ground truth videos were analyzed in a standard electronic spreadsheet. Files containing the positional information (latitude and longitude) of the each video recording were analyzed in one second increments which corresponded to approximately 1-2 m of seafloor. A single individual analyzed all of the underwater video and used consistent standards for classification in order to minimize differences between different interpretations. After classification data were imported into a Geographic Information System (ArcGIS 10, ESRI, 2010).

The ground-truth data were split into two datasets. The first dataset (hereafter referred to as the "training data") was used to assign a habitat class to each of the initial acoustic classes resulting from the unsupervised classification. The remaining half of the dataset (hereafter referred to as the "validation data") was used to conduct the accuracy assessment of the acoustic habitat maps.

Table 2.3 - Habitat classification scheme used to analyze ground-truth video data.

Level 1	Description	Level 2	Description	Picture
Brown algae	*Fucus* spp. presen Occurs in upper intertidal regions	Dense brown algae	dense *Fucus* spp. present and seafloor not visible.	
		Sparse brown algae	sparse *Fucus* spp. present and seafloor not visible	
Green algae	*Ulva* spp. present Occurs in lower intertidal regions	Dense green algae	dense *Ulva* spp. present and seafloor not visible	
		Sparse green algae	sparse *Ulva* spp. present and seafloor not visible	

Eelgrass	*Zostera marina* present Occurs in lower intertidal and shallow subtidal regions	Dense eelgrass	dense *Z. marina* present and seafloor not visible	
		Sparse eelgrass	sparse *Z. marina* present and seafloor not visible	
Red algae	*Chondrocanthus exasperatus* present Occurs in shallow subtidal regions	Dense red algae	dense *C. exasperatus* present and seafloor not visible	
		Sparse red algae	sparse *C. exasperatus* present and seafloor not visible	
Unvegetated	No vegetation present on seafloor Occurs throughout site	Unvegetated	No vegetation present on seafloor	 

2.3.4 Acoustic data analysis

2.3.4.1 Acoustic classes

In the QTC5 system, the echo sounder generates a signal that travels through the water column, reflects off the seafloor, and records the first echo return. The echo is then characterized based on the reflected waveform in order to generate habitat classifications which are products of the diversity of scattering and penetration properties of the seafloor (Preston et al., 1999). Each echo is time-stamped, dGPS geo-located and digitized by the QTC5 system. The following section describes the steps of acoustic data processing.

Echo data were processed in the software QTC IMPACT (Quester Tangent Corporation, Sidney, British Columbia). During data acquisition echoes are recorded as full-waveform (fwf) time series (where each echo signal is the raw electric signal that is proportional to the actual pressure in the water). These fwf files are subjected to a bottom picking algorithm which detects the seabed/water interface (Biffard, 2011). Accurate bottom-picking is essential for the detection of any signal preceding the seafloor that indicates the presence of vegetated habitat. A bottom picking threshold of 50% was used for this analysis to ensure that bottom-picks were attributed to the seabed/water interface and not to overlying vegetation (personal communication, Biffard, 2012).

To improve the acoustic classification of submerged vegetation the window of echo analysis was adjusted (Preston et al., 2006). In IMPACT, the window of analysis contains 256 samples and typically the echo must fit entirely within that envelope (with alignment of the window established by the bottom pick) (Biffard, 2011). The default setting for this window is 5 samples before the bottom pick and 251 samples after the bottom pick. However, these settings eliminate the detection of any signal precursor to the bottom pick that may contain information about overlying vegetation. Results from Preston et al. (2006) demonstrated that moving this window to 128 samples before the bottom and pick and 128 samples after the bottom pick significantly increases the ability of the acoustic classification for mapping seabed vegetation. This is done by changing the TNORM_ABOVE and TNORM_BELOW settings in the .cfg file that QTC IMPACT generates each time it runs. TNORM_ABOVE and TNORM_BELOW were both set to 128 in this analysis. See Figure 2.3 for a visual description of this methodology (adapted from Preston et al, 2006).

After bottom-picking, echoes were stacked to reduce the consequences of ping-to-ping variability (QTC IMPACT manual, 2004). Stacks of 5 (the default standard) were created for this work. Echo stacks are then subjected to a series of algorithms which create 166 descriptive features for each stack (Preston & Collins, 2000; Preston et al., 2004). At this stage echoes that did not have correct time-stamps, correct depths or signal strengths below 5% were filtered and not used for further processing.

After poor-quality data were removed, the dataset was subjected to a Principal Components Analysis (PCA) for data reduction. This produces a reduced description of each echo consisting of three values (labeled Q1, Q2 and Q3) that correspond to the coordinates of the three first PCA axes. These "Q values" can be plotted into a pseudo-three-dimensional space ("Q-Space"), and, in theory, acoustically similar echo stacks will form clusters (QTC IMPACT manual, 2004).

Following PCA analysis, both acoustic datasets (50 kHz and 200 kHz) were classified using an unsupervised classification method based on an automated clustering tool available in

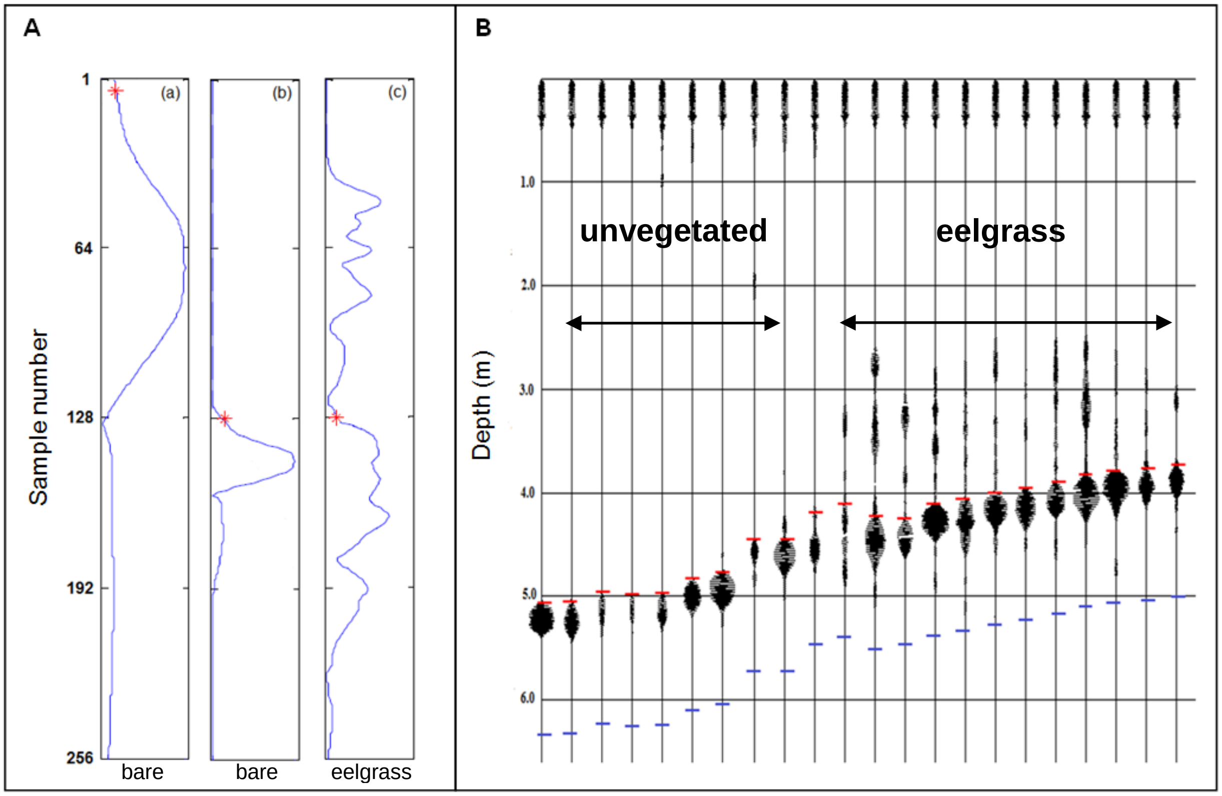


Figure 2.3 (A) Three panels show the portion of the echo time series from which features are made occur in a window consisting of 256 sample. Echoes are shown solid and asterisks indicate bottom picks (seabed-water interface). In panel (a) the pick is at sample 5 and in panels (b) and (c) the pick at sample is at 128. By putting the pick at 128 this reserves the first half for backscatter from eelgrass. (B) Echo data collected over bare substrate and eelgrass. Evidence of eelgrass is obvious prior to the bottom-pick (red line).

the QTC IMPACT software. The ACE (automated clustering engine) is an objective Bayesian k-means clustering procedure that provides a means to determine, based on the Bayesian Information Criterion (BIC), the optimal number of clusters or classes for the dataset (QTC IMPACT manual, 2004). The optimal number of clusters is determined by the classification with the lowest BIC score. Any points that fall within that cluster space are assigned to that particular class (QTC IMPACT Manual, 2004).

The user may choose the number of classes and iterations to run. In this study the 50 kHz and 200 kHz data were subjected to 99 iterations from 2-15 classes. This range was selected based on previous clustering results and time restraints in data processing (2 is the minimum input required and BIC scores were found to increase for classes greater than 15). The result with the lowest score BIC score was selected. In the case where two classes had similarly low scores, the lower class was selected. The final output is a file where each data point (echo stack) has been assigned an acoustic class and can be viewed in a GIS environment.

2.3.4.2 Interpolation

To produce a spatially continuous map surface the classified data were interpolated using QTC CLAMS (Quester Tangent Corporation, Sidney, British Columbia). This program uses categorical interpolation suitable for discrete categorical data. This method also ensures that no fractional classes are created (QTC CLAMS manual, 2004). 50 kHz and 200 kHz data were interpolated to a regular grid size of 10 m and 2 m cell size, respectively. These cell sizes were chosen based on the mean footprint size of the acoustic beam in each survey, which was calculated from the mean survey depth and beam width based on the equation $d = 2z\tan(\Theta/2)$, where d is diameter of the echosounder footprint on the seafloor, z is the depth to the seafloor and θ is the echosounder beam width.

2.3.4.3 Interpretation of acoustic classes

Prior to assessing the accuracy of the habitat maps, acoustic classes generated from the unsupervised classification (i.e. the ACE clustering method) were assigned a habitat class. The ground-truth training data were used to interpret acoustic classes. To assign a habitat class to an acoustic class the training data were (1) superimposed over the acoustic maps in a GIS to examiner visual agreement between acoustic classes and ground-truth data and (2) acoustic classes were extracted to the overlying video data to examine the quantitative distribution of habitat data among acoustic classes.

Interpretation of acoustic classes was conducted at Level 1 and Level 2 of the habitat classification scheme developed from the ground-truth video (described above). Acoustic classes that did not show any association with a vegetated habitat were classified as “unvegetated” as acoustic data were processed to distinguish between vegetated and unvegetated habitats.

2.3.4.4 Validation of habitat classes

Two groups of validation data were created from the ground-truth validation dataset to account for the different spatial resolution between acoustic frequencies. Given that the minimum mapping unit of the video data is finer than either acoustic dataset, the validation data needed to be sampled at the same resolution of the map that was being validated. Validation data for the 50 kHz and 200 kHz datasets were selected at a 10 m and 2m resolution, respectively. This was done by overlaying validation data over a 10 m and 2 m grids and selecting pixels in regions that contained only a single, homogeneous substrate type.

To assess map accuracy standard confusion matrices were constructed to calculate user's, producer's and total accuracy for each habitat class present. Producer's accuracy is defined as the percentage of testing pixels of a specific substrate that were classified correctly (i.e. how well the training sites were classified or the probability of misclassifying a training site) (Story & Congalton, 1986). User's accuracy is the percentage of pixels classified as a specific substrate which are truly that substrate (i.e. how well the classification represents ground-truth) (Story & Congalton, 1986). Total accuracy is the percentage of sites of all substrate types classified correctly. Tau coefficients were also calculated which serves as another measure of classification accuracy (Ma & Redmond, 1995). For example, a tau coefficient of 0.75 indicates that 75% more pixels were classified correctly than would be expected by chance alone (Green et al., 2000).

2.4 Results

2.4.1 Video analysis

Seven hours of video footage was recorded which covered a linear distance of ~ 20 km. Four predominant submerged vegetation habitats were identified (Fig. 2.2B) - eelgrass (*Z. marina*), a benthic foliose red algae (*Chondrocanthus exasperatus*), green algae (*Ulva* spp.) and brown algae (*Fucus* spp.). Eelgrass was present in large continuous patches along the north, south and east shores of the site. Red algae were found in the subtidal regions neighbouring the eelgrass meadows. Green algae were present in patches in the intertidal zone bordering eelgrass meadows. Brown algae was predominantly present in small patches (~ <2 m^2) on boulders and cobbles in the upper intertidal zone.

2.4.2 Acoustic results

2.4.2.1 50 kHz survey

A total of 9945 echo stacks from the 50 kHz survey were processed in QTC IMPACT. The results of the ACE clustering algorithm found the optimal number of acoustic classes to be six (Fig. 2.4A). When the acoustic data were plotted along the first three principal components they formed a relatively homogeneous cluster indicating that overlap could be expected between acoustic classes (Fig. 2.4B). A review of the data found that one class, class 6, constituted less than 1% (n= 44) of the total dataset and showed no distinct spatial distribution (Fig. 2.4C Panel 6) and was therefore removed from further analysis. Of the remaining five classes, classes 1 and 3 showed distinct spatial distributions (Fig. 2.4C Panels 1 and 3) while classes 2 (Fig. 2.4C Panel 2), 4 (Fig. 2.4C Panel 4) and 5 (Fig. 2.4C Panel 5) had a more ubiquitous distribution.

2.4.2.2 200 kHz survey

A total of 8036 echo stacks from the 200 kHz survey were processed by the ACE clustering algorithm (Fig. 2.5A). Clustering was more pronounced between the 10 acoustic classes (Fig. 2.5B) compared to the 50 kHz data. Class 1 was removed because it constituted less than 2% (n=150) of the total dataset and showed a sparse distribution with no distinct spatial patterns (Fig. 2.5B Panel 1). Compared to the 50 kHz survey, more acoustic classes from the 200 kHz survey appeared to show distinct spatial patterns throughout the study site. In particular classes 2, 3, 6, 7 and 10 showed very distinct spatial patterns in bands and patches around the entire study site. Classes 4, 5, 8 and 9 showed fairly ubiquitous distributions. The spatial distribution of each class is shown in Figure 2.5C.

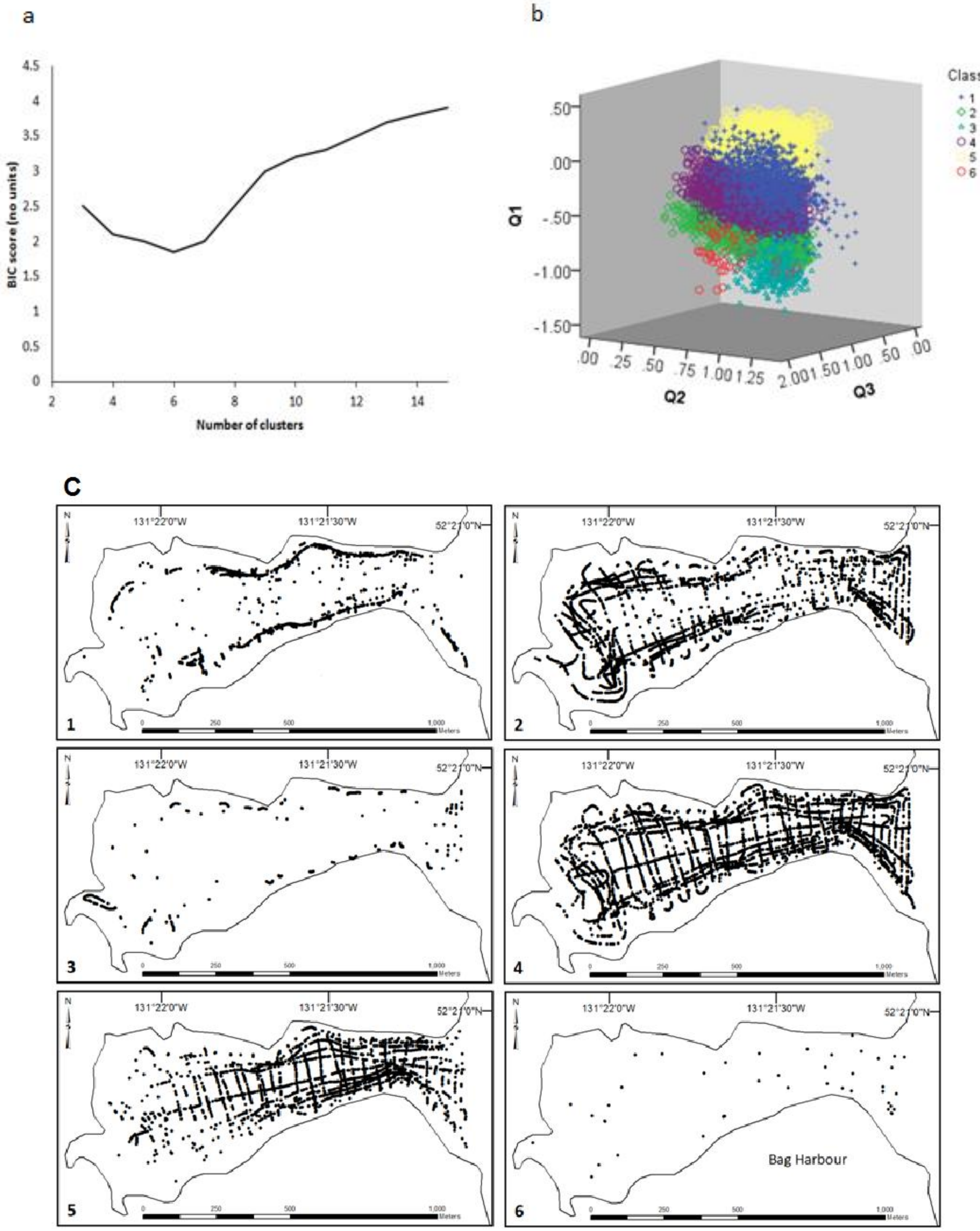


Figure 2.4 (a) Clustering results from the 50 kHz acoustic survey. (b) PCA plot. (c) Distribution of 6 50 kHz acoustic classes.

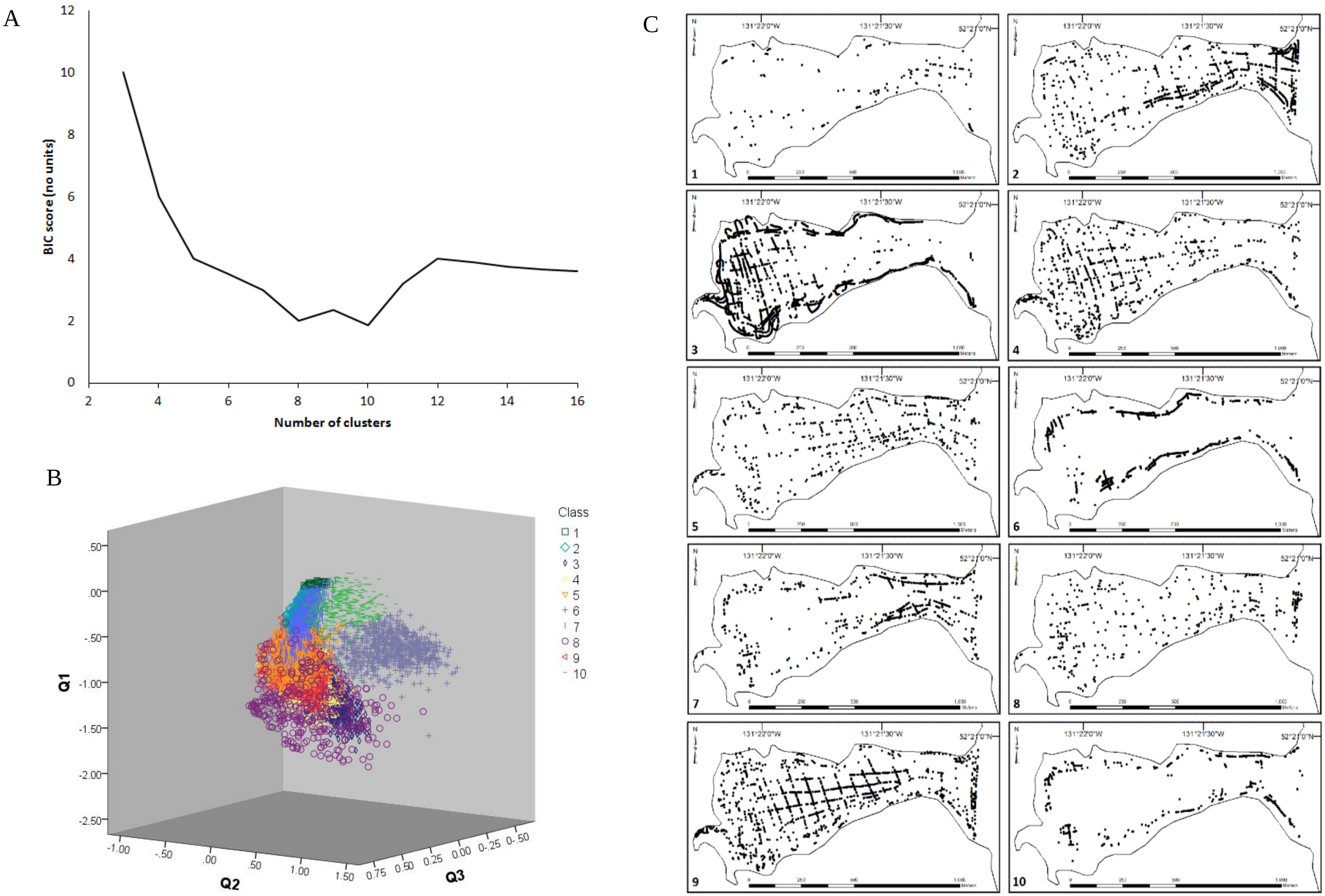


Figure 2.5 (A) Clustering results from the 200 kHz acoustic survey. (B) PCA plot. (C) Distribution of 6 50 kHz acoustic classes over the survey area.

2.4.2.3 Interpretation of acoustic classes

The results of the interpretation of acoustic classes for the 50 kHz and 200 kHz surveys are shown in Table 2.4. For the 50 kHz survey at the Level 1 habitat classification, class 1 was closely associated with eelgrass habitat both visually and with 50% of eelgrass training data occurring within class 1. In the case of red algae, 50% of training data overlapped with acoustic class 4 but based upon the visual examination of the data it was concluded that this trend was due to the ubiquitous distribution of class 4 throughout the study site. The majority of training data from green algae (48%), brown algae (51%) and unvegetated substrates (42%) were all associated with Class 2. Given the patchy distribution of brown algae and green algae in Bag Harbour (as seen in the video data) it was concluded that this association did not reflect the true distribution of these vegetated habitats. In the end, acoustic classes 2, 3, 4 and 5 were labeled as "unvegetated". In reality, there may be submerged vegetation in these areas but, from the perspective of the 50 kHz transducer, are unvegetated.

For the 50 kHz survey at the Level 2 habitat classification, class 1 was associated predominantly with dense eelgrass. Based on the analysis of training data, no acoustic classes were found to be associated with dense or sparse green algae, brown algae, and red algae, or sparse eelgrass therefore, classes 2, 3, 4 and 5 were labeled as unvegetated. Figure 2.6 Panel A shows the distribution of the interpolated acoustic classes prior to interpretation and Panel B shows the final habitat map generated from the habitat classification.

For the 200 kHz survey at the Level 1 habitat classification the visual assessment and analysis of training data indicated that classes 2 and 7 were associated with red algae (~75% of training data) and classes 6 and 10 were associated with eelgrass (~70% of training data). The majority of green algae (71%), brown algae (67%) and unvegetated (67%) training data were

Table 2.4 - Interpretation of 50 kHz and 200 kHz interpolated datasets at two levels of thematic resolution (Level 1 and Level 2).

Frequency	Acoustic Class	Habitat classification	
		Level 1	Level 2
50 kHz	1	Eelgrass	Dense eelgrass
	2	Unvegetated	Unvegetated
	3	Unvegetated	Unvegetated
	4	Unvegetated	Unvegetated
	5	Unvegetated	Unvegetated
	6	Removed	Removed
200 kHz	1	Removed	Removed
	2	Red algae	Dense red algae
	3	Unvegetated	Unvegetated
	4	Unvegetated	Unvegetated
	5	Unvegetated	Unvegetated
	6	Eelgrass	Eelgrass dense
	7	Red algae	Sparse red algae
	8	Unvegetated	Unvegetated
	9	Unvegetated	Unvegetated
	10	Eelgrass	Sparse eelgrass

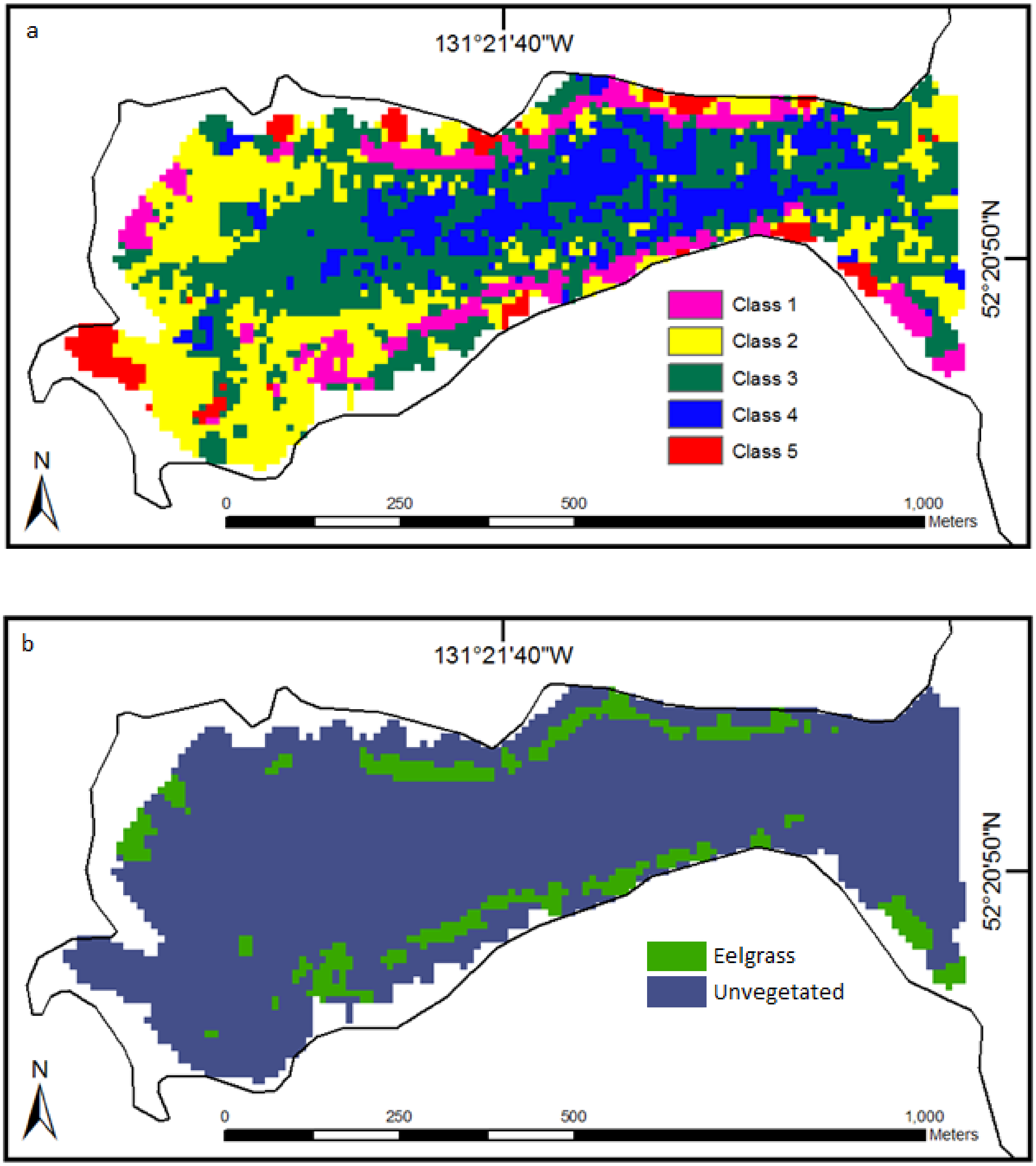


Figure 2.6 (a) Distribution of 5 acoustic classes from the 50 kHz data in Bag Harbour. (b) Habitat classification of acoustic classes at Bag Harbour based on 50 kHz data.

found in Class 3 due to its ubiquitous distribution. Therefore, based on the training data and visual assessment, classes 3, 4, 5, 8 and 9 were all labeled as unvegetated habitat. For the 200 kHz survey at the Level 2 classification class 2 was closely related to dense red algae (60% of training data) and class 7 was associated with sparse red algae (48% of training data). Class 6 was closely associated with dense eelgrass (60% of training data). Sparse eelgrass was also associated with classes 3 (32%), 6 (26%) as well as class 10 (12%), however, class 10 was selected as this was the other class associated with eelgrass at the Level 1 classification, class 3 was too ubiquitous to represent sparse eelgrass and class 6 had already been associated with dense eelgrass. The distribution of training data in multiple acoustic classes indicated that this class would likely suffer from misclassification during the accuracy assessment. The majority of training data from dense and sparse green and brown algae were associated with class 3 but, as was mentioned before, class 3 was present in the majority of the site and also encompassed the majority of unvegetated substrate training data (68%). Classes 3, 4, 5, 8 and 9 were labeled as unvegetated habitat. The classified habitat maps are shown in Figure 2.7 Panel A (Level 1) and Panel B (Level 2).

2.4.3 Accuracy assessment

2.4.3.1 50 kHz data

Confusion matrices for the Level 1 and Level 2 50 kHz habitat classifications are shown in Table 2.5. The Level 2 habitat map showed a somewhat higher overall accuracy (70% compared to 63%) the eelgrass user's and producer's accuracy were very similar; 97%/44% and 95%/44% for Level 1 and Level 2 habitat maps, respectively. The low producer's accuracy indicate that less than 50% of the ground-truth data were classified as eelgrass. Furthermore, a Z-test found no statistically significant difference between tau coefficients ($Z=1.42$, $p = 0.05$).

Table 2.5 - Confusion matrices for Level 1 and Level 2 habitat maps based on 50 kHz acoustic data.

Level 1 50 kHz habitat map				
Ground-truth	Eelgrass	Unvegetated	Sum	Producer's Accuracy
Eelgrass	92	119	211	43.6%
Unvegetated	3	119	122	97.5%
Sum	95	238	333	
User's Accuracy	96.8%	50.0%		Overall accuracy
Tau coefficient	0.472			63.4%

Level 2 50 kHz habitat map				
Ground-truth	Dense Eelgrass	Unvegetated	Sum	Producer's Accuracy
Dense eelgrass	59	74	133	44.4%
Unvegetated	3	119	122	97.5%
Sum	62	193	255	
User's Accuracy	95.2%	61.7%		Overall accuracy
Tau coefficient	0.540			69.8%

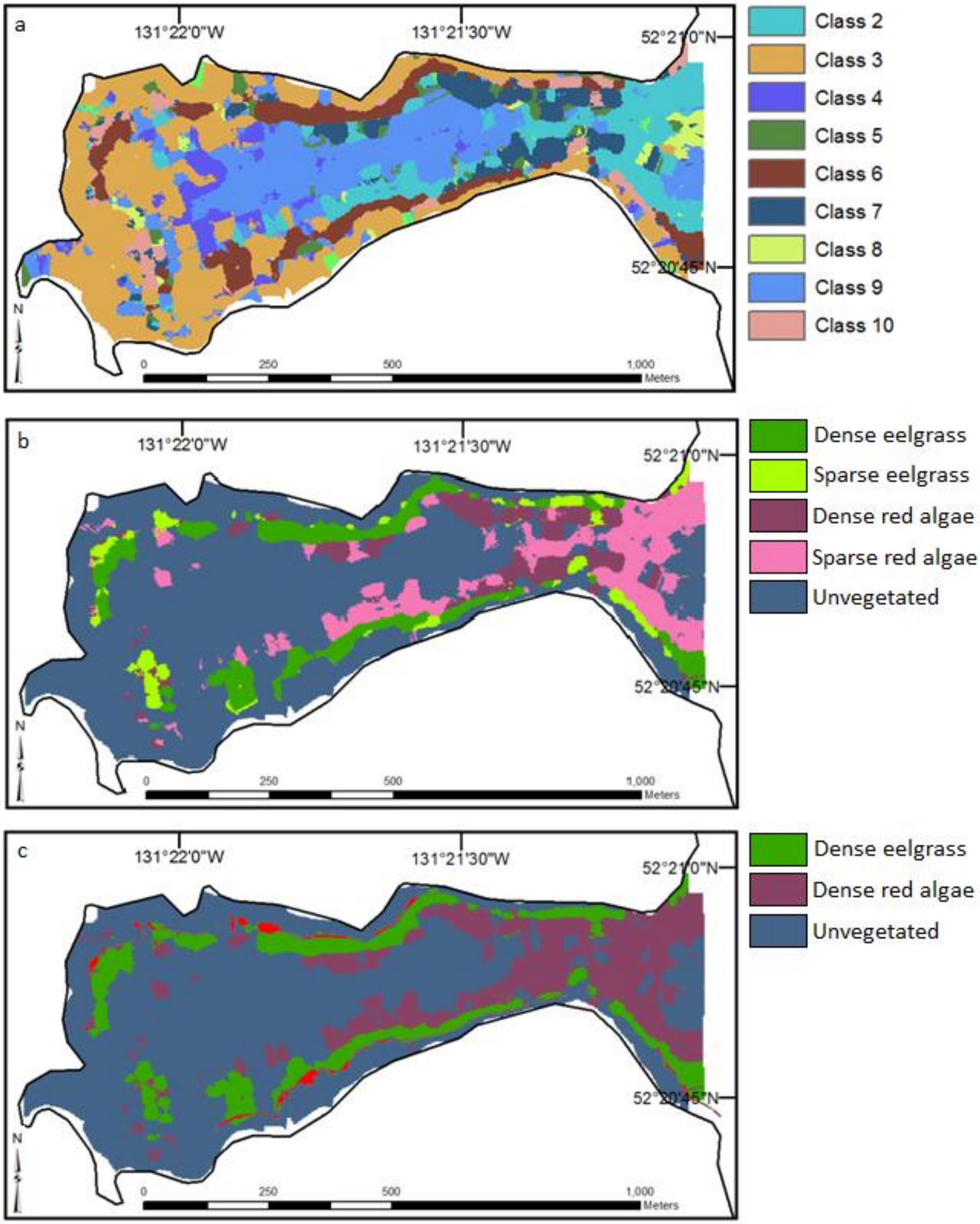


Figure 2.7 (a) Distribution of 9 acoustic classes from the 200 kHz data in Bag Harbour. (b) Level 2 habitat classification of acoustic classes at Bag Harbour based on 200 kHz data. (c) Simplified Level 2 habitat classification of acoustic classes at Bag Harbour based on 200 kHz data. Red polygons indicate extent of eelgrass meadows mapped with a handheld GPS.

These results indicate that the ability for the 50 kHz frequency is most sensitive to the detection of dense eelgrass.

2.4.3.2 200 kHz data

Confusion matrices for the 200 kHz data are shown in Table 2.6. The overall accuracy of the Level 1 habitat map was 81% and a tau coefficient of 0.72. The red algae and eelgrass habitat classes had user's and producer's accuracy of 90%/74% and 68%/73%, respectively. The majority of misclassification within both habitat classes was with unvegetated substrate. The poorer performance in the red algae class is due to the misclassification of red algae in shallow regions of the study where no red algae was found during the ground-truth survey. In comparison to the 50 kHz Level 1 habitat map, the 200 kHz data show a significant improvement in the ability in mapping the distribution of eelgrass with higher eelgrass producer's accuracy (74% compared to 44%) as well as being able to detect the distribution of red algae habitat.

The overall accuracy of the Level 2 200 kHz habitat map was 66% and included 5 classes – dense eelgrass, sparse eelgrass, dense red algae, sparse red algae and unvegetated habitat. The dense eelgrass habitat had the highest user's and producer's accuracy (80%/61%) while the sparse eelgrass class performed the poorest with14% for both user's and producer's accuracy. The majority of misclassifications for sparse eelgrass were with dense eelgrass (32% of ground-truth data) and unvegetated substrate (38% of ground-truth data). User's and producer's accuracy for dense red algae were 31% and 39% and 49% and 48% for sparse red algae, respectively. Sparse red algae showed significant confusion with dense red algae (22% of ground-truth data) and unvegetated substrates (23% of ground-truth data). The majority of confusion with dense red algae was with sparse red algae (39% of ground-truth data).

Table 2.6 - Confusion matrices for habitat maps derived from 200 kHz dataset.

Level 1 Habitat map					
Ground-truth	Eelgrass	Red algae	Unvegetated	Sum	Producer's Accuracy
Eelgrass	447	52	105	604	74.0%
Red algae	17	159	42	218	72.9%
Unvegetated	31	23	524	578	90.5%
Sum	495	234	671	1400	
User's Accuracy	90.3%	67.9%	78.1%		Overall accuracy
Tau coefficient	0.720				80.7%

Level 2 Habitat map							
Ground-truth	Sparse eelgrass	Dense eelgrass	Sparse red algae	Dense red algae	Unvegetated	Sum	Producer's Accuracy
Sparse eelgrass	18	42	13	8	50	131	13.7%
Dense eelgrass	97	290	23	8	55	473	61.3%
Sparse red algae	6	4	71	33	35	149	47.6%
Dense red algae	2	5	28	27	7	69	39.1%
Unvegetated	7	24	11	12	524	578	90.6%
Sum	130	365	146	88	671	1400	
User's Accuracy	13.8%	79.5%	48.63%	30.682%	78.1%		Overall Accuracy
Tau coefficient	0.563						66.4%

	Level 2 simplified habitat map				
Ground-truth	Dense Eelgrass	Dense Red algae	Unvegetated	Sum	Producer's accuracy
Dense Eelgrass	387	31	55	473	81.8%
Dense Red algae	7	55	7	69	79.1%
Unvegetated	31	23	524	578	90.6%
Sum	425	109	586	1120	
User's Accuracy	91.0%	50.4%	89.4%		Overall Accuracy
Kappa	0.756				86.2%

Given the relatively poor performance of sparse eelgrass and sparse red algae in comparison to their dense class counterparts a second accuracy assessment was conducted with only dense eelgrass and dense red algae habitats (Figure 2.7C). The overall accuracy of this map was 86% (Table 2.6). At this level of classification dense eelgrass showed a slight improvement over the Level 1 eelgrass class with user's and producer's accuracy of 91% and 82%, respectively, compared to 90% and 74%. Dense red algae achieved slightly higher producer's accuracy poorer compared to the Level 1 classification (79% compared to 73%) however achieved lower with user's accuracy (50% compared to 68%).

According to the most accurate classification (Fig. 2.7C), Bag Harbour contains several large eelgrass meadows along its periphery. The total area delineated as eelgrass in the classification of the 200 kHz data was 66, 304 m^2. Red algae are present in large subtidal expanses, neighbouring eelgrass meadows. The total area delineated as red algae is 99, 816 m^2. When compared to field data of eelgrass bed peripheries walked at low tide there was excellent visual agreement between these data and the eelgrass habitat class derived from the 200 kHz data (Figure 2.7C).

2.5 Discussion

The objective of this study was to examine the utility of the QT5 single-beam acoustic ground discrimination system to classify submerged vegetation. To do this, two acoustic surveys were conducted for two frequencies - 50 kHz and 200 kHz. Results showed that the 200 kHz data were more effective at generating habitat maps with greater thematic and spatial resolution. The 50 kHz data failed to identify the presence of red algae (*C. exasperatus*) while the 200 kHz data demonstrated the ability to detect the distribution of both red algae and eelgrass. This thematic difference is likely based on the physical characteristics of each frequency. At greater depths, the footprint of the 50 kHz frequency is greater than the 200 kHz (due to beam width), therefore, there is an increased likelihood that the return echoes contain both vegetated and unvegetated habitat. This heterogeneity in the return echo likely reduces the ability for the 50 kHz data to differentiate species of submerged vegetation at greater depths. In contrast, the 200 kHz has a narrower beam width and is therefore more likely to collect acoustic data over homogeneous seafloor containing a single habitat. In addition to differences in beam width, lower echo sounder frequencies (i.e. 50 kHz) have been found to impart more energy into the seabed causing the signal to penetrate deeper and acquire information about the sediment column. In contrast, higher frequencies (ie. 200 kHz), which do not transmit as much energy into the seabed, suffering greater attenuation in the water column and therefore respond more to the superficial layer as well as the underwater vegetation overlying the seafloor sediment (Collins & Rhynas, 1998). This phenomenon has also been demonstrated in a study by Quintino et al. (2009). Using the QTC5 system, the authors demonstrated that 200 kHz was more sensitive to the presence and biomass of macroalgae, regardless of differences in underlying substrate. The authors also found that the 50 kHz data were strongly related the sedimentary composition of the seabed. The strong relationship between 50 kHz and the sedimentary characteristics of seafloors has also been demonstrated by Freitas et al, (2008) who found that only 50 kHz data corresponded with sedimentary gradients in the Bay of Cadiz, Spain.

The 200 kHz dataset was able to discriminate between two species of submerged vegetation - eelgrass and red algae. The ability of the 200 kHz dataset to detect these habitats performed best for dense occurrences of eelgrass and red algae and was limited in mapping sparse occurrences of these same habitats. The 200 kHz data was also incapable of mapping other occurring submerged vegetation including green algae (*Ulva* spp.) and brown algae (*Fucus* spp.). These results indicate that the ability to discern submerged aquatic vegetation using AGDS may be dependent on the biomass of that vegetation on the seafloor. It is likely that dense habitats are more susceptible to acoustic mapping because they generate a unique acoustic signal discernible by the acoustic transducer. For example, the acoustic signals over bare substrate and eelgrass are clearly differentiable based on the echo shape (Fig. 2.3B). In areas where vegetation is sparsely present the signal may be overwhelmed by the strong return signal from the underlying substrate. The majority of error for the dense classes was found with their sparse class counterparts (ie. dense eelgrass misclassified as sparse eelgrass) which we deem to be acceptable error as the confusion is within the same habitat. The poor performance of the 200 kHz for sparse classes was due to acoustic confusion with unvegetated seafloor (Table 2.6). These results are consistent with Riegl and Purkis (2005) who conducted acoustic mapping with the QTC5 system off the coast of Dubai, United Arab Emirates. They deliberately sampled over very sparse seagrass (*Halodule uninervis* and *Halophila ovalis*) and did not observe any unique acoustic signature. This may indicate a biomass threshold at which the 200 kHz data are capable of discerning the presence of eelgrass. It would be valuable in the future to collect ground truth data in which it is possible to estimate vegetation biomass in a more quantitative manner to examine the relationship between acoustic detection and biomass as demonstrated by Quintino et al. (2009). Quintino et al. (2009) were able to distinguish between vegetatation (*C. prolifera*) biomass by carefully extracting echo samples from locations with known vegetation densities and analyzing the echo data using novel software. The analysis done in this study was conducted strictly using QTC IMPACT for echo analysis and was therefore limited to the process of reduction and clustering as described above. Future work could address using Quintino et al's (2009) software which they have made available on request.

Neither the 200 kHz or the 50 kHz datasets were able to detect the distribution of green algae (*Ulva* sp) or brown algae (*Fucus* spp.). This is likely due to several factors. Firstly, these two algal species occur from the mid- to high intertidal range. Consequently, the footprint of the transducer in these shallow areas is very small. At a depth of 1 m (the minimum depth maintained below the transducer in this study) the footprint area sampled by the 200 kHz transducer was 0.023 m^2. While studies have shown that the QTC5 system can sample adequately in water as shallow as 1 m (Hutin et al, 2005; Quintino et al, 2009; Riegl et al, 2005) acoustic mapping in shallow regions is technically more demanding (Preston & Collins, 2000). It is likely that brown and green algae were undersampled by the QTC5 system. For example, within Bag Harbour, *Fucus* spp. is present in the high intertidal in very sparse, patchy spatial arrangements and therefore presents a difficult habitat to map based on point sample collection along a transect. It is likely that not enough echoes were collected over brown and green algal habitats during the survey to generate unique acoustic classes in QTC IMPACT.

Secondly, unlike red algae and eelgrass which have relatively tall canopies (>0.3m), green and brown algae have relatively small canopies (0.1-0.2 m). It is surmised that given these low canopy heights there is insufficient algal biomass to interact with the acoustic signal and/or the signal from the underlying substrates masks the signal from these habitats. According to Chivers et al. (1990), the first peak(s) of the return echo is strongly influenced by subsurface reverberation and this may overwhelm the signal from the overlying algae. Based on these results, future mapping using the QTC5 system could test a supervised classification approach where acoustic data would be collected over known occurrences of habitats to generate a catalogue of acoustic data, thus ensuring enough echoes are collected (e.g. Anderson, 2002). Also, other mapping techniques, such as satellite imagery or aerial photography may be more suitable for mapping these habitats. For example, over the past 20 years in British Columbia, the ShoreZone project has mapped large portions of the coastline based on the classification of aerial photographs and videography of intertidal zones (Howes et al., 1994) and includes inventories of both brown algae and green algae occurrence.

While previous studies have demonstrated the ability to map submerged vegetation using the QTC5 system (Table 2.1), only three of these studies tested the accuracy of a final habitat map (Reigl and Purkis, 2005; Riegl et al., 2005; Moyer et al., 2005). Off the coast of Florida, Moyer et al. (2005) were able differentiate between three broad habitat classes (sand, rubble and reef) with an overall accuracy of 61% using a 50 kHz transducer. Using both 50 and 200 kHz frequencies Reigl and Purkis (2005) found that the 50 kHz acoustic seafloor classification was able to determine two classes (unconsolidated sand versus hardground) and the 200 kHz classification could differentiate between high rugosity (i.e. corals and sand ripples) versus low rugosity (i.e. flat areas). The habitat map produced from these data was found to be 66% accurate when compared to an IKONOS dataset from the same site. In another study, Reigl et al. (2005) produced a three class habitat maps (sand, seagrass and algae) in the Indian River Lagoon, Florida, using both 50 and 200 kHz. Their results found no difference in overall accuracy for maps produced with different frequencies (approximately 60% for both datasets) for habitat maps produced from both datasets. In comparison, the results obtained in this study - 81% overall accuracy with 3 habitat classes for the 200 kHz data - are the highest reported using QTC5 for mapping submerged vegetation.

Overall, the results of this study indicate that the 200 kHz frequency is more suitable for mapping submerged vegetation in the inter- and subtidal regions compared to the 50 kHz frequency. 200 kHz data had higher thematic resolution - the data were able to detect the distribution of two species of submerged vegetation (red algae and eelgrass), compared to only one habitat with the 50 kHz data. The 200 kHz data had a smaller spatial resolution (2 m) compared to the 50 kHz data (10 m) which more realistically represented the spatial distribution (e.g. patch shape) of habitat classes at Bag Harbour.

The benefits from a single beam acoustic mapping system such as QTC5, in comparison to multibeam echosounders (Collins & Galloway, 1998b) and sidescan sonars (Brown et al., 2005), is the ability to navigate shallow sites inaccessible that are inaccessible the larger vessels and to adequately map shallow habitats in these regions. From a conservation management perspective, the QTC5 system appears to be well suited to mapping the distribution of ecologically important habitat such as eelgrass and could be applied in the production of baseline maps of these habitats.

2.6. Conclusion

In this study, the QTC View V system was used in a small estuary in the Gwaii Haanas National Marine Conservation Area Reserve, Haida Gwaii, off the northwest coast of British Columbia, Canada. At the site, several species of submerged aquatic vegetation, including eelgrass, are present and part of an ecological monitoring program within the parks (Robinson et al., 2011; Robinson & Yakimishyn, 2013). Mapping their distribution is vital to the conservation and zoning management planning for the GHNMCA (GHNMCA Interim Management Plan and Zoning Plan, 2010).

The present work has shown the suitability for using AGDS for mapping submerged aquatic vegetation. The results demonstrated that 200 kHz data are better able to differentiate not only the spatial distribution of submerged vegetation but is capable of distinguishing between different species of submerged aquatic vegetation (red algae and eelgrass). The 50 kHz data were found to be less suitable for mapping submerged vegetation. Neither frequency was able to identify two other algal species present at the site – brown algae and green algae. This study provides evidence that the ability to identify the distribution of submerged vegetation is likely influenced by its canopy and depth, however, further studies are needed.

From a coastal resource management and conservation perspective the high level of accuracy of the 200 kHz habitat map for dense eelgrass and dense red algae prove that this technology can provide useful information on coastal marine ecosystems inform conservation management within a marine protected area. Also surveys can also be conducted from small vessels which offers safety and maneuverability in shallow areas that are inaccessible to other sonar technologies (side-scan and multibeam sonar) which require larger vessels to operate. The QTC VIEW V system offers a relatively quick means to map certain types of nearshore habitats, under ideal environmental conditions. In this study, data collection consisted of 7 hours of ground-truthing video collection, however, future surveys could be more time efficient by first conducting acoustic surveys, creating interpolated acoustic maps and then conducting video sampling for ground-truthing based these maps using a random stratified collection method (Story and Congalton, 1999). Given that each acoustic survey took 4 hours it is likely that data collection could be accomplished in two days or less. The evidence from this study indicates that this system is best suited to mapping certain types of submerged vegetation such as eelgrass and red algae which occur in high densities. Submerged vegetation that has sparse distribution and low canopy may not be as suitable for mapping using single beam acoustic ground discrimination. Given the abundance of data that the QTC VIEW system can collect and the high accuracy of submerged vegetation maps produced from these data using the 200 kHz frequency, there is definite applicability of this system to map important habitat, such as seagrass, in the nearshore zone.

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Appendix 1

Interpretation of 50 kHz acoustic classes based on extraction of acoustic classes to ground-truth data at the Level 1 habitat classification. Acoustic classes that are in bold were classified as that habitat type.

Eelgrass		
Acoustic class	No. training data	% total
1	**1265**	**48.96%**
2	576	22.29%
3	24	0.93%
4	529	20.47%
b	172	6.66%
Total	2584	

Red algae		
Acoustic class	No. training data	% total
1	48	2.54%
2	421	22.28%
3	0	0.00%
4	**1013**	**53.60%**
5	398	21.06%
Total	1890	

Brown algae		
Acoustic class	No. training data	% total
1	15	4.78%
2	**160**	**50.96%**
3	101	32.17%
4	34	10.83%
5	4	1.27%
Total	314	

Green algae		
Acoustic class	No. training data	% total
1	96	17.61%
2	**264**	**48.44%**
3	72	13.21%
4	102	18.72%
5	11	2.02%
Total	545	

Unvegetated		
Acoustic class	No. training data	% total
1	238	5.95%
2	**1720**	**42.97%**
3	348	8.69%
4	874	21.83%
5	249	6.22%
Total	4003	

Interpretation of 50 kHz acoustic classes based on extraction of acoustic classes to ground-truth data at the Level 2 habitat classification. Acoustic classes that are in bold were classified as that habitat type

Dense eelgrass		
Acoustic class	No. training data	% total
1	**1070**	**55.87%**
2	319	16.66%
3	23	1.20%
4	377	19.69%
5	123	6.42%
Total	1915	

Sparse eelgrass		
Acoustic class	No. training data	% total
1	176	27.41%
2	214	33.33%
3	13	2.02%
4	189	29.44%
5	37	5.76%
Total	642	

Dense red algae		
Acoustic class	No. training data	% total
1	28	2.44%
2	284	24.78%
3	0	0.00%
4	**610**	**53.23%**
5	194	16.93%
Total	1146	

Sparse red algae		
Acoustic class	No. training data	% total
1	3	0.76%
2	70	17.68%
3	0	0.00%
4	192	48.48%
5	131	33.08%
Total	396	

Dense brown algae		
Acoustic class	No. training data	% total
0	127	46.35%
1	0	0.00%
2	35	12.77%
3	10	3.65%
4	102	37.23%
5	0	0.00%
Total	274	

Sparse brown algae		
Acoustic class	No. training data	% total
0	448	58.79%
1	15	1.97%
2	160	21.00%
3	101	13.25%
4	34	4.46%
5	4	0.52%
Total	762	

Dense green algae		
Acoustic class	No. training data	% total
1	69	20.12%
2	124	36.15%
3	66	19.24%
4	76	22.16%
5	8	2.33%
Total	343	

Sparse green algae		
Acoustic class	No. training data	% total
1	36	17.39%
2	108	52.17%
3	49	23.67%
4	12	5.80%
5	2	0.97%
Total	207	

Interpretation of 200 kHz acoustic classes based on extraction of acoustic classes to ground-truth data at the Level1 habitat classification. Acoustic classes that are in bold were classified as that habitat type.

Eelgrass		
Acoustic class	No. training data	% total
1	0	0.00%
2	63	2.44%
3	343	13.28%
4	50	1.94%
5	49	1.90%
6	**1358**	**52.59%**
7	166	6.43%
8	12	0.46%
9	69	2.67%
10	**472**	**18.28%**
Total	2582	

Red algae		
Acoustic class	No. training data	% total
1	11	0.58%
2	**833**	**44.07%**
3	66	3.49%
4	11	0.58%
5	59	3.12%
6	185	9.79%
7	**553**	**29.26%**
8	19	1.01%
9	109	5.77%
10	44	2.33%
Total	1890	

Brown algae		
Acoustic class	No. training data	% total
1	26	2.54%
2	59	5.77%
3	**685**	**67.03%**
4	14	1.37%
5	38	3.72%
6	2	0.20%
7	62	6.07%
8	20	1.96%
9	94	9.20%
10	22	2.15%
Total	1022	

Green algae		
Acoustic class	No. training data	% total
1	1	0.16%
2	1	0.16%
3	**443**	**70.88%**
4	37	5.92%
5	16	2.56%
6	17	2.72%
7	4	0.64%
8	1	0.16%
9	45	7.20%
10	60	9.60%
Total	625	

Unvegetated		
Acoustic class	No. training data	% total
1	48	1.20%
2	179	4.47%
3	**2674**	**66.82%**
4	96	2.40%
5	102	2.55%
6	173	4.32%
7	207	5.17%
8	91	2.27%
9	369	9.22%
10	63	1.57%
Total	4002	

Interpretation of 200 kHz acoustic classes based on extraction of acoustic classes to ground-truth data at the Level 2 habitat classification. Acoustic classes that are in bold were classified as that habitat type

Dense eelgrass		
Acoustic class	No. training data	% total
1	0	0.00%
2	18	0.94%
3	140	7.31%
4	15	0.78%
5	31	1.62%
6	**1192**	**62.25%**
7	89	4.65%
8	4	0.21%
9	38	1.98%
10	388	20.26%
Total	1915	

Sparse eelgrass		
Acoustic class	No. training data	% total
1	0	0.00%
2	34	5.30%
3	**205**	**31.93%**
4	30	4.67%
5	15	2.34%
6	**172**	**26.79%**
7	73	11.37%
8	4	0.62%
9	35	5.45%
10	**74**	**11.53%**
Total	642	

Dense red algae		
Acoustic class	No. training data	% total
1	2	0.18%
2	**678**	**60.75%**
3	0	0.00%
4	1	0.09%
5	48	4.30%
6	127	11.38%
7	190	17.03%
8	7	0.63%
9	38	3.41%
10	25	2.24%
Total	1116	

Sparse red algae		
Acoustic class	No. training data	% total
1	9	2.23%
2	76	18.81%
3	39	9.65%
4	14	3.47%
5	4	0.99%
6	18	4.46%
7	**192**	**47.52%**
8	6	1.49%
9	27	6.68%
10	19	4.70%
Total	404	

Dense brown algae		
Acoustic class	No. training data	% total
1	0	0.00%
2	29	10.78%
3	**117**	**43.49%**
4	13	4.83%
5	0	0.00%
6	0	0.00%
7	55	20.45%
8	21	7.81%
9	10	3.72%
10	24	8.92%
Total	269	

Sparse brown algae		
Acoustic class	No. training data	% total
1	26	3.46%
2	15	2.00%
3	**562**	**74.83%**
4	7	0.93%
5	39	5.19%
6	2	0.27%
7	8	1.07%
8	5	0.67%
9	85	11.32%
10	2	0.27%
Total	751	

Dense green algae		
Acoustic class	No. training data	% total
1	0	0.00%
2	0	0.00%
3	**221**	**59.09%**
4	30	8.02%
5	23	6.15%
6	12	3.21%
7	4	1.07%
8	0	0.00%
9	39	10.43%
10	45	12.03%
Total	374	

Sparse green algae		
Acoustic class	No. training data	% total
1	2	0.78%
2	0	0.00%
3	**214**	**83.92%**
4	13	5.10%
5	7	2.75%
6	3	1.18%
7	0	0.00%
8	1	0.39%
9	6	2.35%
10	9	3.53%
Total	255	

3.0 REMOTE SENSING OF NEARSHORE HABITAT USING SATELLITE AND ACOUSTIC REMOTE SENSING

3.1 Abstract

Mapping nearshore marine habitat is an important tool for providing crucial information for the management and conservation of coastal ecosystems. The purpose of this study is to compare the efficacy of high resolution satellite imagery (WorldView-2) and a single-beam acoustic ground discrimination system (QTC View V) for mapping the distribution of submerged aquatic vegetation at a study site in the Gwaii Haanas National Marine Conservation Area (GHNMCA), British Columbia, Canada. Ground-truth data for training and validation were collected using a towed underwater video camera. A WorldView-2 image (8 bands, 2 m resolution) was acquired and image pre-processing involved orthorectification, radiometric calibration, atmospheric correction, glint correction land and optically deep water masking. Supervised classification was conducted using a maximum likelihood classifier. An acoustic survey was conducted using a 200 kHz echosounder and data were processed and interpolated using the QTC Impact software to identify acoustic classes which were assigned to habitat using ground-truth data. The WorldView-2 imagery performed best in mapping habitat in regions shallower than 3 m (overall accuracy of 75%) where it could identify the distribution of green algae (*Ulva* spp.), brown algae (*Fucus* spp.) and shallow eelgrass (*Zostera marina*). The QTC View V 200 kHz data were unable to resolve brown and green algae but were able to map the distribution of both shallow and deep eelgrass as well as a subtidal red algae (*Chondrocanthus exasperatus*) (overall accuracy 80%). A final habitat map was produced using the output from both datasets. The discussion examines the limitations and advantages of satellite and acoustic remote sensing technologies for mapping benthic habitat in temperate marine regions.

3.2 Introduction

Submerged aquatic vegetation, such as seagrasses and algae (seaweeds), are vital to coastal ecosystem health and resilience. For instance, eelgrass (*Zosterna marina*) and other seagrass species have been shown to provide crucial ecosystem services including sediment retention (Mateo, Sanchez-Lizaso & Romero, 2003), carbon cycling (Hemming & Duarte, 2000) and physical stability by baffling against wave and current action (Hemming & Duarte, 2000). Furthermore, seagrasses provide important habitat for a variety of fish and invertebrate species including juvenile salmon (*Onchorhynchus* sp.) and Pacific herring (*Clupea harengus*) (Borg et al., 2006; Chittaro et al., 2009; Robinson et al., 2011). In Canada, eelgrass has been identified as an ecologically significant species under the Canada Oceans Act which recognizes the vital role that eelgrass plays in maintaining coastal ecosystem health (DFO, 2009). However, as coastal ecosystems continue to decline in health and in coverage (Duarte, 2002; Lotze et al., 2006) understanding the distribution and spatial extent of nearshore marine habitats is vital to their conservation and management (Horning et al., 2010).

Mapping of inter- and subtidal habitats has typically been conducted using field-based techniques which provide a high level of detail but can be prohibitively time- and labour-intensive for mapping large areas of coastline (Environment Canada, 2002; Roelfsema et al., 2009). A proposed alternative is the creation of habitat maps based on remotely sensed data that can summarize ecologically meaningful information across large, remote, geographic extents (Mumby & Harborne, 1999). Further benefits of remote sensing include the potential for automation and repeatability, which could improve the spatial and temporal coverage for coastal monitoring of marine ecosystems.

Remote sensing methods of marine habitat include passive optical sensors and active acoustic sensors. Both techniques and their associated methods of data collection vary with regards to their spatial, temporal and, in the case of optical sensors, spectral resolution, and these properties will affect the scale and accuracy of the final habitat map.

Presently, passive optical sensors are common tools for mapping shallow benthic habitat (<30 m). In particular, multispectral sensors (e.g. IKONOS, Quickbird) are used to map nearshore benthic habitat (Fornes et al., 2006; Urbański, Mazur, & Janas, 2009; O'Neill & Costa, 2013) with newer sensors continuing to enter the market. Launched in October 2009, the WorldView-2 multispectral sensor provides the highest spatial and spectral resolution of any multispectral satellite imagery currently available (DigitalGlobe, 2009). The sensor has an 8 band multispectral resolution with six bands in the visible spectrum and two near-infrared bands at a 2 m spatial resolution (Table 3.2). The increased spectral resolution (8 bands), as compared to other sensors such as Quickbird and IKONOS (which each have 4 bands), has shown to improve the accuracy of bathymetric mapping applications (Collin & Planes, 2011; Kerr, 2011) but also in the enhanced detection of marine habitats (Botha et al., 2013). Therefore, with its higher spatial and spectral resolution, WorldView-2 imagery appears to be an ideal tool for mapping fine-scale features of benthic habitats. However, the ability to map benthic habitat using satellite imagery is also dependent on the depth of the habitat, the light attenuation characteristics of the overlying water column and the reflectance contrast between the target habitat and the surrounding substrate (Green et al., 2000).

Acoustic remote sensing technologies can be applied to map subtidal habitats that occur outside shallow areas that are discernible by passive optical sensors. One way of doing this is by employing acoustic ground-discrimination systems (AGDS) such as multi-beam sonar (Collins &

Galloway, 1998), side-scan sonar (Brown et al., 2005), and single beam echosounders (SBES) (Greenstreet, 1997). Signals emitted by acoustic transducers can reach the seafloor hundreds of meters deep and the returning echo signals can be used to characterize the seafloor. In particular, single beam echosounders (SBES) present an inexpensive, mobile and non-invasive means of mapping seafloor habitat in coastal areas inaccessible to larger vessels. The QTC VIEW Series V (QTC5) is one such system which has been shown to be effective at mapping both sedimentary habitats of the seafloor (e.g. Freitas et al., 2003 and 2006) and, more recently, mapping underwater vegetation (e.g. Quintino et al., 2009). Overall, acoustic sensors can achieve greater depth penetration, are unconstrained by optical water properties and can measure seabed structures that may be biologically relevant. Conversely the acoustic sensor are restricted in mapping very shallow substrate (<0.5 m), are limited in their spatial resolution and require interpolation between transects and cannot differentiate substrates based on pigmentation (Mumby et al., 2004). However, it may be possible to overcome the disadvantages present within optical and acoustic remote sensing systems by combining the mapping technologies to produce benthic habitat maps (Solan, 2003; Bejarano, Mumby, Hedley, & Sotheran, 2010).

The purpose of this study was to (1) evaluate habitat discrimination from passive optical and single-beam active acoustic methods, with particular reference to detecting aquatic vegetation (seagrass and algae); and, (2) examine the applicability of these systems in supporting habitat mapping for conservation management. The study site, on the west coast of British Columbia, Canada, was selected because it is a monitoring site with known presence of eelgrass within the Gwaii Haanas National Marine Conservation Area and Haida Heritage Site. The primary sources of data were a QTC View V acoustics unit operated at 200 kHz, WorldView-2 satellite imagery, and *in situ* videography of the substrate.

3.3 Methods

3.3.1 Study area

The research took place at Bag Harbour, a small estuary south of the Burnaby Narrows in Haida Gwaii, British Columbia, Canada. The site is located within the Gwaii Haanas National Marine Conservation Area Reserve and Haida Heritage Site (GHNMCA) (Fig. 3.1). Bag Harbour is roughly 600 m long and 300 m wide and is largely protected from predominant south-easterly winds by surrounding land masses and mountains. The maximum depth at the Bag Harbour is approximately -12 m. Multibeam bathymetry has been collected at Bag Harbour, however the coverage is incomplete in the intertidal region (Fig. 3.2a).

Since 2004, Bag Harbour has been visited as a part of the GHNMCA eelgrass monitoring survey program which collects data on the water conditions, biological characteristics of eelgrass meadows and fish sampling (via beach seines) (Robinson et al., 2011; Robinson & Yakimishyn, 2013). Turbidity data from all eelgrass monitoring sites within the GHNMCA are shown in Table 3.1, with Bag Harbour demonstrating middling turbidity conditions. In 2008, an eelgrass assessment by Parks Canada in Bag Harbour produced the following average metrics for eelgrass: density = 800 shoot m^{-2}, biomass = 937 g m^{-2} which represented a higher mean than the GHNMCA sites' mean of 746 shoot m^{-2} and 698 g m^{-2} for density and biomass, respectively. Leaf area index was 1.76 which is slightly below the GHNMCA sites' mean of 2.8 (Robinson & Yakimyshyn, 2008). At least 20 fish species inhabit the eelgrass meadows, as determined by beach seine (Robinson et al., 2011; Robinson & Yakimishyn, 2013). The areal extent of inter- and subtidal eelgrass meadows have never been mapped at Bag Harbour. According to the British Columbia ShoreZone coastal resource information system there are patches of continuous green algae (*Ulva* spp.) and brown algae (*Fucus* spp.) present at the site (Howes et al,1994).

Table 3.1 - Turbidity measurements of eelgrass monitoring sites within the GHNMCA from July 2004-2011.

Site name	**Years sampled**	**Range of turbidity (NTU)**	**Mean turbidity (NTU)**
Sedgwick	2005-2006, 2008-2010	0.000-0.339	0.072
Murchison	2005-2006, 2008-2010	0.000-0.380	0.088
Kendrick point	2008-2011	0.022-0.325	0.113
Huxley	2006, 2008-2010	0.000-0.712	0.161
Swan Bay	2005-2006, 2008-2010	0.000-0.617	0.164
Bag Harbour	2004-2006, 2008-2011	0.023-0.876	0.196
Balcolm Inlet	2005-2006, 2008-2011	0.000-1.396	0.278
Rose Inlet	2005-2006, 2008-2011	0.010-1.750	0.374
Ikeda	2005, 2008, 2010	0.081-1.166	0.399
Louscoonee	2005-2006, 2008-2010	0.001-2.323	0.473
Head of Louscoone Inlet	2005-2006, 2008-2010	0.002-3.095	0.605
Heater Harbour	2005-2006, 2008-2011	0.000-5.941	0.952
Section Cove	2005-2006, 2008-2010	0.002-6.619	1.157

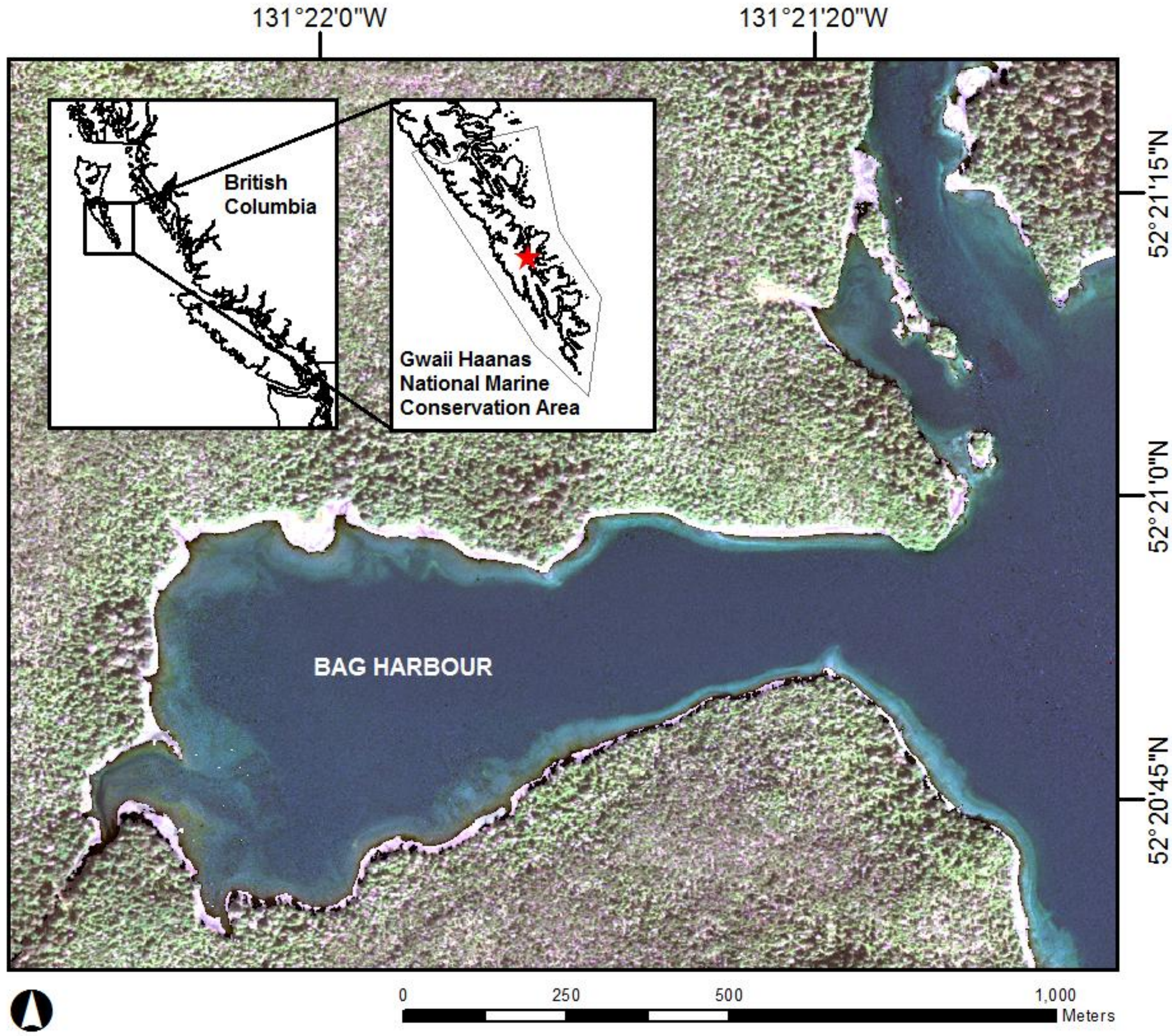

Figure 3.1. WorldView-2 imagery of Bag Harbour, Gwaii Haanas National Marine Conservation Area, Haida Gwaii, British Columbia. Insets show study site location.

3.3.2 Field survey

A benthic habitat ground-truthing survey was conducted at Bag Harbour on June 3rd and 4th, 2012 (weather was sunny and calm both days) via a towed underwater video transects using a small colour video camera (Deep Blue Pro, Ocean Systems Inc.) mounted on a custom-made aluminum wing. Live feed was visible via a field computer and allowed the operator to maintain the camera 1-2 m above the seafloor using an electrical downrigger. This provided an imagery swath width of approximately ~2 m. Video transects were run both parallel to shore (approximately 5-10 m apart) and orthogonal to shore (approximately 50 m apart) (Fig. 3.2c). Vessel speed was maintained between 1-2 knots during video surveys to guarantee video quality (blurring was significant at speeds over 2 knots). A depth logger (Sensus Ultra U-04133, Reefnet Inc.) was attached to the camera and recorded depth every second during deployment. A dGPS was mounted next to the downrigger to maximize positional accuracy and logged positional data and current local time every second. Video and dGPS data were recorded directly to a field laptop computer hard drive. Additionally, the edges of exposed intertidal eelgrass meadows were mapped using a handheld dGPS at low tide (+0.9 m) on June 2nd, 2012.

To analyze the video data, geopositional data and time were imported into a standard electronic spreadsheet and habitat was mapped in 1 second increments, which corresponded to approximately 1-2 m of seafloor. Five major habitats were identified from the video: (1) green algae (*Ulva* spp.); (2) brown algae (*Fucus* spp.); (3) eelgrass (*Z. marina*); (4) a benthic red algae (*Chondrocanthus exasperatus*); (5) unvegetated substrate (e.g. sand, cobble, gravel) (Fig. 3.3). Their distribution at Bag Harbour is shown in Figure 3.2d. Unvegetated seafloor was recorded where approximately <10% of the seafloor was covered by vegetation. After classification, the

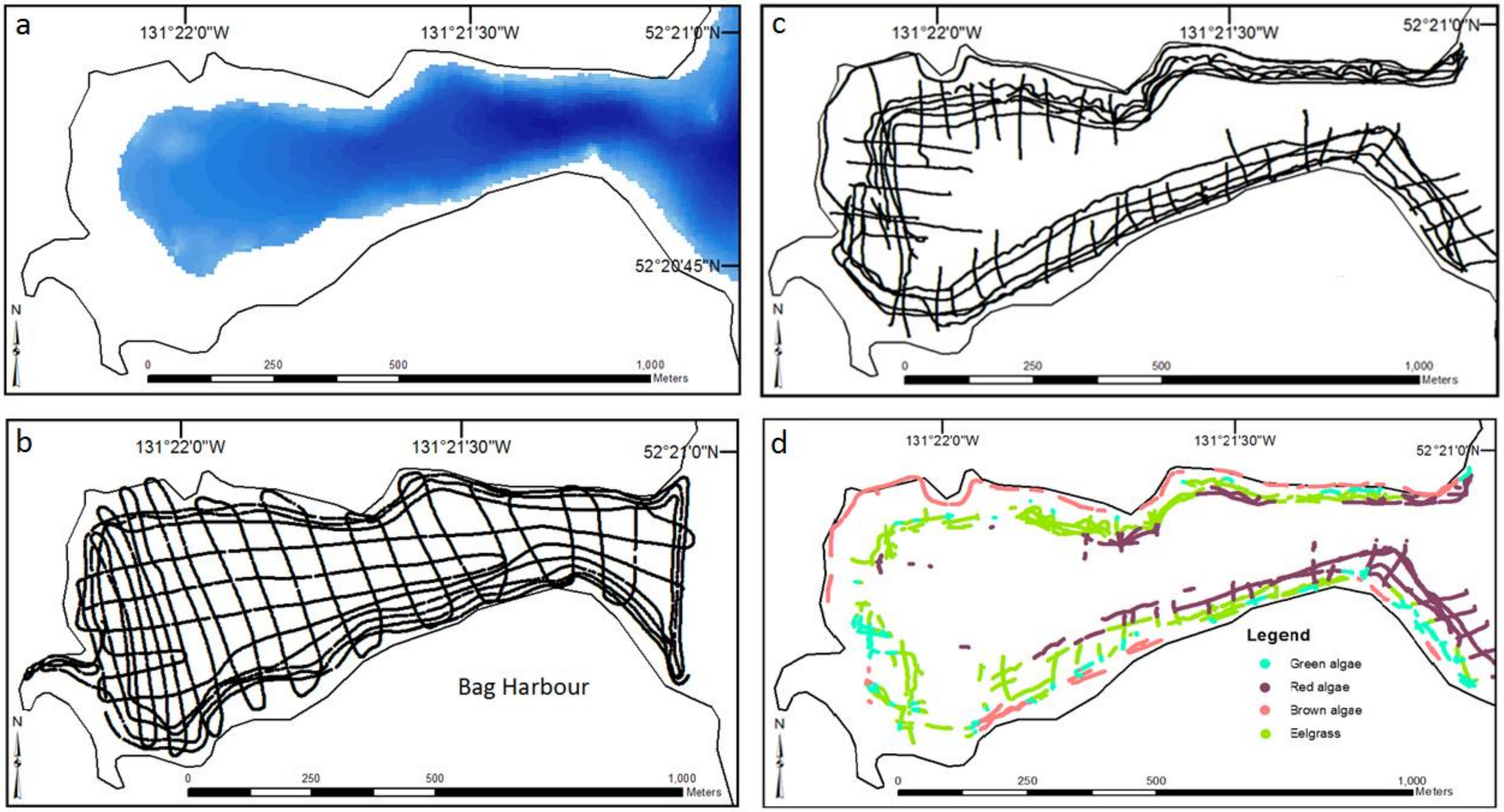

Figure 3.2. (a) Bathymetry data from multi-beam survey (courtesy of Parks Canada). (b) Survey tracklines of 200 kHz acoustic data collected on June 24th, 2012. (c) Ground-truth survey tracklines of towed underwater video collected on June 3rd and 4th, 2012. (d) Study area showing classified video track lines for four main vegetated habitats: brown algae (*Fucus* spp.), green algae (*Ulva* spp.), eelgrass and red algae (*C. exasperatus*).

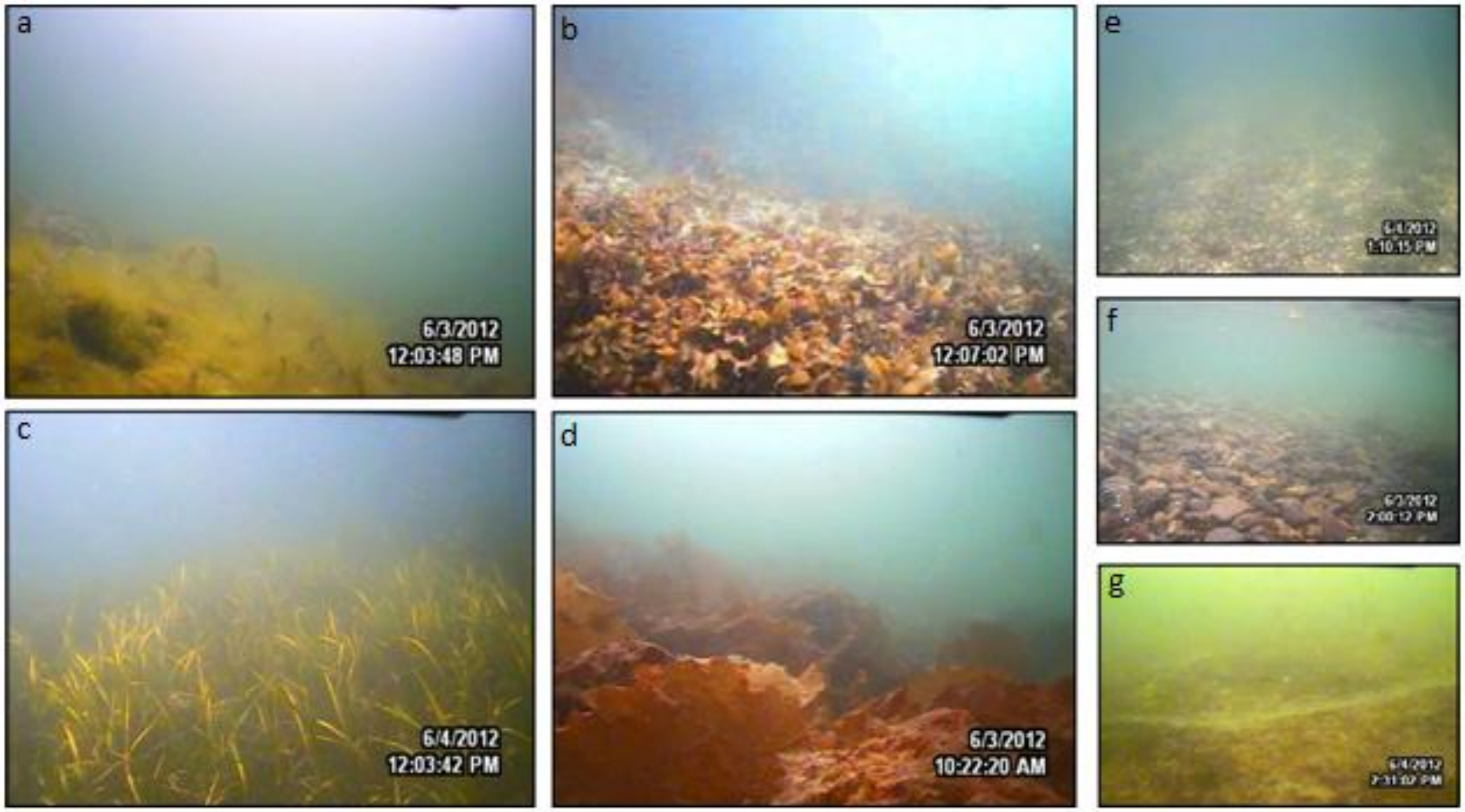

Figure 3.3. Benthic habitats present at Bag Harbour. (a) Green algae (*Ulva* spp.). (b) Brown algae (*Fucus* spp.). (c) Eelgrass (*Zostera marina*). (d) Red algae (*Chondrocanthus exasperatus*). (e) Gravel, (f) cobble and (g) fine sediment are all examples of unvegetated substrate.

data were imported into a geographic information system, ArcGIS 10 (ESRI, 2010), and used as ground-truth data to train and validate the different classifications.

Ground-truth data were split into two datasets. The first dataset (hereafter referred to as the “training data”) was used to assign a habitat class to each of the initial acoustic classes resulting from the unsupervised classification. These data were also used to select regions of interests (ROIs) for training the WorldView-2 imagery for the supervised classification. The remaining half of the dataset (hereafter referred to as the “validation data”) was used to assess the accuracy of the final acoustic, WorldView-2, and combined acoustic-satellite habitat maps.

3.3.3 Optical dataset

A WorldView-2 image was acquired on July 26th, 2010 at 20:20:56 UTC at a 13° off-nadir angle from MDA Geospatial Services Inc (Fig 3.1). Tide at acquisition was +3.1 m above chart datum, approximately 2 hr before high-tide. The image was provided in UTM coordinates (zone 9 N, datum: WGS84) at full radiometric resolution (16 bit). While unaffected by cloud cover, significant wave action causing specular reflection affected the majority of the image. WorldView-2 is a multispectral sensor with 8 spectral bands covering coastal, blue, green, yellow, red, red edge, NIR1 and NIR2 (Table 3.2). It has a pixel size of 2 x 2 m and a swath width of 17.7 km (Digital Globe, 2010).

Although field data post-dates the image acquisition by two years, Bag Harbour has demonstrated consistently low turbidity throughout its sampling history (Table 3.1) (C. Robinson, personal communication). Furthermore, turbidity was recorded at Bag Harbour on July 22th, 2010 (0.077 NTU) as part of the eelgrass monitoring program. It is assumed that these conditions were present when the imagery was acquired. No dramatic anthropogenic disturbances are known to have occurred during the intermediate period.

Table 3.2 - WorldView-2 sensor band names and spectral resolution.

Band Name	Band number	Spectral resolution (nm)	Centre Wavelength (nm)
Coastal Blue	1	400-450	425
Blue	2	450-510	480
Green	3	510-580	545
Yellow	4	585-635	605
Red	5	630-690	660
Red edge	6	705-745	725
NIR-1	7	770-895	833
NIR-2	8	860-1040	950

3.3.3.1 Image processing

Step 1: Geometric and atmospheric correction

The WorldView-2 image was geometrically corrected using six ground control points acquired using a portable dGPS system (MobileMapper100, Ashtech) with a horizontal accuracy of <1 m. This yielded an average root mean square (RMS) error of 0.88 m. Subsequently, the image was atmospheric corrected to minimize interference from the light attenuation processes by the atmospheric constituents, which are known to decrease the ability to use imagery to classify coastal substrates (Werdell & Roesler, 2003). The image was corrected for atmospheric effects using the ATCOR module (PCI Geomatica, 2013). This step converts raw digital numbers (DN) values to top-of-atmosphere reflectance (%). An intermediary step of the atmospheric correction is a radiometric correction of DN values to 'at-sensor' radiance (μW) / (cm^2*nm*sr). The settings for ATCOR were chosen iteratively by checking the resulting reflectance values for plausibility a known region of optically deep water (> 30 m). The final ATCOR settings were: atmospheric model: subarctic summer; aerosol model: maritime; initial visibility: 60 km.

Step 2: Glint removal and land mask

Sun glint, the specular reflection of light from water surfaces, is a detrimental factor in the remote sensing of marine benthic habitat (Kay et al., 2009). Sun glint occurs in imagery when the water surface orientation causes the sun to be directly reflected towards the sensor; and hence is a function of sea surface state, sun position and viewing angle (Kay et al., 2009). As a significant portion of the scene was affected by specular reflection caused by wind-induced waves interacting with incoming light, the image was corrected for surface glint following

Hedley et al. (2005). This method relies on two assumptions: (1) that the NIR reflectance over water is caused solely by sun glint and (2) that the magnitude of NIR reflectance is linearly related to the magnitude of glint reflectance in the visible wavelengths. By determining that linear relationship the entire glint spectrum for each pixel can be derived from its NIR value and then subtracted from the pixel to obtain the glint-free value. Mathematically,

$$R'_i = R_i - b_i\,(R_{NIR} - Min_{NIR}) \qquad (1)$$

where R'_i is the new pixel value after glint correction, R_i is the original pixel value in the *i*th band, b_i is the regression slope between the reflectance at each visible band and the reflectance in the NIR for a sample of sun-glint pixels over optically deep water, R_{NIR} is the pixel NIR value and Min_{NIR} is the minimum NIR value found in the regression sample (Hedley et al., 2005). Following glint removal, land pixels were masked out.

Step 3: Deep water masking

Classification was attempted on imagery with masked and non-masked optically deep water regions. Other studies have demonstrated the improvement in submerged substrate classification with the masking of deep water (Ackleson & Klemas, 1987; Zainal, Dalby, & Robinson, 1993). Optically deep water was defined according to the detectability threshold of non-biofouled eelgrass; i.e. the mean depth at which non-biofouled eelgrass was no longer spectrally discernible from water. Non-biofouled eelgrass was selected based on results and spectra available from O’Neill et al. (2011). The authors found that non-biofouled eelgrass had high reflectance in the green range, where the measured water attenuation coefficient was the lowest. To define an approximation for optically deep water, the vertical attenuation coefficient (K_d) was calculated. In this first step, secchi depth (Z_{SD}) measured at the site was used to derive the K_d, according to Holmes (1970). As previously mentioned, the assumption was made that water quality conditions were similar at the time of image acquisition and field data collection.

$$K_d = 1.44/Z_{SD} \tag{2}$$

Following O'Neill & Costa (2013) and Dekker, Brando, & Anstee (2005) the detectability depth limit of a substrate for the WorldView-2 sensor was computed by solving for the depth of the optically deep water, z, and rounding up to the nearest 0.5 m value:

$$z = \frac{1}{2Kd} \ln \left[\frac{R_{rs}^{b} - R_{rs}^{dp}}{R_{rs}^{DT}} \right] \tag{3}$$

where R_{rs}^{b} is the mean endmember spectra of the substrate, R_{rs}^{dp} is the average deep water (>30m) reflectance just below the surface (obtained by a 33x33 pixel ROI from the image) and R_{rs}^{DT} is the wavelength-dependent standard deviation of reflectance within a homogeneous 33x33 pixel ROI of deep water (Dekker et al., 2005), and K_d (Eq.2) . The derivation of this equation can be found in O'Neill and Costa (2013). Mean endmember spectra for non-biofouled eelgrass were provided from those measured by O'Neill et al. (2011) who collected samples from another site in coastal British Columbia. A mask was created based on the calculated depth using bathymetric data available from Parks Canada and the single-beam acoustic survey (conducted in this study).

Step 4: Spectral indices

In addition to using the original eight WorldView-2 spectral bands, band ratios were calculated between all bands except for the NIR bands (which were used in the glint removal step). The list of spectral indices are shown in Table 3.3. Studies have shown that spectral shape of a benthic class may define a cover type more effectively than spectral magnitude (O'Neill et al., 2011; Vahtmäe et al., 2006). In order to determine which of the original bands and band

Table 3.3 - Names and wavelengths of spectral indices.

Spectral Indice	Wavelength (nm)
Band 1	425
Band 2	480
Band 3	545
Band 4	605
Band 5	660
Band 6	725
B1:B2	425:480
B1:B3	425:545
B1:B4	425:605
B1:B5	425:660
B1:B6	425:725
B2:B3	480:545
B2:B4	480:605
B2:B5	480:660
B2:B6	480:725
B3:B4	545:605
B3:B5	545:660
B3:B6	545:725
B4:B5	605:660
B4:B6	605:725
B5:B6	660:725

ratios (hereafter referred to as spectral indices) provided the best discrimination between substrate types the M-statistic was calculated at every band and band ratio for each substrate pairing case (e.g. shallow eelgrass- shallow green algae, shallow green algae- deep eelgrass, etc.). The M-statistic is a statistical method that provides a measure of class separation, which normalizes the difference between the means of two benthic classes ($\mu_{1(\lambda)} - \mu_{2(\lambda)}$) by the sum of their standard deviations ($\sigma_{1(\lambda)} + \sigma_{2(\lambda)}$) as follows (Kaufman & Remer, 1994):

$$M_{(\lambda)} = \frac{\mu_{1(\lambda)} - \mu_{2(\lambda)}}{\sigma_{1(\lambda)} + \sigma_{2(\lambda)}} \quad (4)$$

A large M-statistic indicates good separation between the two classes as within-class variance is minimized and between-class variance maximized. Following Kaufman and Remer (1994), M > 1.0 indicates good class separation and M < 1.0 indicates poor separation. Since the M-statistic assesses separability for each benthic class pair independently, it allows for an examination of spectral separability between substrate classes and the identification of indices that are important for classification. Only those spectral variables with the highest M-statistic values (i.e. >1.0) were retained for classification.

Step 5: Image classification and validation

Three benthic habitat maps were produced using a Maximum Likelihood (ML) classifier and the spectral variables identified from the previous step: (1) without a deep water mask, (2) with a deep water mask and (3) with a 3.0 m depth mask (described below). Each classification was performed with (a) the original 8 spectral bands and (b) the spectral indices identified from the previous step.

Benthic habitat data for classification were grouped into seven classes, defined by vegetation type and depth. The stratification of data by depth was introduced to reduce the bias related to the fact that a given assemblage can present different spectral signatures according to their depth (Belsher et al., 1988; Pasqualini et al., 1997). Depth for all field observations was corrected to the tide level at image acquisition. The following classes were used for classification of each image: deep unvegetated substrate (dUV), deep water (dW), deep red algae (dRA) and deep eelgrass (dEG) (>3 m); shallow unvegetated substrate (sUV), shallow eelgrass (sEG), shallow green algae (sAG) and shallow brown algae (sBA) (<3 m). No red algae sites were found shallower than three metres and no green algae or brown algae sites were found deeper than 3 m.

Within a water column, light is attenuated due to absorption and scattering owing to the presence of particulate organic matter, dissolved organic matter, total suspended mineral, and water itself (Kirk, 1994). As a result, restricting the depth range helps improve the ability of the imagery to discern between different habitats that may have similar spectral characteristics at different depths (Phinn et al., 2005). In this study, the depth stratification was defined at 3.0 m based on the optical depth of 3.1 m derived from Secchi depth which was calculated as the inverse of K_d (Mobley, 1994). This threshold is also in agreement with other studies that have found seagrass species and broad cover classes to be inseparable at depths greater than 3.0 m (Brando & Dekker, 2003; Phinn et al., 2005; Phinn et al., 2008; O'Neill et al., 2011). Image stratification is different from masking optically deep water regions. The purpose of stratifying the classification of the image is to reduce the bias of varying spectral signatures for a given habitat with depth (Pasqualini et al., 1997). This stratification does not remove the possibility that certain habitats may be detectable at greater depths. Conversely, the optical depth is derived from the spectral properties of a selected benthic class, known (or estimated) water column characteristics (ie. Kd) and values derived from the satellite imagery in order to remove those parts of the image that the substrate can no longer be detected by the imagery.

For the purpose of training the ML classifier, regions of interest (ROIs) were selected based on the ground-truth training data-set, and considering the areas that were spatially and spectrally homogeneous (McCoy, 2005). After the supervised ML classification, the products were treated with a 3x3 pixel majority filter to eliminate speckle before validation (Mumby & Edwards, 2002). A confusion matrix was constructed to calculate user's, producer's, and total accuracy for all benthic habitats using the validation dataset. Producer's accuracy is defined as the percentage of testing pixels of a specific substrate that were classified correctly (i.e. how well the training sites were classified or the probability of misclassifying a training site) (Story & Congalton, 1986). User's accuracy is the percentage of pixels classified as a specific substrate which are truly that substrate (i.e. how well the classification represents ground-truth) (Story & Congalton, 1986). Total accuracy is the percentage of sites of all substrate types classified correctly. The tau coefficient was calculated for each classification. The Tau coefficient accounts for chance agreement within the matrix and is a readily interpretable value that permits hypothesis testing of differences between two classifications (Ma & Redmond, 1995). For example, a tau coefficient of 0.75 indicates that 75% more pixels were classified correctly than would be expected by chance alone.

3.3.4 Acoustic dataset

A 200 kHz acoustic survey was conducted on June 24th, 2012, approximately 4 hours in total survey time (Fig. 3.2c). The acoustic data were obtained with the acoustic system QTC VIEW Series V (QTC5) connected to a dual frequency (50 and 200 kHz) echosounder (Hondex 7380). The echosounder was mounted to the side of a small vessel (~ 6.7 m long) and was submerged 0.5 m below the water's surface. The base settings of the 200 kHz echosounder were: a pulse duration of 300 µs; ping frequency of 7 pings s^{-1}; and beam width of 10°. Survey speed did not exceed 4 knots. A differential Global Positioning System (dGPS) (Ashtech MobileMapper100), with sub-meter (<1m) horizontal accuracy, acquired positional data which was logged continuously during the survey. The QTC5 system was operated from a field laptop computer that allowed for real time data display and storage. The 200 kHz frequency was used as previous research conducted by the authors and other published literature have shown that 200 kHz is more suitable for mapping submerged vegetation compared to 50 kHz (Quintino et al., 2009a).

3.3.4.1 Acoustic data processing

In the QTC5 system, the echo sounder generates a signal that travels through the water column, reflects off the seafloor, and records the first echo return. The echo is then characterized based on the reflected waveform in order to generate habitat classifications that are based on the diversity of scattering and penetration properties of the seafloor (Preston et al., 1999). Each echo is time-stamped, dGPS geo-located and digitized by the QTC5 system. The following section describes the steps of acoustic data processing.

Echo data were processed in the software QTC IMPACT (Quester Tangent Corporation, Sidney, British Columbia). Data are subjected to a bottom picking algorithm which detects the seabed/water interface (Biffard, 2011). Accurate bottom-picking is essential for the detection of any signal preceding the seafloor that indicates the presence of vegetated habitat. A bottom picking threshold of 50% was used for this analysis to ensure that bottom-picks were attributed to the seabed/water interface and not to overlying vegetation (B. Biffard, 2012, personal communication). Any echoes which showed poor bottom picking were discarded.

In order to improve the acoustic classification of submerged vegetation the window of echo analysis was adjusted according to the methods suggested by Preston et al. (2006). In QTC IMPACT, the window of echo analysis contains 256 samples (with alignment of the window established by the bottom pick) (Biffard, 2011). The default setting for this window is 5 samples before the bottom pick and 251 samples after the bottom pick (Fig. 3.4), however, these settings eliminate the detection of any signal precursor to the bottom pick that may contain information about overlying vegetation. Results from Preston et al. (2006) demonstrated that moving this window to 128 samples before the bottom and pick and 128 samples after the bottom pick significantly increases the ability of the acoustic classification for mapping seabed vegetation.

After bottom-picking, groups of 5 echoes (the default standard) were stacked to reduce the consequences of ping-to-ping variability (QTC IMPACT manual, 2004). Each echo stack is subjected to a series of algorithms by the QTC IMPACT software which create 166 variables describing each stack (Preston & Collins, 2000; Preston et al., 2004). At this stage echoes that did not have correct time-stamps, correct depths or signal strengths below 5% were discarded.

The dataset was subjected to a Principal Components Analysis (PCA) for data reduction. This process produces a reduced description of each echo consisting of three values (labeled Q1, Q2 and Q3) that correspond to the coordinates of the three first PCA axes. These "Q values" can be plotted into a pseudo-three-dimensional space ("Q-Space"), and, in theory, acoustically similar habitat will form clusters (QTC IMPACT manual, 2004).

Following PCA, the acoustic dataset was classified using an unsupervised classification method based on an automated clustering tool available in the QTC IMPACT software. The ACE (automated clustering engine) is an objective Bayesian k-means clustering procedure that

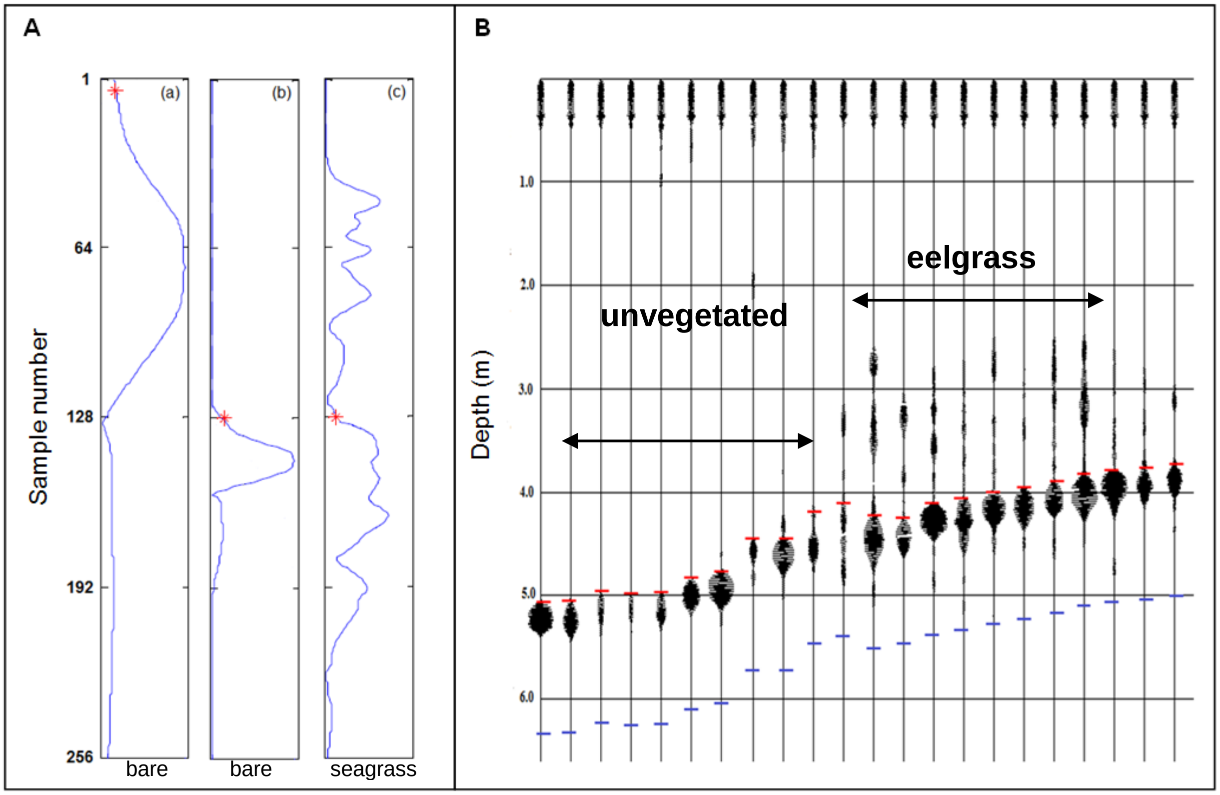

Figure 3.4. (A)The portion of the echo time series from which features are made occur in a window consisting of 256 samples. Echoes are shown solid and asterisks indicate bottom picks (seabed-water interface). In panel (a) the pick is at sample 5 and in panels (b) and (c) the pick at sample is at 128. By putting the pick at 128 this reserves the first half for backscatter from seaweed. (B) Echo data collected over bare substrate and eelgrass. Evidence of eelgrass is obvious prior to the bottom-pick (red line).

provides a means to determine, based on the Bayesian Information Criterion (BIC), the optimal number of clusters or classes for the dataset (QTC IMPACT manual, 2004). The optimal number of clusters is determined by the classification with the lowest BIC score. Any points that fall within that cluster space are assigned to that particular class (QTC IMPACT Manual, 2004). The 200 kHz data were subjected to 99 iterations from 2-15 classes. This range was selected based on previous clustering results and time restraints in processing the large dataset. The result with the lowest BIC score was selected. In the case where two classes had similarly low scores, the lower score class was selected. The final output was a file where each data point (echo stack) has been assigned an acoustic class and was imported into ArcGIS 10.0.

To produce a spatially continuous map surface, the classified data were interpolated using QTC CLAMS (Quester Tangent Corporation, Sidney, BC). This program uses categorical interpolation suitable for discrete categorical data by ensuring that no fractional classes are created (QTC CLAMS manual, 2004). The 200 kHz data were interpolated to a regular grid size of 2 m. This cell size was chosen based on the mean footprint size of the acoustic beam on the seafloor during the survey, which was calculated from the mean survey depth and beam width based on

$$d = 2z\tan(\Theta/2) \qquad (5)$$

where d is diameter of the echosounder footprint on the seafloor, z is the depth to the seafloor and θ is the echosounder beam width. This cell size was also preferable as it matched the spatial resolution of the WorldView-2 data.

Acoustic classes were assigned habitat classes through (1) a visual assessment of training data superimposed over the acoustic maps in ArcGIS 10.0; and (2) extracting acoustic classes to the overlying training data to examine the quantitative distribution of habitat data among acoustic classes. Acoustic classes that did not show any association with a vegetated habitat were classified as “unvegetated”. At this point it should be noted that some of the areas labeled as unvegetated could, in reality, contain submerged vegetation but from the perspective of the 200 kHz frequency, these areas are indistinguishable from unvegetated substrates.

Validation of the acoustic habitat map was performed using the validation ground-truth dataset to create a standard confusion matrix (as mentioned above). In order to be able to compare the classification accuracy results between optical and acoustic output eelgrass habitat maps, the same depth stratifications as the WorldView-2 classification (above and below 3.0 m) was applied to the acoustic data. This was unnecessary for red algae as this habitat only occurs below 3.0 m.

3.3.5 Merged dataset

Given the respective benefits and limitations of acoustic and passive optical remote sensing technologies it was useful to access not only the accuracy of the products generated from the different methods, but also a combined product. To examine whether a combination of WorldView-2 imagery and 200 kHz single-beam acoustic could be combined to create an accurate map of benthic habitat, the most accurate output from each dataset was merged into a single habitat map. The accuracy of this habitat map was also assessed using validation data to create a confusion matrix.

3.4 Results

3.4.1 Optical dataset

3.4.1.1 Pre-processing

The application of the ATCOR atmospheric correction showed clear improvements to the spectral reflectance within the WorldView-2 image. Fig. 3.5a illustrates a portion of the WorldView-2 image over optically deep water (>30 m) where correction for Rayleigh scattering is obvious in short visible wavelengths, band 1 and band 2, centered at 425nm and 480nm, respectively.

The Hedley et al. (2005) glint correction method was extremely effective in removing surface glint from the WorldView-2 image. After glint correction, the evidence of specular reflectance was greatly reduced for all the visible bands, and deep water regions showed expected spectrally homogeneous signature (Fig. 3.5b). Fig.3.5 shows a portion of the WorldView-2 image from Bag Harbour that was originally heavily glinted.

The optically deep water threshold was calculated to be 8.5 m, meaning that in regions deeper than this threshold the reflectance from the substrate was no longer discernible from the reflectance from deep water. The K_d, measured from Secchi depth, was 0.31 m^{-1}.

3.4.1.2 Spectral characteristics of the substrates and spectral indices

Figure 3.6 shows the spectral reflectance curve for all benthic habitat classes. Shallow benthic habitats (<3.0 m) appear to be spectrally distinct compared to deep benthic habitats (>3.0 m). For the shallow habitat classes, unvegetated substrate showed the highest reflectance (2.4%) from 425-550 nm while brown algae had the highest reflectance from 625 nm - 725 nm which is consistent with the brown pigmentation of *Fucus* spp. seen in the ground-truth video (Fig. 3.3b).

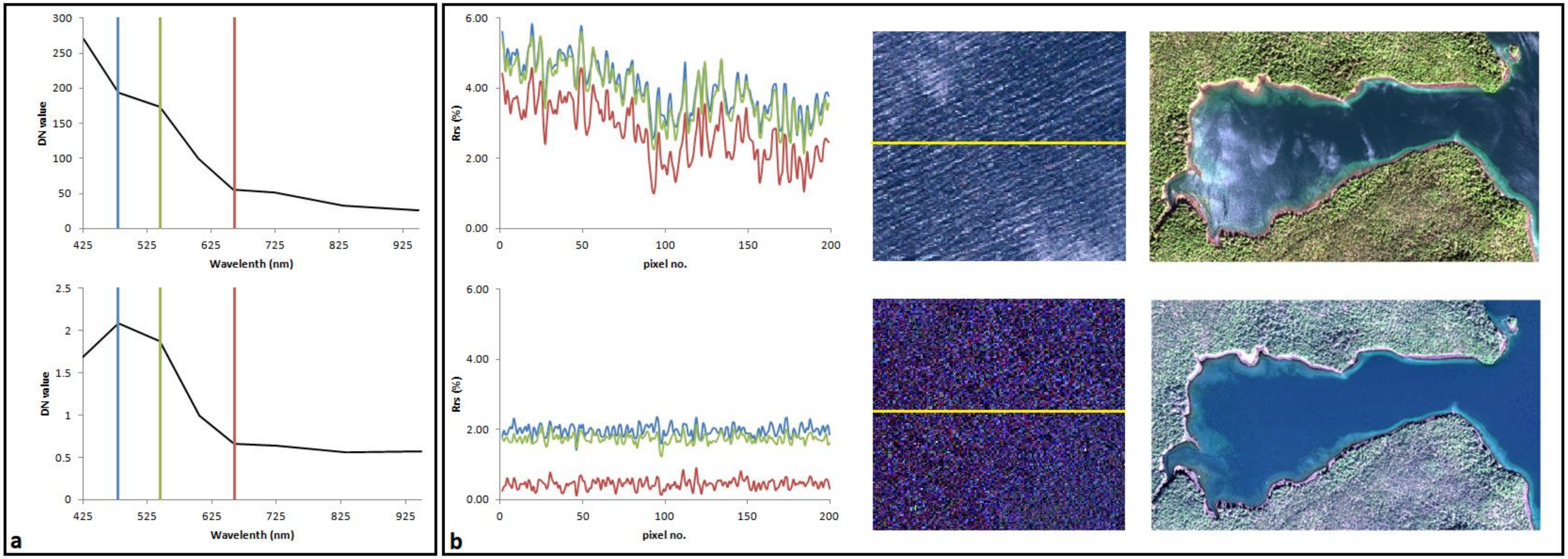

Figure 3.5. (a) Spectral profile over optically deep water before (top) and after (bottom) atmospheric correction using ATCOR. (B) Glint correction example in a portion of heavily glint affected optically deep water in the WorldView-2 image. Image profile showing reflectance at 480 nm (blue line), 545 nm (green line) and 660 nm (red line) before (top) and after glint correction (bottom). Bag Harbour WorldView-2 imagery before (top) and after (bottom) glint correction.

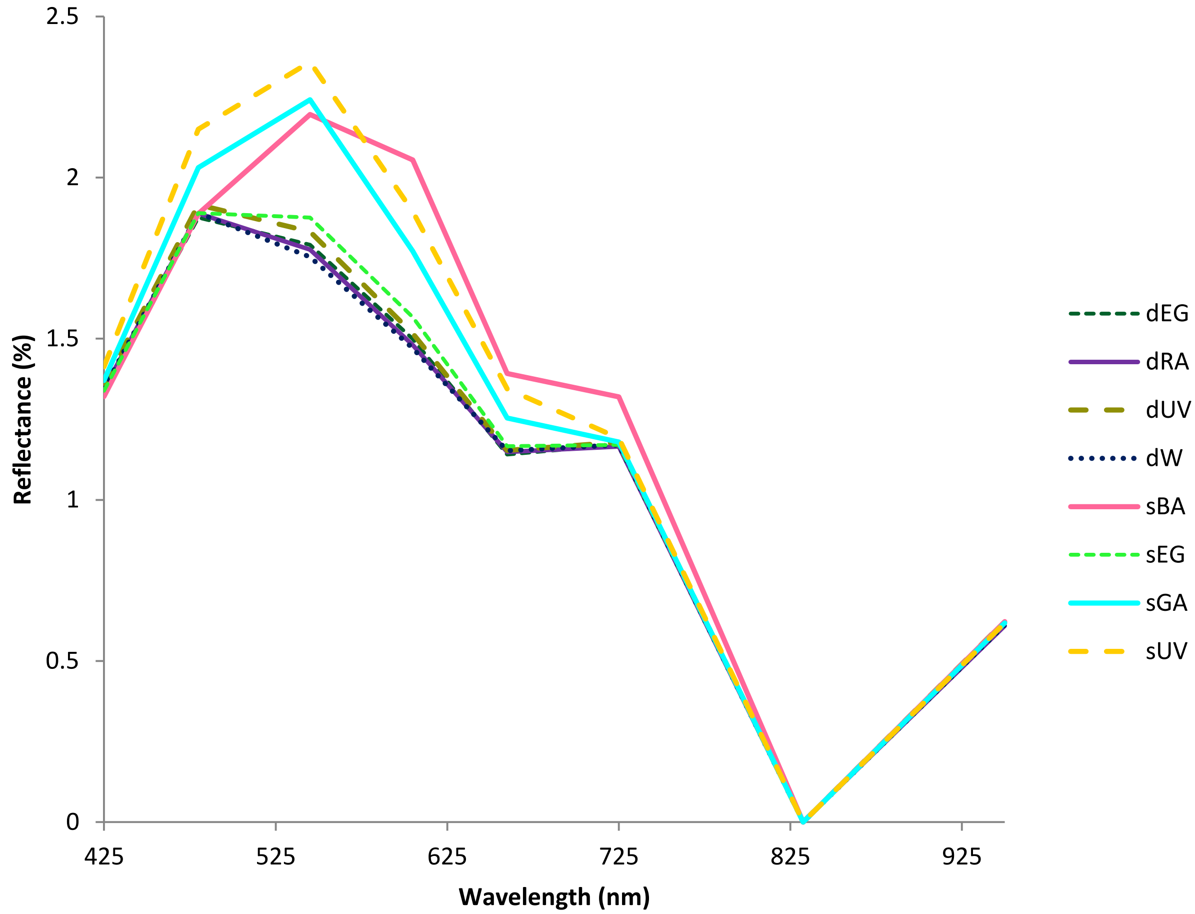

Figure 3.6. Reflectance (%) spectra of all benthic substrates at Bag Harbour: shallow unvegetated (yellow), green algae (cyan), brown algae (coral), shallow eelgrass (green), deep eelgrass (sea foam), red algae (purple), deep unvegetated (dark yellow), deep water (red)

Shallow unvegetated substrate, green algae and brown algae all showed peak reflectance at 550 nm (2.4%, 2.25% and 2.2%, respectively) while all other substrate classes (deep and shallow eelgrass, deep unvegetated substrate, deep water, and red algae) had similar peak reflectances at 450 nm (approximately 1.85%). The reflectance curves for deep eelgrass, red algae and deep water were nearly identical with deep unvegetated substrate showing slightly higher reflectance from 500-600 nm. These results indicated that the imagery would likely be limited in its ability to discriminate between these habitats.

Figure 3.7 shows the M-statistic separability results for all benthic substrate pairs in the deep and shallow regions. The results showed that four of the original bands (B2, B3, B4 and B5) and seven of the band ratios (B1:B3, B1:B4, B1:B5, B2:B3, B2:B4, B2:B5, B3:B4 and B3:B5) produced M-statistics greater than one for at least one of the substrate pairs. In shallow water (<3.0 m), no indices were found that could discriminate between green algae and unvegetated substrate. In deep water, no spectral indices were identified that could discriminate between any deep substrate pairs including optically deep water. Furthermore, no indices were identified that could differentiate shallow eelgrass from any deep substrate classes. These results indicated which classes (ie. those below 3.0 m) would likely suffer significant confusion during classification.

3.4.1.3 Classification and validation

Ground truth data points (n=1683) were used to assess the accuracy of the WorldView-2 classifications. The field data were distributed among eight benthic habitat classes: shallow eelgrass (n= 297), brown algae (n= 86), green algae (n= 134), shallow unvegetated substrate (n= 282), deep eelgrass (n= 307), red algae (n= 91), deep unvegetated substrate (n= 296) and optically deep water (n=63). The habitat maps resulting from each classification is shown in

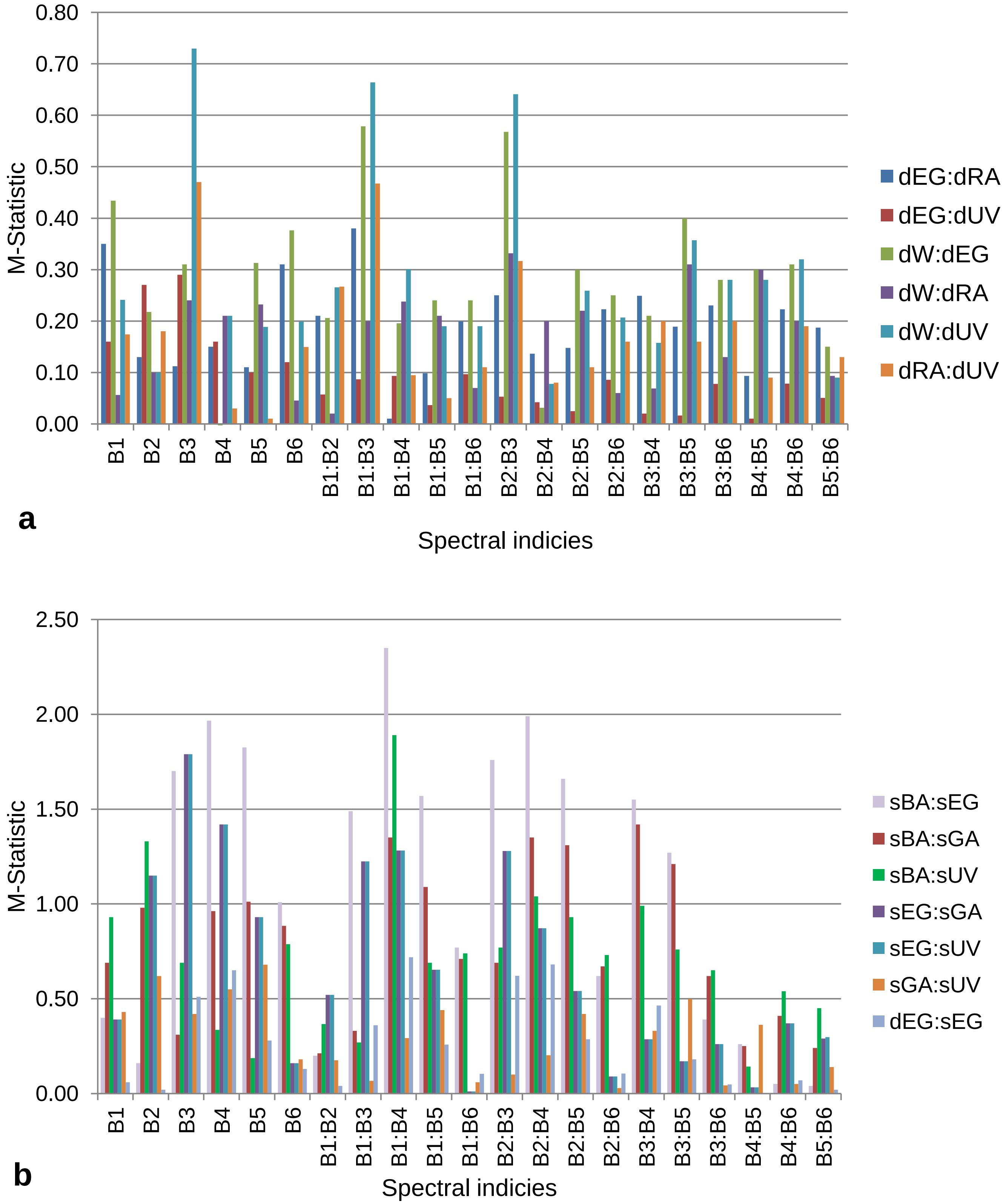

Figure 3.7. M-statistic calculation for all pairs of benthic substrates below 3.0 m (a) and above 3.0 m (b).

Fig.3.8. Overall, producer's and user's accuracy for all benthic substrate classifications of the WorldView-2 image are reported in Tables 3.4, 3.5 and 3.6.

The application of the optically deep water mask improved the overall accuracy of habitat classification by 5% in comparison to classifications where the mask was not applied, regardless of the spectral inputs. This improvement can be attributed to the improvement within the red algae class. The application of the optically deep water mask improved the user's and producer's accuracy of red algae for classification with the original 8 bands (16%/8% and 19%/63%, without and with the mask, respectively) and the spectral indices (9%/7% and 16%/87%, without and with the mask, respectively). Shallow habitat classes did not show an improvement in user's or producer's accuracy with the application of the optically deep water mask.

Classifications performed with the spectral indices identified from the M-statistic analysis did not result in greater overall accuracy for any of the classifications. On a per class basis, the use of spectral indices did improve either the user's or producer's accuracy of certain habitat classes. For example, for the classification with the optically deep water mask, the red algae class showed a higher producer's accuracy for the classification with the spectral indices compared to the classification with the original 8 bands (87% and 63%, respectively). However, in the same example, the user's accuracy decreased slightly (16% compared to 19%). Only one class, brown algae, showed improvement in both user's and producer's accuracy for classifications performed with the spectral indices.

Overall, the classification of benthic habitats below 3.0 m depth performed poorly. In particular, the deep eelgrass class achieved producer's accuracy below 15% and user's accuracy below 68% in all classifications. The highest user's accuracy for red algae was 19% (optically

Table 3.4 - Confusion matrices for habitat maps based on WorldView-2 imagery (without optically deep mask).

Confusion matrix for Worldview classification without optically deep water mask and original 8 bands										
	Classification data									
Reference data	sEG	sBA	sGA	sUV	dEG	dRA	dUV	dW	Sum	Producer's accuracy
sEG	182	0	27	16	12	19	18	23	297	61.28%
sBA	1	57	0	28	0	0	0	0	86	66.28%
sGA	8	2	77	47	0	0	0	0	134	57.46%
sUV	17	8	34	218	0	1	4	0	282	77.30%
dEG	50	0	0	2	43	52	69	91	307	14.01%
dRA	1	0	0	0	9	17	22	169	218	7.80%
dUV	23	0	0	0	0	16	218	39	296	73.65%
dW	0	0	0	0	0	0	0	63	63	100.00%
Sum	282	67	138	311	64	105	331	362	1683	
User's accuracy	64.54%	85.07%	55.80%	70.10%	67.19%	16.19%	65.86%	16.36%		Overall accuracy
Tau coefficient	0.52									52.0%

Confusion matrix for WorldView-2 classification without optically deep water mask and spectral indices										
	Classification data									
Reference data	sEG	sBA	sGA	sUV	dEG	dRA	dUV	dW	Sum	Producer's accuracy
sEG	163	0	25	8	10	43	11	37	297	54.88%
sBA	3	59	0	24	0	0	0	0	86	68.60%
sGA	16	0	91	27	0	0	0	0	134	67.91%
sUV	19	6	67	183	3	2	2	0	282	64.89%
dEG	36	0	1	0	15	58	47	150	307	4.89%
dRA	1	0	0	0	2	15	8	192	218	6.88%
dUV	33	0	0	0	8	41	145	69	296	48.99%
dW	0	0	0	0	0	0	1	62	63	98.41%
Sum	271	65	184	242	38	159	214	473	1683	
User's accuracy	60.15%	90.77%	49.46%	75.62%	39.47%	9.43%	67.76%	13.11%		Overall accuracy
Tau coefficient	0.40									43.6%

Table 3.5 - Confusion matrices for habitat maps based on WorldView-2 imagery (with optically deep mask).

Confusion matrix for WorldView-2 classification with water mask and 8 original spectral bands									
	Classification data								
Reference data	sEG	sBA	sGA	sUV	dEG	dRA	dUV	Sum	Producer's accuracy
sEG	181	0	27	16	11	44	18	297	60.94%
sBA	1	57	0	28	0	0	0	86	66.28%
sGA	8	2	77	47	0	0	0	134	57.46%
sUV	17	8	34	218	0	1	4	282	77.31%
dEG	51	0	0	2	43	142	69	307	14.01%
dRA	2	0	0	0	13	57	19	91	62.64%
dUV	25	0	0	0	2	54	215	296	72.64%
Sum	285	67	138	311	69	298	325	1493	
User's accuracy	63.51%	85.07%	55.80%	70.10%	62.32%	19.13%	66.15%		Overall accuracy
Tau coefficient	0.52								56.8%

Confusion matrix for WorldView-2 classification with water mask and spectral indices									
	Classification data								
Reference data	sEG	sBA	sGA	sUV	dEG	dRA	dUV	Sum	Producer's accuracy
sEG	166	0	25	8	7	82	9	297	55.89%
sBA	3	59	0	24	0	0	0	86	68.60%
sGA	16	0	91	27	0	0	0	134	67.91%
sUV	19	6	67	183	3	2	2	282	64.89%
dEG	36	0	1	0	9	213	48	307	2.93%
dRA	1	0	0	0	2	79	9	91	86.81%
dUV	33	0	0	0	6	109	148	296	50.00%
Sum	274	65	184	242	27	485	216	1493	
User's accuracy	60.58%	90.77%	49.46%	75.62%	33.33%	16.29%	68.52%		Overall accuracy
Tau coefficient	0.45								49.2%

Table 3.6 - Confusion matrices for habitat maps based on WorldView-2 imagery (with 3m depth mask).

Confusion matrix for Worldview classification with 3 m depth mask and original 8 bands						
	Classification data					
Reference Data	sEG	sBA	sGA	sUV	Sum	Producer's Accuracy
sEG	241	0	28	28	297	81.14%
sBA	0	57	0	29	86	66.28%
sGA	7	2	77	48	134	57.46%
sUV	20	8	34	220	282	78.01%
Sum	268	67	139	325	799	
User's Accuracy	89.93%	85.07%	55.40%	67.69%		Overall accuracy
Tau coefficient	0.67					74.47%

Confusion matrix for Worldview classification with 3 m depth mask and spectral indices						
	Classification data					
Reference Data	sEG	sBA	sGA	sUV	Sum	Producer's Accuracy
sEG	260	0	25	12	297	87.54%
sBA	2	59	0	25	86	68.60%
sGA	15	0	91	28	134	67.91%
sUV	24	6	66	186	282	65.96%
Sum	301	65	182	251	799	
User's Accuracy	86.38%	90.77%	50.00%	74.10%		Overall accuracy
Tau coefficient	0.67					74.59%

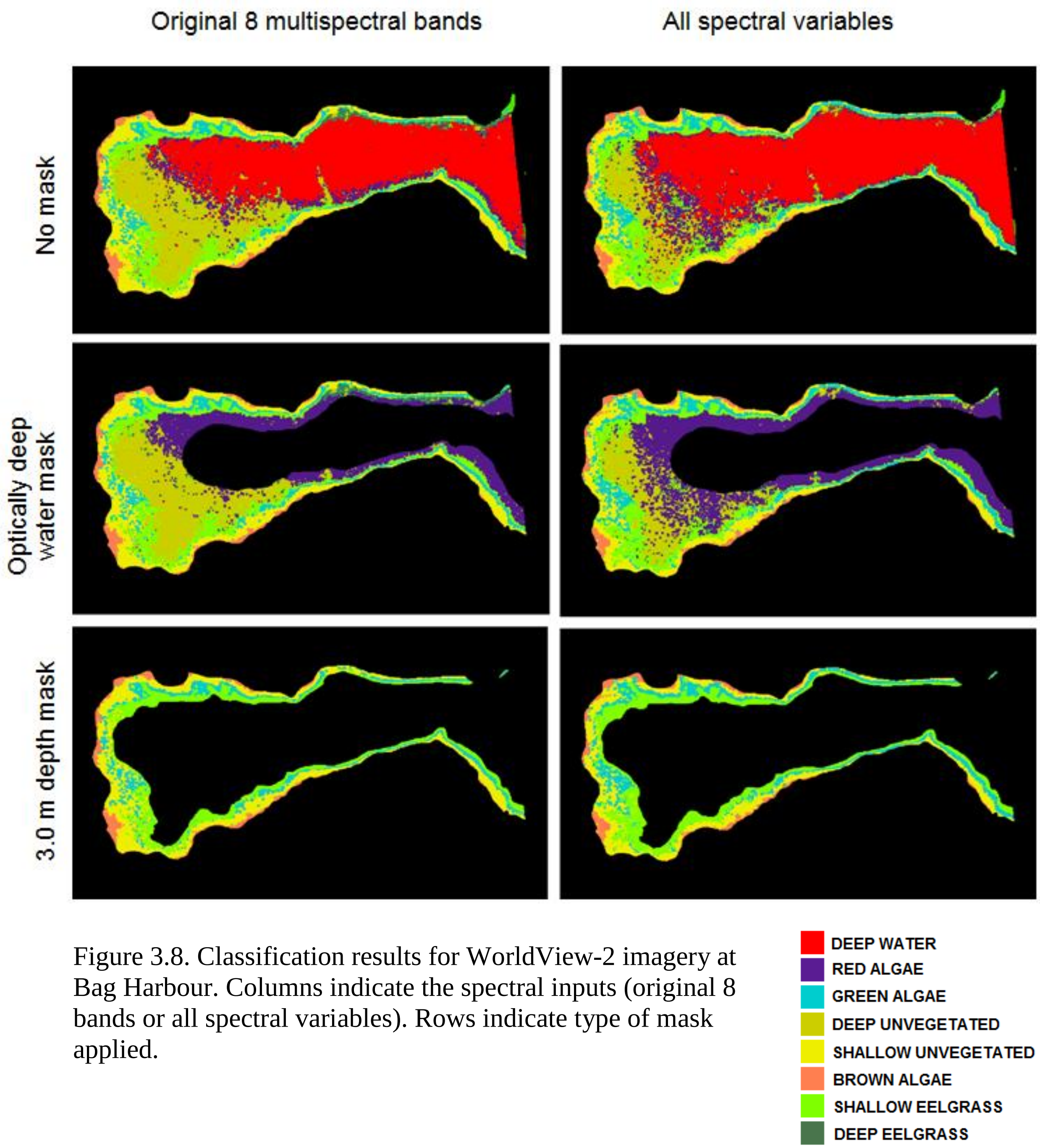

Figure 3.8. Classification results for WorldView-2 imagery at Bag Harbour. Columns indicate the spectral inputs (original 8 bands or all spectral variables). Rows indicate type of mask applied.

deep water mask and original 8 bands) and the highest producer's accuracy was 87% (optically deep water mask and spectral indices). The deep unvegetated substrate class performed fairly consistently for all classifications obtaining the highest user's and producer's accuracy with no masking for the classification (68%/74%) with the original 8 bands and spectral indices, respectively. These results are likely due to the lack of differentiation seen in the spectral signatures between all substrate classes below 3.0 m (M-statistics below 1) (Fig. 3.6).

The most accurate classification was achieved with the application of a 3.0 m depth mask. Between classifications performed with the original bands and the new spectral indices, the overall accuracy were almost identical (74.5% and 74.6%, respectively) and no statistically significant difference was found between tau coefficients (Z= 0.11, p-value = 0.05). Individual class user's and producer's accuracy were found to be different depending on which spectral input was used. For example, user's accuracy was higher for shallow eelgrass classification with the original spectral bands (90% compared to 86) while higher producer's accuracy was achieved when using the new spectral indices (88% compared to 81%). User's and producer's\s accuracy were slightly improved for brown algae (91%/69% compared to 85%/66%) Producer's accuracy also increased for eelgrass (88% compared to 81%) and green algae (68% compared to 57%). User's accuracy of shallow unvegetated substrate increased as well (74% compared to 68%).

Overall, the eelgrass achieved the highest user's and producer's accuracy, followed by brown algae, and shallow unvegetated substrate. The green algae performed the poorest. The highest user's and producer's accuracy for this class were 57% and 68%, respectively, for classification with the spectral indices. Classification of green algae showed significant confusion with unvegetated substrate (28 ground-truth points misclassified) and shallow eelgrass (15 ground truth points misclassified).

For the purposes of comparing results between acoustic and optical datasets, the classification using the original 8 bands with the 3.0 m depth mask was selected. The reasoning for this selection was to reflect the original purpose of the project - to produce reliable maps of shallow subtidal seafloor habitat to support conservation decision-making within the GHNMCA. As user's accuracy is a measure of map reliability (ie. indicative of the probability that a pixel classified on the map actually represents that category (Story & Congalton, 1986), user's accuracy was the criterion for selection. Therefore, even though the two classifications (with the original 8 bands and with the spectral indices) achieved similar results across all habitat classes, the classification with the original 8 bands achieved higher user's accuracy for eelgrass and green algae. Given that eelgrass has been identified as critical habitat within the GHNMCA, it is reasonable to select the map with the most reliable classification of this habitat.

3.4.2 Acoustic dataset

A total of 8036 echo stacks were processed by the ACE clustering algorithm (Fig. 3.9a). Clustering was evident between the 10 acoustic classes (Fig. 3.9b). Class 1 was removed as it constituted less than 2% (n=150) of the total dataset and showed a sparse distribution with no distinct spatial patterns (Fig. 3.9b Panel 1). Acoustic classes from the 200 kHz survey appeared to show more distinct spatial patterns throughout the study site. In particular classes 2, 3, 6, 7 and 10 showed very distinct spatial patterns in bands and patches around the study site. In contrast, classes 4, 5, 8 and 9 showed fairly ubiquitous distributions. The spatial distribution of each class is shown in Figure 3.9c.

For the interpolated acoustic data (Fig. 3.10a) the visual assessment and analysis of training data indicated that classes 2 and 7 were associated with red algae and classes 6 and 10 were associated with eelgrass (Table 3.7). The majority of green algae, brown algae and

Table 3.7 - Interpretation of 200 kHz interpolated dataset.

Acoustic Class	Habitat classification
1	Removed
2	Red algae
3	Unvegetated
4	Unvegetated
5	Unvegetated
6	Eelgrass
7	Red algae
8	Unvegetated
9	Unvegetated
10	Eelgrass

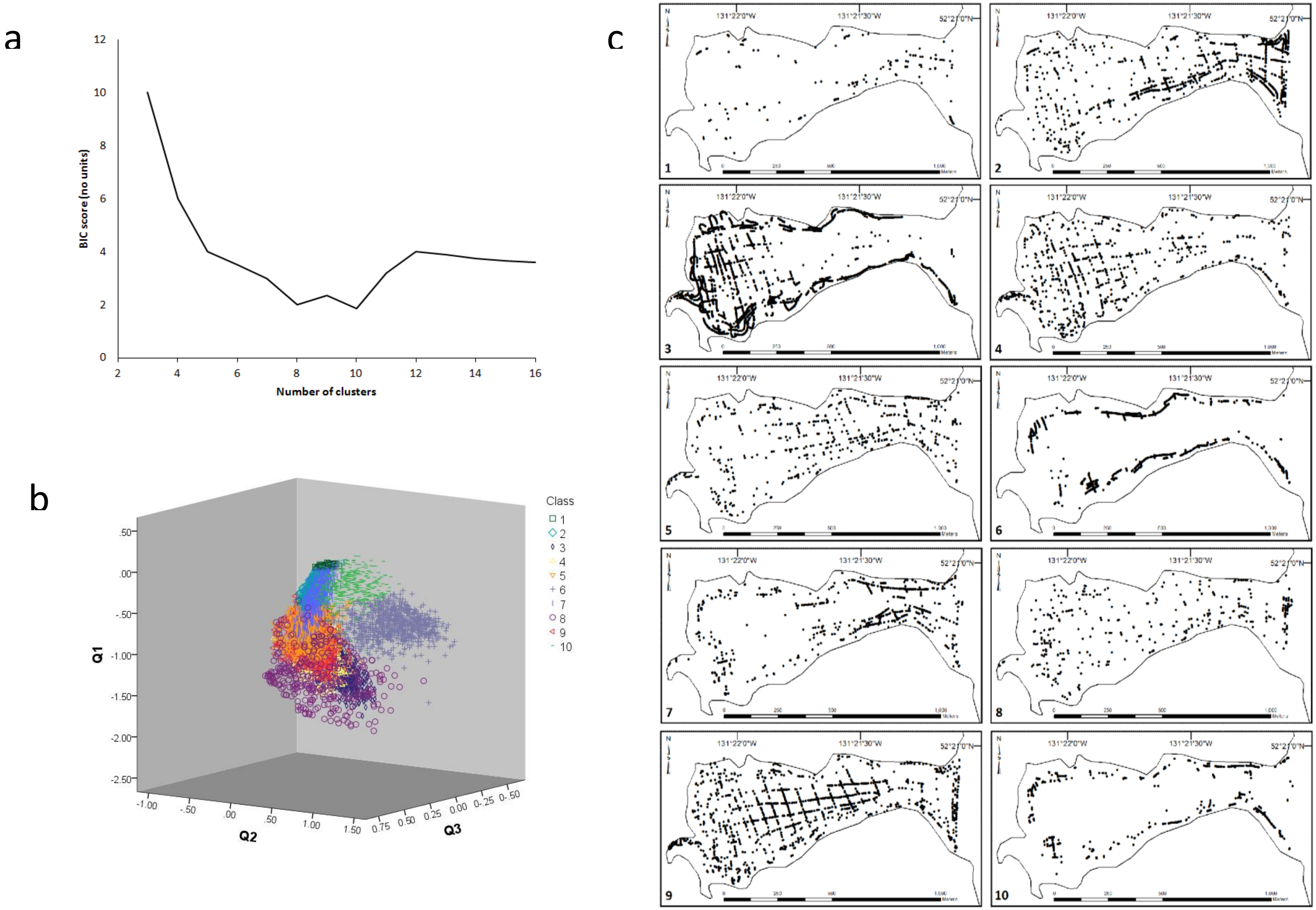

Figure 3.9. (a) Clustering results from the 200 kHz acoustic survey. (b) PCA plot. (c) Distribution of 10 200 kHz acoustic classes.

unvegetated training data were found in Class 3 due to its ubiquitous distribution in the study site. No acoustic classes were found to be uniquely associated with brown algae and green algae, therefore, these habitats were deemed undetectable by the 200 kHz acoustic system and were not included in the final habitat map. Figure 3.10a shows the distribution of interpolated acoustic classes (n=10) and the final habitat map.

The accuracy of the acoustic habitat map was tested using the same depth stratification of habitat classes (<3.0 m and >3.0 m). This allowed the comparison of results between of the acoustic habitat classification and the classifications derived from the WorldView-2 imagery, The overall accuracy of the 200 kHz acoustic habitat map was 81% and a Tau coefficient of 0.72. and included 5 classes – shallow eelgrass, shallow unvegetated substrate, red algae and deep unvegetated substrate (Table 3.8). The deep and shallow eelgrass habitats performed best with user's and producer's accuracy of 86%/81% for deep eelgrass and 96%/67% for shallow eelgrass, respectively. Red algae demonstrated slightly lower classification accuracy with user's and producer's accuracy of 68% and 73%, respectively with approximately 20% of red algae ground truth data were misclassified as deep unvegetated substrate.

In comparison to the WorldView-2 classification the acoustic classification achieved higher user's and producer's accuracy for deep eelgrass (86%/81% compared to 68%/74%) and deep unvegetated substrate (78%/86% compared to 68%/74%). For the red algae class, producer's accuracy was slightly lower for the acoustic classification compared to the highest producer's accuracy achieved with the WorldView-2 data (73% and 87%, respectively), however, the acoustic data achieved much higher user's accuracy (68% compared to 19%). For shallow eelgrass the QTC5 system achieved higher user's accuracy (96% compared to 90%) but lower producer's accuracy (67% compared to 88%). Shallow unvegetated substrate did perform better

Table 3.8 - Confusion matrix for habitat maps based on 200 kHz data.

	Classification data						
Reference Data	sEG	dEG	dRA	sUV	dUV	Sum	Producer's Accuracy
sEG	199	0	24	74	0	297	67.00%
dEG	0	248	28	0	31	307	80.78%
dRA	0	17	159	0	42	218	72.94%
sUV	8	0	4	270	0	282	95.74%
dUV	0	23	19	0	254	296	85.81%
Sum	207	288	234	344	327	1400	
User's Accuracy	96.14%	86.11%	67.95%	78.49%	77.68%		Overall accuracy
Tau coefficient	0.72						80.71%

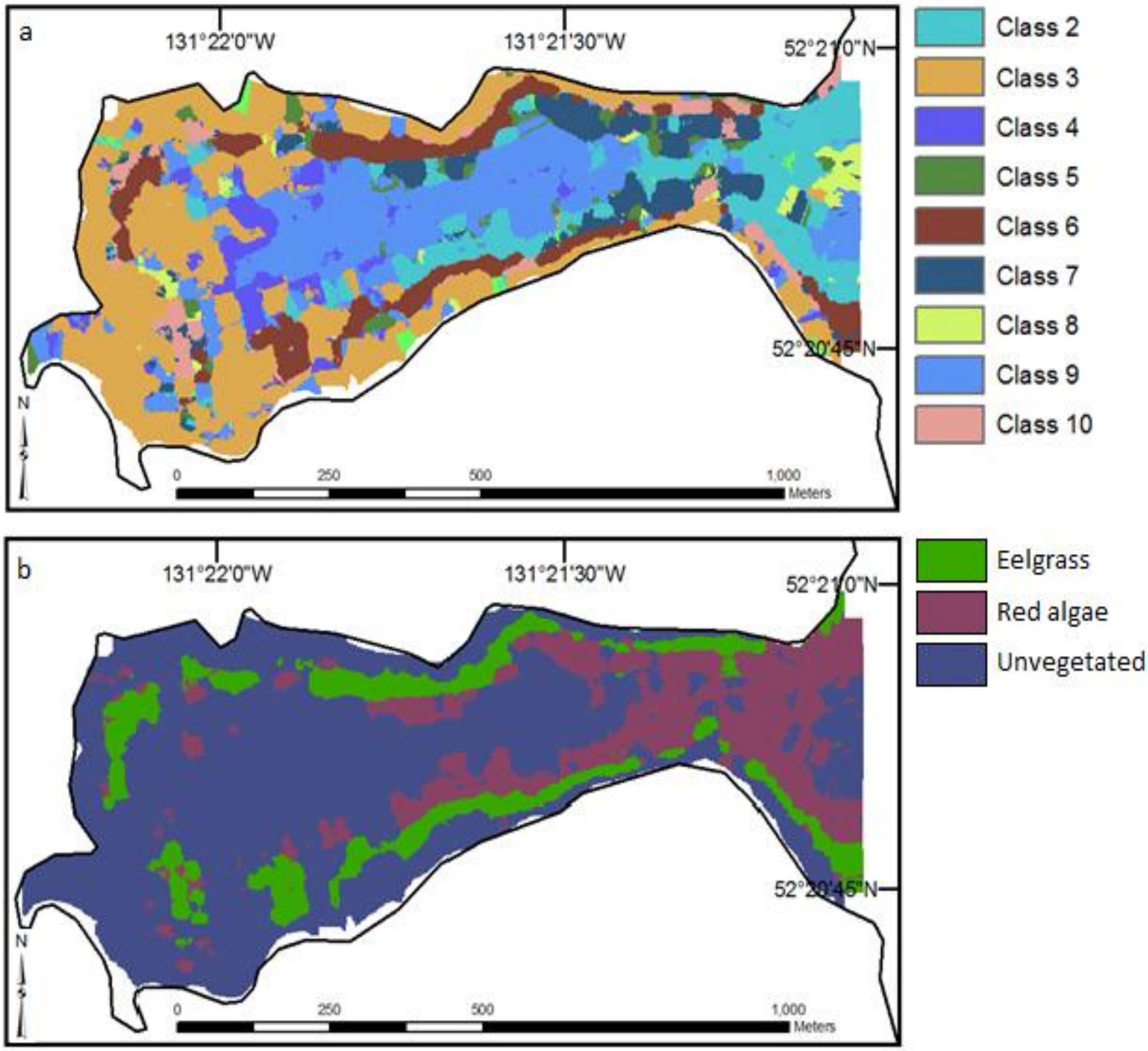

Figure 3.10. (a) Distribution of 9 interpolated acoustic classes identified by QTC Impact (Class 1 was removed in a previous step). (b) Habitat classification of acoustic data with eelgrass (green), red algae (maroon) and unvegetated substrate (blue).

for the acoustic classification (78%/96% compared to 74%78%), however, this performance is misleading as it does not reflect the presence of other habitat classes present at Bag Harbour (ie. green and brown algae).

3.4.3 Merged dataset

The merged habitat map was created from the shallow (<3.0 m) WorldView-2 map (using the spectral variables) and the 200 kHz habitat map (>3.0 m). This selection was made taking into account several considerations. Firstly, the WorldView-2 classification performed best in the shallow regions and was also able to distinguish the distribution of brown and green algae, which the acoustic dataset could not. Furthermore, in the classification of shallow eelgrass, the WorldView-2 imagery achieved equally high user's and producer's accuracy in comparison to the 200 kHz data which had lower producer's accuracy (86%/89% and 96%/67%). Secondly, the WorldView-2 image is a continuous surface of pixels which improves the mapping of smaller patches of habitat and habitat edges. In contrast, the acoustic habitat map was generated from interpolated data which, based on the distance between survey tracks and the small size of the echosounder footprint in shallow regions, likely misses small patches and habitat edges. Secondly, the acoustic data performed much better in the detection of deep eelgrass and red algae. Simply put, WorldView-2 performed better at depths less than 3 m and the 200 kHz data performed better at depths greater than 3 m. Furthermore, the artifact of the 3 m depth stratification reflects the distribution of benthic classes in Bag Harbour, with green and brown algaes present only above 3 m and red algae present only below 3 m.

The habitat classification created from the merged datasets is shown in Fig. 3.11 and the confusion matrix in Table 3.9. While overall, user's and producer's accuracy are reported, these represent the mean of the two best classifications into a single habitat map. For example, the overall accuracy of the merged habitat map (76%) is the average of the best overall accuracies

Table 3.9 - Confusion matrix for habitat maps for habitat classification of WorldView-2 imagery (3m depth mask) and 200 kHz data.

	Classification data								
Reference data	sEG	sBA	sGA	sUV	dEG	dRA	dUV	Sum	Producer's accuracy
sEG	260	0	25	12	0	0	0	297	87.54%
sBA	2	59	0	25	0	0	0	86	68.60%
sGA	15	0	91	28	0	0	0	134	67.91%
sUV	24	6	66	186	0	0	0	282	65.96%
dEG	0	0	0	0	248	28	31	307	80.78%
dRA	0	0	0	0	17	159	42	218	72.94%
dUV	0	0	0	0	23	19	254	296	85.81%
Sum	301	65	182	251	288	206	327	1620	
User's accuracy	86.38%	90.77%	50.00%	74.10%	86.11%	77.18%	77.68%		Overall accuracy
Tau coefficient	0.743								77.6%

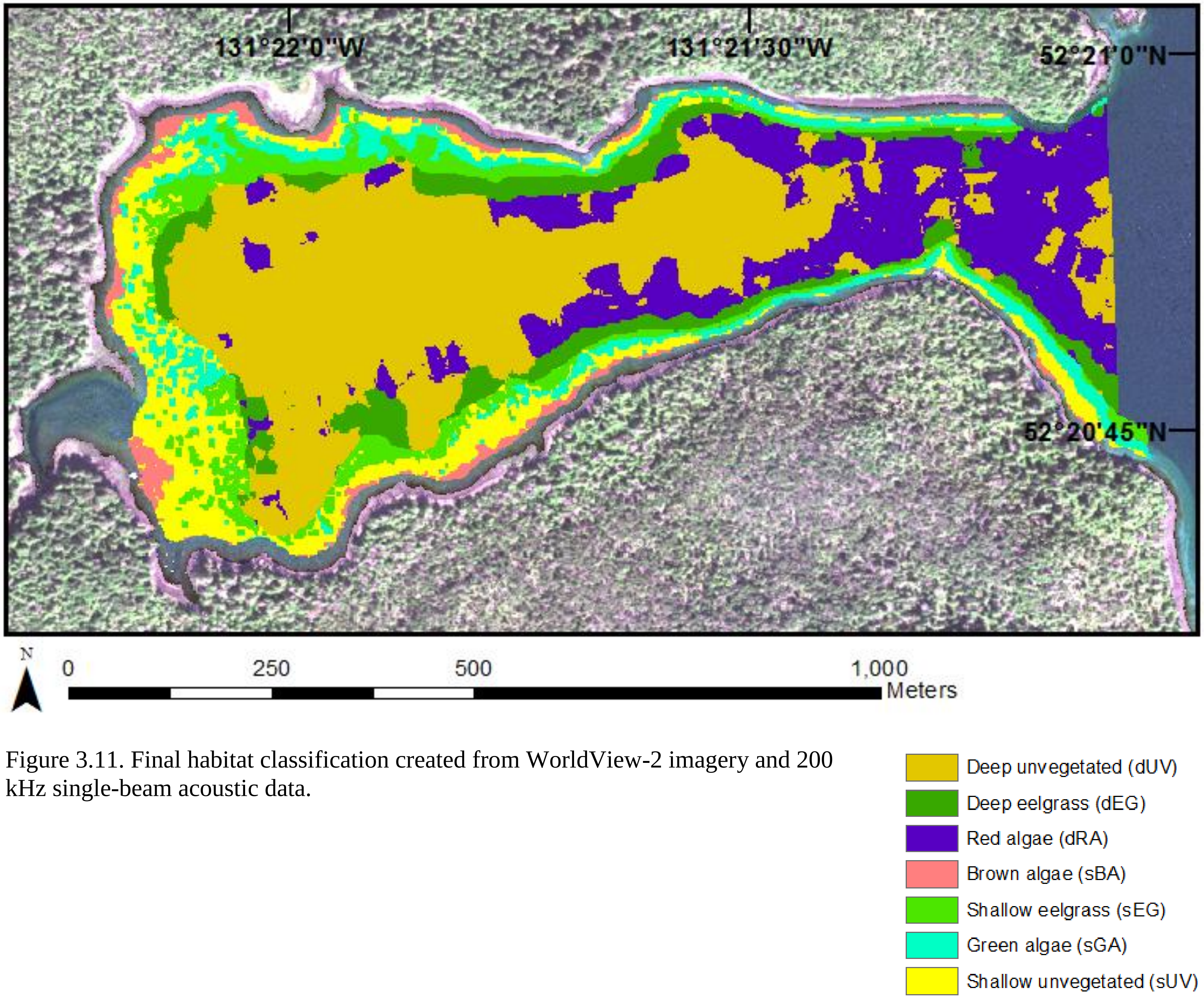

Figure 3.11. Final habitat classification created from WorldView-2 imagery and 200 kHz single-beam acoustic data.

from the WorldView-2 and the 200 kHz habitat maps. It should be noted again that green and brown algae were not found to occur below 3.0 m and red algae was not found above 3.0 m.

3.5 Discussion

3.5.1 WorldView-2 dataset

Many studies have highlighted the ability of high resolution satellite imagery to create maps of benthic marine habitat (Andrefouet et al., 2008), however, the majority of these studies have been applied in tropical regions, where water clarity is very high and seafloor characteristics can be resolved up to depths of 30 m. Fewer studies have applied high resolution satellite imagery for mapping benthic substrates in temperate marine waters, which are characterized by high cloud cover and more turbid waters reducing the penetration of light through the water column and making the interpretation of substrates types increasingly difficult. However, There is strong evidence from this study and others that optical remote sensing from high resolution multispectral sensors can provide crucial data for supporting conservation management in coastal temperate regions (e.g O'Neill & Costa, 2013; Vahtmäe & Kuster, 2013).

To date, studies using WorldView-2 imagery are predominantly focused on bathymetric applications (Collin & Hench, 2012; Doxani et al., 2012). Only one study was identified where WorldView-2 imagery has been used to produce marine habitat maps. In that study, Vahtmäe and Kutser (2013) compared the classification of shallow marine habitats using WorldView-2 imagery and the hyperspectral sensor CASI in coastal Estonian waters. Their classification achieved an overall accuracy of 72% overall accuracy with 5 habitat classes using the WorldView-2 sensor (78% with CASI). While no seagrass was present within their study site, the authors did map several classes of aquatic vegetation at depths less than 2.0 m. In comparison, this study achieved an overall accuracy of 75% for benthic habitat present at depths shallower than 3.0 m. These results indicate that WorldView-2 imagery can successfully be applied for mapping submerged aquatic vegetation in temperate marine regions, however, more studies are required to ascertain the limitations of this sensor under different marine conditions.

In this study the highest user's and producer's accuracy were achieved for shallow eelgrass, 81% and 90%, respectively. This means that 81% of all shallow eelgrass ground-truth data were assigned correctly and that there is a 90% probability that an area on a map indicating the presence of shallow eelgrass represents shallow eelgrass in reality. These values represent results in the higher range of user's and producer's accuracy achieved with satellite imagery of similar spatial resolution. Other studies that have used high resolution satellite imagery to map seagrass habitat are summarized in Table 3.10. This list of reported seagrass accuracy, while not exhaustive, does provide a context for the performance of WorldView-2 imagery in this study. Within Table 3.10, user's and producer's accuracy for seagrass habitat are reported. Overall accuracy are reported as well but these values are not directly comparable as overall accuracy has been shown to increase for classifications with fewer classes (ie. lower thematic resolution) (Andrefouet et al., 2003).

For shallow eelgrass, the main peak of reflectance occurred as a plateau between 480 nm and 545 nm. Other studies which have recorded *in situ* spectra of eelgrass have shown that this peak to occur between 550 nm and 600 nm (Zimmerman, 2003; O'Neill & Costa, 2013). The spectra were likely affected by the method of atmospheric correction. The ATCOR model relies on the selection of an aerosol model which simulates the assumed atmospheric conditions within the imagery, however, these spectra indicate that there may have been a bias in correcting the blue end of the spectrum. Other methods of atmospheric correction such as Tafkaa (Montes, Bo-

Table 3.10 - Reported accuracies for mapping seagrass using high spatial resolution satellite sensors (<5 m).

Study	Sensor	User's accuracy	Producer's accuracy	Overall accuracy (number of habitat classes)
This study	WorldView-2	90%	81%	75% (7)
O’Neill & Costa (2013)	IKONOS/AISA	91%/93%	79%/85%	68%/83% (7)
Fornes et al. (2005)	IKONOS	91%	93%	84% (3)
Mishra et al. (2006)	IKONOS	66%	76%%	80.6 (6)
Mumby & Edwards (2002)	IKONOS/CASI	86%/89%	NR	64%/81% (9)
Vela et al. (2008)	IKONOS	85%	NR	73% (4)
Purkis (2005)	IKONOS	81%	53%	69% (8)
Phinn et al. (2008)	Quickbird-2	34%	56%	31% (7)

*NR = not reported
*Where two sensors were reported (e.g. IKONOS/AISA), the respective accuracy are reported in the same position (e.g. 91%/93% represents IKONOS and AISA user's accuracy, respectively).

Cai, & Davis, 2004) or empirical line correction (ELC) should be tested in future mapping studies as they have been shown to produce spectra that agree with *in situ* spectra (O'Neill & Costa, 2013).

For the green algae class, which consistently performed the worst out of all shallow habitats, the majority of misclassification occurred with shallow unvegetated substrate. This is likely due to the similarity in shape of the spectral reflectance of the two classes (Fig. 3.7). Furthermore, the M statistic analysis demonstrated that there were no spectral indices capable of discriminate between these substrate classes (Fig. 3.6). Misclassification in the WorldView-2 imagery also occurred between eelgrass and green algae, which is likely due to the similarity in pigment composition (Rowan, 1989). The accuracy of green algae could be improved by re-selecting variables to maximize the separation between green algae and all other classes. However, this comes at the expense of all other classes.

In contrast to the green algae class, the brown algae (*Fucus* spp.) class achieved higher user's and producer's accuracy due to several factors. Firstly, four indices were able discriminate between brown algae and unvegetated substrate (M-statistic > 1) (Fig. 3.6). Secondly, brown algae habitat occurs in the high intertidal region (whereas green algae occurs in the lower intertidal region) meaning that even under high tide conditions the habitat is submerged under less than 1 m of water, and the reflectance signal suffers less attenuation from the overlying water column. In comparison to reflectance spectra of brown algae reported by Thorhaug, Richardson, & Berlyn (2007) the spectra reported in this study show a shift in peak reflectance at 545 nm compared to 560 nm reported by the authors (recorded from *in situ* above water measurements). . Finally, the misclassification of brown algae with unvegetated substrate is likely due not to spectral confusion, but due to the presence of small brown algae patches at Bag Harbour that are below the spatial resolution of the WorldView-2 sensor.

The results of this study also indicate that the inclusion of band ratios do offer some improvement to the classification of all benthic habitats in shallow regions. However, only one class (brown algae) had both user's and producer's accuracy improve with classification with the spectral indices when compared to classification with the original bands. These results suggest with the aim to increase the separability between all habitat classes, the inclusion of more spectral indices (ie. additional band ratios) provided additional data into the maximum liklihood classifier that resulted in poorer overall accuracy of the habitat classification. Other studies, which have focused on maximizing the accuracy in mapping a target habitat, such as eelgrass, have demonstrated that a reduced spectral dataset can improve classification for a target habitat (O'Neill & Costa, 2013).

The greatest source of classification error in this study was for deep (>3.0 m) habitat classes – deep eelgrass, red algae and deep unvegetated substrate. It was expected that the application of an optically deep water mask would improve the accuracy of these classes as this has been demonstrated to improve the classification of submerged vegetation (Ackleson & Klemas, 1987; Zainal et al., 1993; O'Neill & Costa, 2013). In this study the application of the optically deep water mask resulted in only a slight improvement in overall accuracy due to the improvement in the user's and producer's accuracy for red algae. The calculated depth of the mask (8.5 m) was likely overestimated due to two factors. Firstly, the coefficient of attenuation (K_d) was derived from a single Secchi depth measurement collected at the site during the ground-truth survey. The survey predates the imagery by two years and the assumption that water conditions were similar at these two times may not be accurate. Secondly, Secchi depth is very sensitive to turbidity and therefore it is likely that the equation described by Holmes (1970) overestimates or underestimates the value of K_d (Kirk, 1994) and therefore erroneously define the depth at which, based on reflectance, the target substrate cannot be discernible from deep water.

To improve the classification of habitats occurring at greater depths, a water column correction method is often applied (Mumby et al., 1998). Water column correction methods, such as those described by Lyzenga (1978) and Maritorena et al. (1994), are commonly applied but have unique requirements. For example, the Lyzenga method requires the same bottom type be present over a wide range of depths in order to calculate the required depth invariant index (which is necessary to perform the water column correction). However, these conditions did not exist at this site. As well, *in situ* measurements of water column bio-optical properties were unavailable to perform corrections based on radiative transfer theory. Future research in the area could be focused on the improvement of benthic substrate classification through the application of a water column correction technique.

Overall, the results obtained from the classification of WorldView-2 imagery represent a ‘worst-case’ scenario for satellite imagery acquired in this region. In the future, for imagery acquired at a low-tide with minimal specular reflection, it is very likely that accuracy for all habitat classes could be increased. In this study, benthic habitat were successfully mapped to a depth of 3.0 m and the tidal state of the imagery was +3.1 m. Therefore, for imagery acquired at a low tide it would be possible to map habitat occurring to -3.0 m using the same methods presented here. With the application of a water column correction method, higher accuracy for deeper habitat classes could be achieved.

3.5.2 Acoustic dataset

Few studies have examined the abilities of the QTC5 system for mapping submerged vegetation (Preston et al., 2006; Quintino et al., 2009; Moyer et al., 2005; Riegl et al., 2005; Riegl & Purkis, 2005). While each of these studies has demonstrated the ability to map submerged vegetation, only three of studies reported the accuracy of the final habitat map (Reigl and Purkis, 2005; Riegl et al., 2005; Moyer et al., 2005). Off the coast of Florida, Moyer et al. (2005) were able differentiate between three broad habitat classes (sand, rubble and reef) with an overall accuracy of 61% using a 50 kHz transducer. In another study, Reigl and Purkis (2005) using both 50 and 200 kHz frequencies, found that the 50 kHz acoustic seafloor classification was able to determine two classes (unconsolidated sand versus hard ground) and the 200 kHz classification could differentiate between high rugosity (i.e. corals and sand ripples) versus low rugosity (i.e. flat areas). The habitat map produced from these data was found to be 66% accurate when compared to an IKONOS dataset (overall accuracy of 69%) from the same site. In another study by Reigl et al. (2005), three class habitat maps (sand, seagrass and algae) from a small inlet in the Indian River Lagoon, Florida, produced from 50 and 200 kHz found similar accuracy (approximately 60% for both datasets) for habitat maps produced from both datasets. In comparison, the results obtained in this study - 81% overall accuracy with 5 habitat classes for the 200 kHz data - are the highest reported using QTC5 for mapping submerged vegetation.

In this study, the 200 kHz data were able to map the distribution of eelgrass and red algae with high user's and producer's accuracy, improving on the results reported by other studies that have used the same system. However, the QTC5 system not detect the presence of green and brown algal habitat. The most likely explanation for this result is twofold. Firstly, both of these algae have low vertical profile. Unlike eelgrass, which forms a canopy approximately 1-2 m above the seafloor, the species of brown and green algae present at Bag Harbour form very low canopies (<0.3 m). According to Chivers et al. (1990), the first peak(s) of the echo is strongly influenced by subsurface reverberation. Therefore as the 200 kHz pulse insonifies the seafloor, the precursor echo to the seabed/water interface likely overwhelms the acoustic signal of the overlying algae. Secondly, these habitats occur from the mid- to high intertidal range. The consequence for the QTC system is that the footprint of the transducer in shallow areas is very small. These regions were sampled during high tide and in the shallowest regions a depth of 1.0 m was maintained below the transducer. This equates to a 200 kHz transducer footprint diameter of 0.17m or 0.023 m^2. It is therefore likely that these habitats were under-sampled and that during the acoustic survey not enough data was collected from the habitats in order to generate unique acoustic classes. Brown algae is present in the high intertidal zone in very sparse, patchy spatial arrangements and is a difficult habitat to map based on transect sampling.

In comparison to the WorldView-2 classification, the QTC5 system performed significantly better for habitats occurring below 3.0 m. These results suggest that for habitats that can be detected by a single-beam echosounder (ie. eelgrass and red algae) the QTC5 system can be successfully applied for mapping benthic habitats in coastal temperate water that are limited in the application of satellite imagery.

3.5.3 Combining acoustic and optical remote sensing data

There are inherent limitations in mapping nearshore marine habitat using optical and acoustic remote sensing technology, however, the combination of the most accurate outputs from both can capture the spatial distribution of all habitats present at a given site. In this study, the combination of habitat classification using WorldView-2 satellite imagery and a QTC5 200 kHz single-beam acoustic data was able to capture the presence of all species of submerged aquatic vegetation, with an overall accuracy of 78%. Other studies have also examined the ability to map nearshore habitat using similar combinations of acoustic and satellite remote sensing. For example, Riegl and Purkis (2005) examined the abilities to map a coral reef system using IKONOS (4 m resolution) and the QTC5 system (50 kHz and 200 kHz). Their results indicated that some degree of commonality existed between the two datasets, with the acoustic system able to discriminate fewer classes (4 compared to eight for the IKONOS imagery). By combining acoustic data about seafloor conditions and bathymetry with satellite imagery it is possible to map benthic habitats such as coral reefs (Bejarano et al., 2010) or to map target habitats such as seagrass (e.g. Pasqualini, 1998; Sagawa et al., 2010). The results of this study and others demonstrate that data synergy can maximize the thematic resolution of habitat maps and provide synoptic datasets that can inform conservation policy makers.

To map coastal ecosystems using remote sensing Chavaud (1998) outlined three conditions that must be met. The first condition is that the spatial resolution of the thematic map must be adapted to the complexity of the environment. The 2 m by 2 m spatial resolution of the WorldView-2 imagery fulfills this requirement. The spatial resolution of habitat maps derived from the QTC5 system depends the footprint size of the transducer (which varies with depth) and the proximity of transects (to maximize the number of echo returns). Therefore to obtain similar spatial resolution as the satellite imagery transects can be run closer together to provide more complete coverage.

The second condition stipulates that the wavelengths detected by the satellite sensor, (and, additionally in this study, the frequency of the QTC5 system) must exhibit sufficient penetration into the water column to capture the thematic richness of the area. While the increased spectral resolution of WorldView-2 imagery has been shown to increase the depth to which benthic substrates can be resolved (Collin & Hench, 2012; Botha et al., 2013), in this study, the water column under high tide conditions proved to be a limiting factor in mapping the full extent of all habitats present at Bag Harbour. For the QTC5 system, the 200 kHz frequency has ample capability of mapping habitat in subtidal regions outside of the viewing capabilities of any optical sensor.

Finally, the reliability of the final thematic map(s) must be assessed. Towed underwater video proved to be a reliable and successful method for collecting ground-truth data for both training and validating acoustic and optical datasets. Given the volume of data collected in this study future surveys may be designed to reduce the total amount of data, or maximize data collection over target habitats (such as eelgrass).

Both the WorldView-2 imagery and QTC5 system achieved the three conditions outlined by Chavaud (1998). However, for broad-scale remote sensing each of these systems has unique advantages and disadvantages that will depend on the purpose for the final classification output (summarized in Table 3.11).

A large benefit of satellite imagery stems from its synoptic coverage and repeatability. In this study an archived image was obtained from DigitalGlobe, therefore the conditions under which the imagery was collected were present by chance. While future tasking of imagery could be targeted for a low tide event, there is the significant difficulty in obtaining suitable imagery in geographic regions which are susceptible to high cloud coverage and persistently strong winds. If suitable imagery could be acquired reliably, WorldView-2 exists as a very suitable method for mapping long stretches of remote coastline and could be used to conduct studies in seascape changes in habitat distribution.

Table 3.11 - Summary of major advantages and limitations of applying optical and acoustic remote sensing technologies for mapping nearshore marine benthic habitat based on this study.

	Advantages	Disadvantages	Requirements for both methodologies
WorldView-2	• Repeatable • Large geographic coverage • High overall accuracy (75%) • High spatial accuracy (2m pixel resolution)	• Cost of imagery • Limited by depth • Conditions of imagery may vary/be unsuitable (specular reflection, high tide) • Field data needed for geocorrection	• Ground-truth data collection and analysis • User's training in processing acoustic and optical datasets
QTC5	• Repeatable • Lower data cost • Data georeferenced during collection • High overall accuracy (81%) • Field methods for data collection fairly simple	• Cost of data collection (vessel/operator/fuel costs) • Limited by sea conditions for data collection • Resolves fewer habitats	

Satellite imagery will always be limited by the depths to which it can resolve the seafloor, but the properties of acoustic signals allow them to propagate through the water column and are much less influenced by depth. From a monitoring perspective, data collection with the QTC5 system is very simple and can access shallow regions not accessible by larger vessels with sidescan or multibeam sonar systems. The system also creates acoustic catalogues that can be applied when mapping new regions, which allows the real-time identification of previously mapped marine habitat. As discussed previously, the limitations of this system stem mainly from the inability to detect submerged vegetation that occurs in very shallow (<1m) regions, the point nature of the echo data which requires interpolation and the time required in conducting field surveys. Single-beam acoustic ground discrimination is also unsuitable for studying change in eelgrass patch dynamics, as it lacks the fine spatial coverage to capture small patches and complex meadow edges. In contrast WorldView-2 provides a more appropriate resolution to measure these small-scale dynamics (2 m x 2m pixel resolution) (Habeeb et al., 2007; Kirkman, 1996). The QTC5 is ideal for mapping the general distribution of habitats such as seagrasses as surveys are repeatable and resolution can be improved by running more survey track lines spaced closer together.

3.5.4 Spatial distribution of benthic habitat

According to the merged habitat map classification, Bag Harbour contains 56,588 m^2 of eelgrass, 65,960 m^2 of red algae, 9,012 m^2 of brown algae and 23,640 m^2 of green algae. Eelgrass meadows are present around the entire periphery of the estuary. Red algae is found in large expanses in the subtidal regions neighbouring the eelgrass meadows. Green algae is found in narrow patches neighbouring eelgrass in the shallow intertidal region. Brown algae occur as large isolated patches within the high intertidal regions.

Ancillary data from exposed eelgrass meadows mapped at low tide using a handheld dGPS, provide, some qualitative validation, of the accuracy of these results. These data demonstrate the ability of the WorldView-2 imagery to capture the complex patch structure of eelgrass meadows. In Figure 3.12 there is evidence of excellent visual agreement between these data and the results of the classification for eelgrass at Bag Harbour.

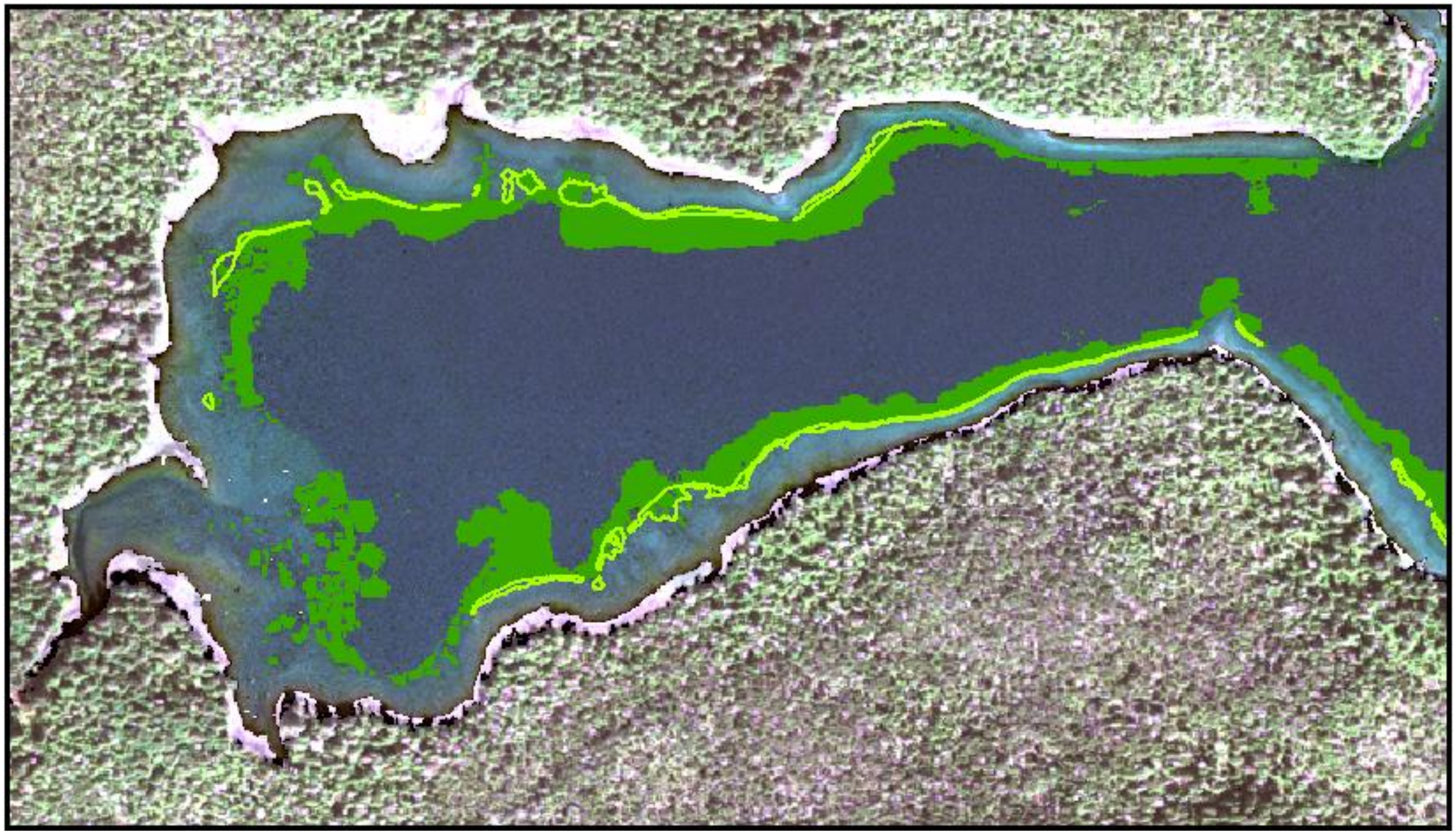

Figure 3.12. Eelgrass (green) mapped at Bag Harbour from WorldView-2 imagery and 200 kHz single-beam acoustic data. Bright green polygons indicate the extent of intertidal eelgrass meadows mapped by walking edges of exposed meadows.

3.6 Conclusion

Marine habitat mapping is a core requirement for informing conservation management and planning within MPAs. However, only a few studies evaluate the use of RS techniques for the purposes of large scale mapping, especially in costal temperate waters. The purpose of this study was to evaluate the ability to create habitat map that captured the distribution of all habitats (ie. submerged aquatic vegetation) present at Bag Harbour to identify methods of habitat mapping suitable for application within the Gwaii Haanas National Marine Conservation Area. This objective was achieved by using two remote sensing technologies - WorldView-2 high resolution satellite imagery and QTC View V single-beam acoustic ground discrimination system. The findings are as follows:

1) WorldView-2 imagery: the most accurate map of benthic habitats (overall accuracy of 75%) was achieved for regions of the study site shallower than 3m. At this depth four major habitats could be distinguished – shallow eelgrass (*Z. marina*), brown algae (*Fucus* spp.), green algae (*Ulva* spp.) and unvegetated substrate.
2) QTC View V 200 kHz: The acoustic data was able to distinguish the presence of eelgrass (shallow and deep), red algae (*C. exasperatus*) and unvegetated substrate, however, it was unable to distinguish between brown algae and green algae. The acoustic data also more accurately mapped benthic habitat in the subtidal region.

These results are directly relevant to marine conservation managers interested in remote sensing of nearshore marine habitats, particularly in temperate regions where water clarity is considerable less than in tropical regions. Site conditions and desired map output (e.g. thematic and spatial resolution) will dictate which method is most suitable for a given mapping project. WorldView-2 imagery is suitable for mapping fine-scale changes in habitat characteristics, however, acquiring imagery under ideal conditions can be challenging. Single-beam acoustics, while being able to resolve fewer habitat but at greater depths, requires additional field time for data collection and is most useful for mapping the broad occurrences of habitats such as eelgrass. Whichever remote sensing method is used it will still be necessary to obtain ground-truth data to assess the accuracy of the final habitat maps.

4.0 Conclusions

The creation of benthic habitat maps is one of the core needs for the implementation of informed conservation practices within coastal marine protected areas (MPAs) (Dalleau et al., 2010). Habitat maps serve as an inventory and a baseline that are used to assess the current status of ecosystems. Furthermore, repeat habitat mapping enables ecological changes in marine ecosystems to be quantified (Leleu et al., 2012). The importance of habitat maps is also reflected by several marine mapping programs that exist in at the continental scale (e.g. Mapping European Seabed Habitats project) and at the national scale (UKSeaMap 2010 project).

The research presented in this thesis is motivated by the need for generating nearshore benthic habitat maps over extensive, remote coastal areas to inform conservation management within the Gwaii Haanas National Marine Conservation Area. As shown in the introductory chapter, the GHNMCA has 1500 km of coastline for which there are few existing maps of shallow subtidal benthic habitat. This study set out to examine the applicability of two remote sensing systems - one optical, one acoustic - for creating benthic habitat maps. The aim of this final chapter is summarize the key findings from this research, address key considerations for benthic habitat mapping within the GHNMCA and consider future research opportunities with regards to optical and acoustic remote sensing within the GHNMCA.

4.1 Summary of key findings

The main findings of this study are briefly summarized in correspondence to the objectives outlined in the introduction chapter.

In Chapter two a single-beam acoustic ground discrimination system (AGDS), QTC View V (QTC5), was examined for its ability to map benthic habitat, specifically the detection of submerged aquatic vegetation (seagrass and algae). Two surveys were conducted at 50 kHz and

200 kHz at a study site within the GHNMCA and towed underwater video was collected for ground-truthing. The results of the research found that 200 kHz data were more suitable for mapping marine habitat with the 200 kHz data able to discriminate between two species of submerged vegetation (eelgrass and red algae), with a higher spatial resolution (2 m) and higher overall accuracy (81%). In comparison, the 50 kHz data were only able to detect the presence of eelgrass at a coarser spatial resolution (10 m) and lower overall accuracy (63%). Evidence from the analysis found both frequencies to be sensitive to the density of habitat present on the seafloor. This research has contributed to the existing knowledge of the applicability of single-beam acoustic ground discrimination systems for mapping benthic habitats. It has corroborated results from previous studies demonstrating the suitability of higher frequencies (ie. 200 kHz) for mapping submerged vegetation in comparison to lower frequencies (50 kHz) (Preston et al., 2006; Quintino et al., 2009).

In Chapter three two remote sensing methods were compared for their utility of mapping nearshore habitat within the GHNMCA. Habitat maps were produced using a high resolution multispectral image from the WorldView-2 sensor and the QTC5 system operated at 200 kHz. The most accurate products obtained from the satellite imagery were for habitat less than 3m deep. At this depth the WorldView-2 imagery was able to discriminate between four habitat types - brown algae (*Fucus* spp.), green algae (*Ulva* spp.), eelgrass and unvegetated substrate with an overall accuracy of (75%). In comparison to the classification achieved with the WorldView-2 imagery, the 200 kHz acoustic data achieved higher overall accuracy (81%) and were able to map habitats below 3 m depth (eelgrass, red algae and unvegetated substrate) with greater accuracy. These classifications were combined to create a final habitat classification that encompassed all submerged aquatic vegetation species present at the study site.

4.2 Remote sensing of nearshore benthic habitats in Gwaii Haanas

The research presented in this thesis contributes to the body of remote sensing knowledge related to mapping marine benthic habitats. The results of each paper demonstrates the utility of acoustic and optical remote sensing technologies for mapping benthic habitats in an efficient manner (compared to using traditional field mapping techniques). This study has also shown that acoustic and optical remote sensing datasets can be combined to create high resolution habitat maps that are thematically comprehensive that enhance the capacity to inform decision maker's knowledge on the location of ecologically important habitats. However, both optical and acoustic remote sensing systems have limitations inherent to each system and limitations with regards to their applicability within the GHNMCA. The question remains: Given limited resources and the conditions for data collection within the GHNMCA which remote sensing method is most suitable for future mapping projects?

Based on the results and experience in conducting the research for this study it is arguable that both single beam acoustic ground discrimination and satellite remote sensing could be effectively applied for mapping nearshore benthic habitat within the GHNMCA. Each system presents unique benefits and limitations that should be considered for future mapping of benthic habitat within the GHNMCA. This conclusion is based on both the final habitat map accuracies (both spatial and thematic) as well as the operational considerations with regards to data collection using both the QTC5 system and WorldView-2 imagery.

With regards to thematic resolution, the habitat maps produced using the QTC5 system were able to map the complete distribution of two species of aquatic vegetation within Bag Harbour (eelgrass and red algae). Notably, the overall accuracy achieved with the 200 kHz in this study represents the highest overall accuracy ever reported in studies that have mapped benthic habitat using the QTC5 system (Table 2.1). In particular, eelgrass, a species recognized within Canada and the GHNMCA for its ecological importance in marine ecosystems (Sloan, 2006; DFO, 2009), was mapped with very high user's and producer's accuracy (90%/74%, respectively). Conversely, the QTC5 system failed to map two other species of submerged aquatic vegetation present at Bag Harbour (green and brown algae). However, while these habitats are not currently the subject of any targeted survey program within the GHNMCA, they were detected by the WorldView-2 imagery.

For habitats that occur in small patches or with convoluted patch shapes the spatial resolution of a remote sensing system is very important in detecting and retaining these features. With the QTC5 system, acoustic maps are generated from interpolated data points, therefore the spatial resolution of the final habitat maps are dependent on two factors - that of the echo sounder footprint and the spacing of the survey track lines. While the area of the echo sounder footprint will always be dependent on beam width of the transducer and the depth of the underlying seafloor, a high spatial resolution can be maintained (if desired) by surveying the seafloor along close track lines. In this study, the distance between survey tracks did not exceed 20 m and was much closer in shallower regions, however, this resolution could be improved in future surveys should higher resolution be desired or required.

The QTC5 system has several operational requirements that make it particularly suitable for mapping benthic habitat in the GHNMCA. Firstly, the most time-intensive step in habitat mapping using the QTC5 system comes from operator training for data collection and data processing. System operability in the field is fairly straightforward following instruction on equipment setup, however, significant training and knowledge are required for processing data. Producing habitat maps using the QTC5 system is heavily reliant on knowledge and experience of the proprietary softwares for data processing (QTC Impact) and for data interpolation (QTC Clams). Secondly, acoustic data collection is not limited by tidal state. In this study, total survey time with the 200 kHz setting was four hours and the survey was conducted in such a manner that high intertidal regions were sampled during high tide to ensure at least 1 m depth below the transducer (minimizing potential damage to the equipment from submerged objects). However, collection of acoustic data requires calm (ideally flat) seas. Calm sea conditions ensure that the acoustic transducer remains orthogonal to the sea surface which reduces the collection of erroneous data through the roll and pitch of the vessel.

Future work for mapping nearshore habitat within the GHNMCA would also require more efficient methods of ground-truth data collection. In this study, ground-truth data consisted of 20 km of towed underwater video transects representing over 70 hours of video data analysis and the data were also collected prior to acoustic surveys. This amount of data would obviously be prohibitively expensive with regards to time spent collecting and analyzing the video for 1500 km of coastline. To minimize the amount of data collection for ground-truthing future acoustic surveys, it is recommended that acoustic surveys are conducted prior to video transects. A benefit of the QTC5 system is that acoustic data can be processed in the field to produce maps of interpolated acoustic classes. Therefore maps of interpolated acoustic classes can be produced in the field (data processing can be performed on a field computer) and used to guide ground-truth data collection in a more efficient manner (ie. maximize data collection over regions where there is a higher rate of acoustic change and ensure sample of both homogeneous and heterogeneous areas). Similarly, unsupervised classifications of WorldView-2 imagery could be used to guide future data collection. However field data are collected in the future, it would be crucial to maintain a consistent methodology for data collection and record changes (if any) to data collection in the future.

Satellite imagery is commonly applied for benthic habitat mapping as it possesses several characteristics that are advantageous from a conservation perspective (Horning et al, 2010).

Firstly, the imagery is continuous (not interpolated) and a single image scene can capture hundreds of kilometers of coastline. Secondly, the imagery also has very high spatial resolution (2x2 m) suitable for mapping small patchy habitats (Habeeb et al., 2007). Thirdly, imagery can be collected for the same site on a monthly or yearly basis (depending on the temporal resolution of the satellite). However, a distinct disadvantage of satellite imagery is the reliance on local environmental conditions for image acquisition.

In this study the condition of the WorldView-2 image represents a truly worst-case scenario for mapping benthic habitat using satellite imagery. The image was heavily affected by sun glint due to wind-induced waves and was captured during high tide (+3.1 m). However, despite these less than ideal conditions the habitat maps produced using the WorldView-2 imagery achieved overall accuracies comparable to other studies using sensors of similar spatial resolution (Table 3.10). This is likely due to the higher spatial and spectral resolution of the WorldView-2 sensor (Botha et al., 2013; Capolsini et al., 2003).

There are several limitations in applying WorldView-2 imagery for mapping nearshore benthic habitat. Firstly, the ability to obtain imagery under ideal conditions (calm seas, low tide) is limited in Haida Gwaii. Climate data for the past decade (2002-2012) indicates that Haida Gwaii experiences an average rainfall of 33 mm of rain in July (an average of 13 rainy days). Furthermore, many days are typified by gusty winds - on average 22 days of the month experience winds greater than 31 km h^{-1} (Environment Canada, 2013). Under these conditions obtaining repeat imagery at low tide with minimal cloud cover, and sun glint becomes less feasible. Secondly, the ability to map benthic habitat using passive optical remote sensing in marine environments is limited by the depth at which habitats occur and the optical properties of the overlying water column (Kirk, 1994). In this study, the best results were achieved benthic habitat classes at depths less than 3.0 m. Therefore, the evidence from this study suggests that the accuracy of benthic habitats located at greater depths could be significantly improved if imagery were to be collected under low tide conditions. Other studies have shown that classification of satellite imagery may be improved by collecting *in situ* spectral data of benthic classes and to characterize the water column (e.g. O'Neill & Costa, 2013). For example, in this study eelgrass spectra obtained by O'Neill et al. (2011) were used to calculate the depth of optically deep water. It is also likely that the *in situ* collection of the attenuation coefficient (Kd) would be more accurate for calculating the depth of the optical mask compared to estimating Kd using Secchi depth. Finally, it should be noted that the imagery in this study predates any field data collection by two years. For future surveys, field data collection should be conducted on the same day (or as close as possible) as imagery acquisition.

Neither remote system represents a perfect solution to mapping all nearshore habitat within the GHNMCA. For example, with the QTC5 system, given average survey speeds of four knots and 1500 km of coastline it would take approximately 200 hours to drive a single alongshore transect. In light of this fact and the results of this study, the QTC5 system would likely be ideally suited for producing high resolution benthic habitat maps in targeted conservation regions (e.g. those areas where eelgrass monitoring occurs within the GHNMCA). It is also unknown how the QTC5 system performs for conditions varying from those found at Bag Harbour. Large sections of the coastline within the GHNMCA are rocky with steep gradients (Sloan, 2006). In these regions it likely that the QTC5 system would suffer from irregular signal returns from a convoluted and steep seafloor topography (Biffard, 2011). However, this presents an excellent avenue for future research into the applicability and limitations of the QTC5 system.

4.3 Research Opportunities

Since the inception of remote sensing technologies, rapid achievements have been made in the accuracy, spatial resolution, and range of habitats researched (Capolsini et al, 2003). Three opportunities have been identified that may improve both the scope and accuracy of the results.

1) Enhance the geographic range and conditions of data collection. As coastlines are dynamic environments that can change over a small geographic scale it would be useful to apply the methods developed here to other sites with similar and different physical, environmental and biological conditions.

2) Examine the applicability of a water column correction for WorldView-2 imagery to improve classification accuracy of benthic substrates. The higher spectral resolution of the WorldView-2 imagery has demonstrated an increased ability in the ability to discern benthic habitats at greater depths compared to other sensors with fewer spectral bands (e.g. IKONOS and Quickbird) (Botha et al, 2013).

3) Collect ground-truth field data in a fully quantitative manner that could include measurements of habitat density. The video data collected in this study lacked an objective frame of reference to calculate density of habitat occurrence the seafloor. Examining the ability of remote sensing systems to resolve more information of marine ecosystems can contribute more detail to maps of benthic habitat and their relative importance.

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