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Detection and characterization of benthic filamentous algal stands (*Cladophora* sp.) on rocky substrata using a high-frequency echosounder

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Abstract

A high-frequency echosounder was used to detect and characterize percent cover and stand height of the benthic filamentous green alga *Cladophora* sp. on rocky substratum of the Laurentian Great Lakes. Comparisons between in situ observations and estimates of the algal stand characteristics (percent cover, stand height) derived from the acoustic data show good agreement for algal stands that exceeded the height threshold for detection by acoustics (~7.5 cm). Backscatter intensity and volume scattering strength were unable to provide any predictive power for estimating algal biomass. A comparative analysis between the only current commercial software (EcoSAV™) and an alternate method using a graphical user interface (GUI) written in MATLAB® confirmed previous findings that EcoSAV functions poorly in conditions where the substrate is uneven and bottom depth changes rapidly. The GUI method uses a signal processing algorithm similar to that of EcoSAV but bases bottom depth classification and algal stand height classification on adjustable thresholds that can be visualized by a trained analyst. This study documents the successful characterization of nuisance quantities of filamentous algae on hard substrate using an acoustic system and demonstrates the potential to significantly increase the efficiency of collecting information on the distribution of nuisance macroalgae. This study also highlights the need for further development of more flexible classification algorithms that can be used in a variety of aquatic ecosystems.

Introduction

The attached filamentous green macroalga *Cladophora* sp. is a well-known indicator species of cultural eutrophication in the Laurentian Great Lakes (Shear and Konasewich 1975). During the 1950s through the 1970s, *Cladophora* sp. growth in the rocky littoral areas and other submerged hard surfaces in the lower lakes (Michigan, Erie, and Ontario) was prolific and supported mainly by elevated lakewide nutrient concentrations. In the upper lakes (Huron and Superior), ambient nutrient concentrations were not sufficient to support extensive growth, and *Cladophora* sp. was principally associated with point source discharges of nutrients (e.g., sewage treatment plants, tributaries) (Auer et al. 1982). Extensive research into the controlling factors of *Cladophora* sp. growth (Auer et al. 1982) and subsequent phosphorus control legislation introduced in the late 1970s was largely successful at reducing the growth of *Cladophora* sp. to levels that were no longer considered a nuisance (Higgins et al. 2008). In recent years, however, Lakes Erie (Higgins et al. 2005), Ontario (DeJong 2000; Malkin et al. 2008), and Michigan (Olapade et al. 2006) have all experienced an increase in shoreline fouling by *Cladophora* sp., and recent studies have found that biomass in many areas can exceed 100 g m^{-2} of dry mass (Higgins et al. 2005; Malkin et al. 2008).

The many problems associated with nuisance *Cladophora* sp. growth and the desire for effective management have triggered renewed interest into the ecology of *Cladophora* sp. in the Great Lakes (Higgins et al. 2008). In particular, little is

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known about the spatial distribution of nuisance crops of *Cladophora* sp. in the littoral zones of the Great Lakes except that which is collected by scuba diving or shoreline sampling to wading depths. Although quadrat sampling by scuba may be more accurate than other quantitative methods, it remains a costly and time-consuming effort (Duarte 1987) and does not provide enough data for large-scale synoptic assessments of spatial patterns, especially in large systems (Wezernak and Lyzenga 1975). Remote sensing and other optical methods such as aerial photo interpretation (Zhu et al. 2007) can provide a more spatially extensive assessment, but image interpretation and the accuracy of spatial characterization depend heavily on uncontrollable factors such as water clarity, surface roughness, and cloud cover (Vis et al. 2003). In the Great Lakes, the invasion by dreissenid mussels in the mid-1980s to 1990s has been credited with greatly increasing water clarity (e.g., Binding et al. 2007), and shell material from both live and dead mussels has created additional hard substrate for *Cladophora* sp. attachment (Hecky et al. 2004). The net effect of theses changes has been to dramatically increase the potential depth range for *Cladophora* sp. to colonize and grow (Higgins et al. 2005; Malkin et al. 2008). Furthermore, since *Cladophora* sp. growth mostly occurs in high-energy, exposed near-shore areas, excessive surface roughness and the presence of tributary plumes and sediment resuspension renders the use of remote sensing technology difficult (Budd et al. 2001).

One method that is not encumbered by limitations inherent to the time-consuming, laborious manual methods or limitations and uncertainty imposed by environmental conditions is the use of hydroacoustics to measure the amount of acoustic energy scattered by vegetation (Sabol et al. 2002a). Coupled with recent advances in GPS technology and acoustic signal processing, hydroacoustics provide a rapid and efficient means to collect data over large areas with significant spatial resolution (Sabol et al. 2002a). Such information would be of considerable value for delineating the spatial distribution of nuisance *Cladophora* sp. or other unwanted vegetation, particularly for evaluating growth patterns as they relate to potential nutrient sources or important infrastructure, such as water intakes or public beaches.

Proper interpretation of acoustic data requires an understanding of the scattering processes occurring within the water column and at the lake bottom. In addition to vegetation, other scattering sources are often present in the water: fish (Rudstam et al. 2003), zooplankton (Gal et al. 1999), bubbles (Ostrovsky 2003), currents (Pawlowicz 2002), and gradients of salinity or temperature (Medwin and Clay 1998). The reflection of acoustic energy by vegetation arises from contrasts in the density and speed of sound as the acoustic wave crosses the medium. For example, many species of vascular macrophytes (e.g., *Myriophyllum spicatum*), marine macroalgae (e.g., *Laminaria* sp.), and seagrasses (e.g., *Zostera* sp.) contain gas vacuoles or inclusions within the tissues (stems and leaves) that strongly scatter acoustic energy (Hohausova et al. 2008). This has been exploited in freshwater (Duarte 1987; Thomas et al. 1990) and marine (Sabol and Burczynski 1998; Warren and Peterson 2007) systems. Considerably less information exists about the scattering properties of vegetation that do not contain gas inclusions (e.g., filamentous macroalgae such as *Cladophora* sp.), yet their presence has been recorded in acoustic surveys (Riegl et al. 2005).

For vegetation that does not contain such sharp density contrasts within their tissues, the critical acoustical properties likely depend on density and elasticity contrasts between the organism and the medium, similar to zooplankton (Holliday and Pieper 1995). The formation of oxygen bubbles during photosynthesis will also greatly influence the scattering of sound (Hermand 2006). We are aware of only one controlled laboratory study (Carbó et al. 1997) in which the acoustic properties of a macroalga were examined. This study confirmed that although the density (g mL^{-1}) of the sesquipedale seaweed *Gelidium* sp. is only marginally greater than that of water, stands of *Gelidium* sp. scattered acoustic energy in proportion to the stand thickness, allowing for detection at frequencies exceeding 200 kHz.

The objectives of this study are twofold. First, we sought to evaluate the ability of a high-frequency echosounder to detect nuisance stands of *Cladophora* sp. commonly found growing on rocky substratum in the lower Great Lakes. Second, we sought to evaluate the performance of the only commercially available software (EcoSAV; BioSonics) and an alternate method of acoustic data analysis and classification via a graphical user interface (GUI) written in MATLAB, based on the processing algorithm of EcoSAV (e.g., Stevens et al. 2008) for generating estimates of percent cover and algal stand height. Processed acoustic data are compared with corresponding ground truth data collected by scuba or snorkeling from selected locations in Lake Ontario. The system and data processing steps are discussed and accuracy and performance examined by comparison with the physical data.

Materials and procedures

Study sites—Surveys to assess algal abundance were conducted at two sites in western Lake Ontario in water depths ranging from 1 to 10 m during the summer months of 2007 and 2008 (Fig. 1). The substratum at the Oakville site was primarily rock, but varied in composition and size from flat bedrock expanses to boulders and small cobble/gravel mixtures. The Pickering site was characterized by a more diverse substrate assemblage that included fine-grained sand and consolidated clay in depositional areas near tributary mouths and embayments. At Pickering, acoustic data collection was restricted to areas with rocky substratum, as *Cladophora* sp. is rarely found growing attached to soft substrate (Whitton 1970).

Acoustic data collection—Acoustic data were collected during daytime hours (0900–1800) using a downward-looking BioSonics single beam echosounder mounted on a 2-m adjustable aluminum sliding mount affixed to the side of the

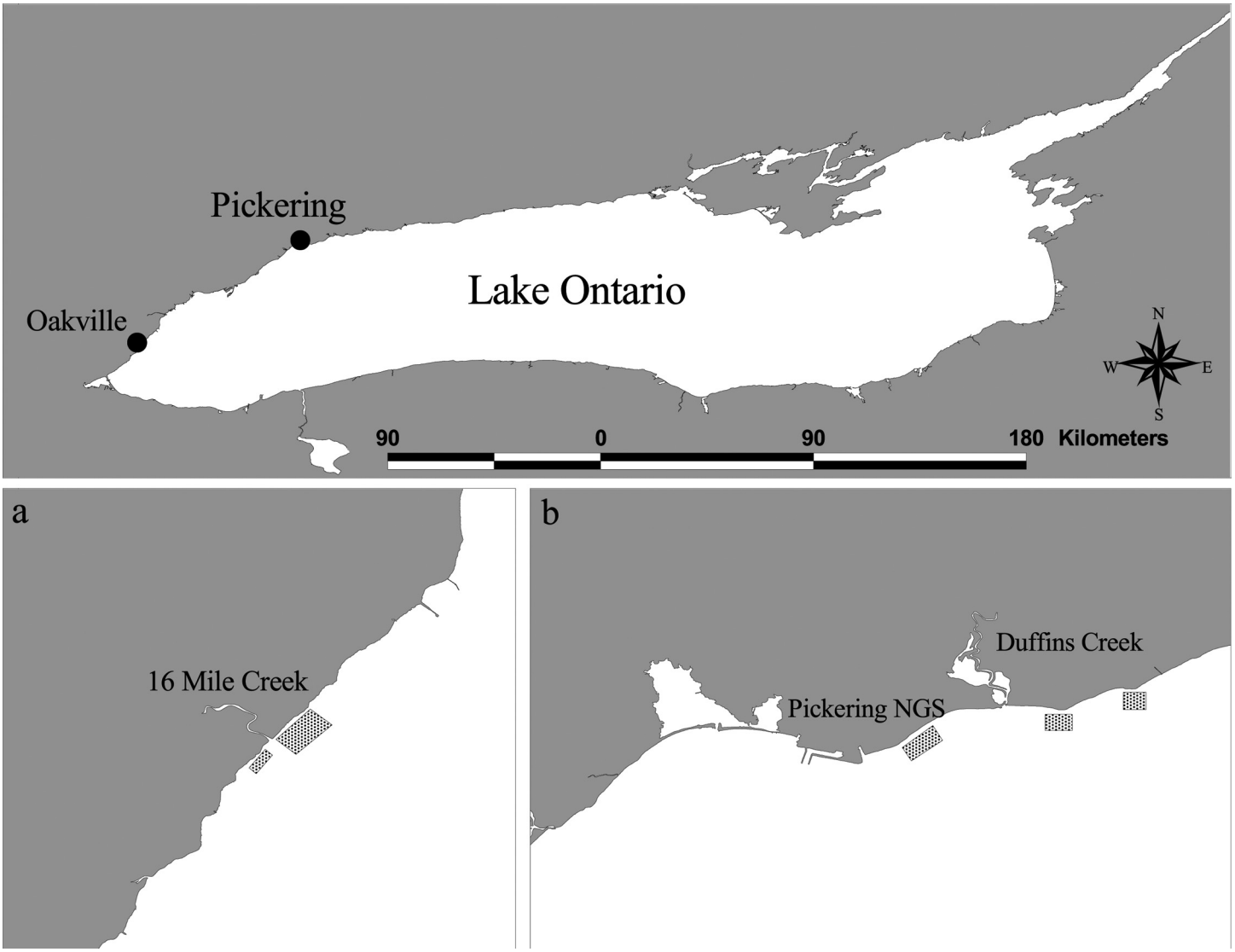

Fig. 1. Map of Lake Ontario showing the sites of acoustic ground truthing. (a), Oakville. (b), Pickering. Hatched boxes approximate locations of ground truth stations and transects.

vessel by a series of clamps and bolts. The transducer was positioned 0.2–0.25 m below the surface of the water. The transducer had a beam angle of 10.2° (full beam angle) and a working frequency of 430 kHz (source level 213 dB re 1 μPa at 1 m). A BioSonics DTX system running Visual Acquisition 5.1 was used to control the echosounder with a pulse width of 0.1 ms and a ping rate between 5 and 8 Hz at full power transmission. The ping rate was increased to allow characterization of the bottom roughness. Full power transmission was required for depths beyond 7–8 m, as the decline in the signal-to-noise ratio caused background noise to approach the desired threshold for analysis. Owing to the use of full power transmission, we noted some saturation of signal in shallow depths (<2 m), but this was not severe enough to interfere with characterization of the SAV signal. Acoustic data were recorded 0.4–0.5 m from the transducer face (e.g., outside the transducer near field) to 50% beyond the bottom depth as determined by an on-board depth sounder (Garmin Fishfinder 90). Positional data were provided by a JRC 212 DGPS with positional accuracy of better than 5 m and a fix update interval of 1 s. Both the acoustic and GPS data were stored on a laptop PC. Algal canopy height and percent cover were quantified during postprocessing using two signal processing techniques described in the next section. The acoustic transducer was calibrated before this study with the use of a 17-mm tungsten carbide sphere with a target strength (TS) of –46.2 dB with a sound velocity in water of 1440 m s^{-1}.

Ground truthing sample collection—Direct measurements of algal canopy height, percent cover, and biomass were made by divers, sampling quadrats for stand cover, height, and biomass at select locations for comparison with acoustic estimates (these were also collected during daylight hours). The first

approach was similar to methods described in Sabol et al. (2002a) and Valley and Drake (2005). Acoustic methods are not immune to environmental conditions affecting the quality of data collected. In large systems, a common source of acoustic interference is entrained air (Kubecka 1996). Bubble-induced acoustic noise can mask the presence of submerged vegetation by raising the ambient noise level to that used to characterize the canopy tops (Sabol et al. 2002b). Because the near-shore areas of the Laurentian Great Lakes are high-energy environments, excessive water column noise is a potential concern. To minimize this, acoustic data were collected on days when wind speed and/or direction were favorable for quiescent conditions.

Acoustic data were collected while the transducer (and vessel) remained at anchor over a fixed position. A distinct area of the bottom was ensonified for ~100–200 pings while slowly sweeping the transducer back and forth and holding the transducer at a horizontal level. After ensonification was complete, divers placed a 0.25-m^2 or 0.0625-m^2 quadrat over the centroid of the ensonified area, measured the height of the algal mat at three random locations (to the nearest 0.01 m), visually estimated the percent cover to the nearest 10%, and harvested all the biomass from within the quadrat using an airlift suction device (Barton and Hynes 1978) or by hand. These quantitative quadrat methods have been used in the Great Lakes for numerous studies (e.g., Higgins et al. 2005).

Acoustic data for estimating vegetation abundance are typically collected over continuous distances with the vessel underway. Therefore, a second approach incorporating vessel motion was adopted to complement the data collected while the vessel was at anchor. Several short, randomly selected transects (50–200 m) were surveyed acoustically at a low speed (~1–3 m s^{-1}), and weighted buoys were dropped at 3–4 locations along the transect. The weights were dropped as close to the transducer beam path as possible without interfering with the data collection, and the approximate ping window (±50 pings) where the buoy was dropped was recorded. Upon completion of the transect, divers measured algal bed characteristics and harvested algal biomass at each buoy location as outlined above. Upon return to the laboratory, algal material was washed in a mesh sieve (pore size ~500 µm) to remove debris and invertebrates and dried in a drying oven at 65°C for 1 week. Dried algal material was weighed to the nearest 0.01 g, and the biomass per unit area in each quadrat was calculated as g m^{-2}. All the ground truth data were compiled into a single database for comparison against acoustic data regardless of the method of collection.

Acoustic data analysis—A single-beam echosounder functions by emitting a short burst of sound (ping) and recording the sound that is reflected back to the receiver (echoes). The intensity of the reflected sound (backscatter intensity) is recorded at a series of time intervals, resulting in a profile of acoustic backscatter intensity versus time. The distance between the transducer and the objects in the water (range) is calculated based on the elapsed time and the speed of sound in water. As the vessel navigates along survey lines, data from successive pings are recorded, resulting in a two-dimensional (ping number, or distance along transect, and range, or depth below the echosounder) record of backscatter intensity (Fig. 2).

Detection of vegetation in acoustic data relies on distinct differences in the acoustic backscatter between vegetated and unvegetated surfaces. Vegetation in single-beam acoustic data are generally visible as a contiguous vertical echo return immediately above the bottom, which is characterized by backscatter intensity weaker than the backscatter from the substrate but stronger than the backscatter of the water column. The basic algorithm is straightforward. For each ping, the range (depth) of the first strong return is determined using a user-specified threshold. Next, the algorithm finds the bottom depth, which is typically the strongest return in the backscatter profile. The region between the first strong return and the bottom is considered the bottom envelope. A ping is classified as "vegetated" or "bare" based on the thickness of the bottom envelope. If the bottom envelope for a given ping is wider than a user-specified minimum plant height, the ping is classified as "vegetated," otherwise the bottom is considered "bare." This process is repeated for a series of pings that are bounded by GPS records. Once complete, summary statistics are computed for the cycle of pings, percent cover is determined by the number of vegetated pings divided by the total pings in the cycle, and the average height of the canopy estimated from those positively classified pings is computed. This process is repeated until the end of the file is reached.

Estimation of percent cover and canopy height—The presence and height of vegetation at the two study sites were quantified from the acoustic data using a prerelease version of the commercial software EcoSAV v2.0 (BioSonics 2004a), and a graphical user interface (GUI) created in MATLAB (Stevens et al. 2008). The prerelease version of EcoSAV (e.g., v2.0) was necessary because the first version (v1.0) does not allow thresholds for vegetation detection to be set lower than –80 dB (BioSonics 2001, *see* below). Unfortunately, the prerelease version of EcoSAV is not yet configured to process data from multiplexed transducers, thus we could compare performance between the two systems only when a single transducer was connected (19 July 2007; Oakville site only). EcoSAV applies a one-way transmission loss (20 log R) time varied gain (TVG) to the raw acoustic data before analysis. The GUI was configured to allow for analysis of raw or TVG corrected data (20 log R or 40 log R) as specified in BioSonics (2004b). For comparisons with EcoSAV, all analyses were conducted using 20 log R TVG, and hereafter, backscatter intensity shall refer to 20 log R–corrected backscatter intensity unless otherwise explicitly stated.

The quantification of plant abundance and height in both algorithms is controlled largely by two adjustable parameters: the classification threshold (noise level above ambient where plant canopy is detected) and the minimum plant height. We selected a classification threshold for *Cladophora* sp. canopy

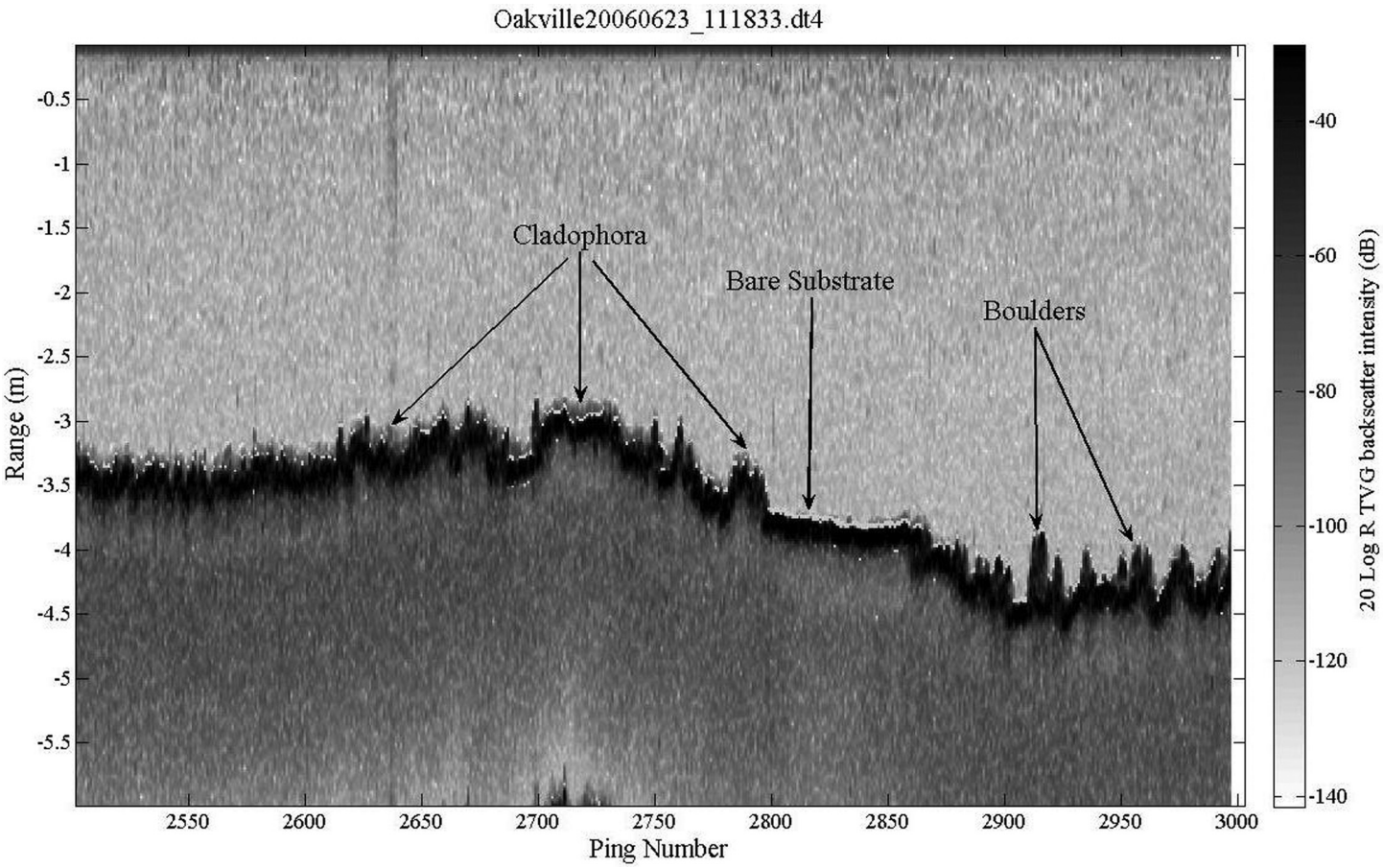

Fig. 2. Sample echogram from the Oakville site in Lake Ontario showing 20 Log R–corrected backscatter as a function of range across a 500-ping segment of a data file. Range here is equivalent to depth (in m), and ping number represents sequential ping numbers in a file, or simply, distance along a transect. 500 pings is equivalent to a distance of ~250 m. The lake bottom is the darkest feature on the echogram. Note the structural differences between flat rock bottom and areas with boulders. Algal stands are represented by a weaker (lighter gray) scattering layer immediately above the lake bottom, but still stronger than background scattering (water column noise).

between –86 and –88 dB for three reasons. First and principally, visual inspection of echograms suggested that a value in this range would be appropriate to identify the algal canopy without substantial interference from water column noise (~ –100 to –120 dB). Second, due to the absence of gas inclusions in *Cladophora* sp. tissue, we reasoned that the acoustic backscatter associated with stands of *Cladophora* sp. would be of lower energy than that associated with vascular macrophytes, for which a value of –65 dB has been successfully applied (Sabol et al. 2002a, Valley and Drake 2005, Istvanovics et al. 2008). Third, a controlled laboratory experiment with the sesquipedale seaweed *Gelidium* sp. estimated the target strength of a single plant at –70 dB re 1 m^2 (Carbó and Molero 1997). Mats of *Gelidium* sp. are morphologically similar to *Cladophora* sp. on a macroscopic level, averaging 20 cm in height (Carbó and Molero 1997), although the filament diameter of *Gelidium* sp. (~2 mm; Carbó and Molero 1997) is at least an order of magnitude larger than that reported for *Cladophora* sp. (~0.04–0.1 mm; Johnson et al. 1996).

The minimum plant height was selected based on acoustic resolution of single targets (for example, two separate fish, or a fish and the bottom), determined according to $R = cf/2$ (i.e., speed of sound in medium, c, [~1500 m s^{-1}] × pulse length, f, [0.1 ms] ÷ 2 = 0.075 m) (Simmonds and MacLennan 2005). Mitson (1983) termed this distance R the "acoustic dead zone" based on the difficulty of discriminating fish echoes from bottom echoes (Ona and Mitson 1996). How suitable this method is for interpreting echoes from vegetation is unclear, as plants tend to occupy the entire area from the canopy top right to the substrate and thus are not spatially separated from the bottom as a fish would be. The EcoSAV algorithm does, by default, use the separation distance rule when setting the minimum height that must be met before the signal is classified as "plant." However, the primary purpose of this is to minimize the rate of false detections, as EcoSAV is intended to be used in an unsupervised mode (B.M. Sabol, Environmental Laboratory [EE-C], US Army Engineer Research and Development Center, pers. comm.). Lacking sufficient precedent and evidence that we could confidently detect signals from vegetation shorter than ~7.5 cm, we elected to incorporate the same level of caution in

our analysis with the GUI. Other adjustable parameters are available to control the extraction of vegetation information in both EcoSAV and the GUI, but their importance is not crucial to the results described herein. Summary output data from the GUI are identical to those provided by EcoSAV and consist of a record combing georeferenced location information, mid-ping number of the cycle sequence, and average stand height and percent cover (e.g., number of plant pings in a cycle) from classified pings. The reader is referred to the previously mentioned literature for more details.

Prediction of biomass—To evaluate the ability of acoustic data to predict the biomass of attached *Cladophora* sp., average backscatter intensity and the volume backscatter (Sv; dB) within the plant canopy for each classified ping was computed following BioSonics (2004b). Both measures were then compared against the dry biomass harvested from each quadrat.

Assessment

A typical echogram collected in midsummer in Lake Ontario is displayed in Fig. 2. Distinct differences in the acoustic signal from the substrate can be observed. Generally, the acoustic signal from rocky substrate ranged from moderately smooth to rough, randomly changing the "thickness" of the echo envelope for the bottom signal (Fig. 2, pings 2500–2800). Large expanses of bedrock sheets were also encountered and generated a very strong return characterized by a very smooth, along-track bottom signal (Fig. 2, pings 2800–2850). More structurally complex substratum usually consisted of larger rocks or boulders sitting on top of cobble or bedrock expanses (Fig. 2, pings 2900–2950), and these produce highly variable shaped echo envelopes. Acoustic backscatter profiles from this area (Fig. 3) revealed that the strongest acoustic return always occurred at the substratum–water interface. For pings classified as "bare," minimal backscatter occurred in the water column and the bottom appears as a distinct peak in the backscatter profile (Fig. 3a). For pings that were classified as plant, a distinct backscatter peak was evident above the bottom ranging in height from ~8 to 25 cm (Fig. 3b). Comparing bare to plant profiles shows that the plant material along this transect was characterized by elevated backscatter relative to ambient backscatter in the water column (Fig. 3c).

Thirty-eight ground truth samples and associated echogram files were collected between 2007 and 2008. In 12 of the 38 cases, in situ estimates of bed height were <7.5 cm; these cases were not included in subsequent analyses because the minimum allowable detection height was set to ~7.5 cm (*see* "Materials and methods"). For the remainder of the data set, close agreement is evident between diver-measured stand height and stand heights estimated using acoustic data and GUI processing (Fig. 4a). The GUI underestimated diver-measured bed heights by an average of 0.2 ± 3.9 cm (mean ± SD), but they were not significantly different from in situ measured heights (paired *t*-test, $t = 0.323$, $P > 0.5$, df = 25). Conversely, based on

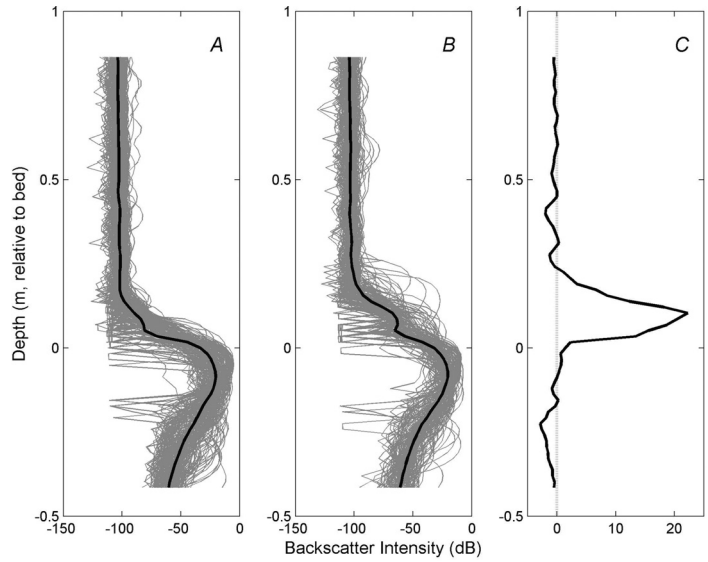

Fig. 3. Profiles of acoustic backscatter intensity from the data displayed in Fig. 2 showing profiles classified as bare rock (A), profiles classified as containing *Cladophora* sp. (B), and the average difference between the backscatter profile of bare and vegetated bottom signals (all units in dB) (C). For both (A) and (B), the mean profile is given by the solid line.

the limited number of comparisons we could do with EcoSAV, EcoSAV significantly overestimated algal bed heights by an average of 12.5 ± 7.0 cm (paired *t*-test, $t = -7.03$, $P < 0.01$, df = 12). For EcoSAV, height overestimation increased significantly as bottom depth increased (Fig. 4b).

Correlations between percent algal cover from quadrats were poor when compared to percent algal cover estimated from the acoustic methods ($r = 0.51$ for EcoSAV and $r = 0.49$ for GUI). This is likely due to the preponderance of high algal coverage in the quadrat data (mean algal cover 84%).

The minimum biomass detection limit was estimated to be 31 ± 18 g m^{-2} (Fig. 5a). The largest biomass value that went undetected was 28 g m^{-2} (Fig. 5a). This sample had a mean bed height of 6 cm, below the threshold allowed for detection. The minimum biomass value that was detected was 41 g m^{-2}, on a relatively flat bottom with an average stand height of 7.5 cm. Detection rates increased rapidly for higher biomass stands. Success of detection also was influenced by stand height (Fig 5b), but this may be due to the strong correlation (Pearson $r = 0.86$, $P < 0.01$) between stand height and biomass (data not shown).

To examine the ability of the classified data to predict algal biomass, we compared diver-estimated biomass with the average and integrated backscatter intensity from the plant canopy for each ping in the successful classifications (Fig. 6a). A positive relationship does appear to exist between biomass and backscatter intensity, but its predictive power is poor due to the large standard deviation between pings in the cycle sequence (Fig. 6a). Integration of the acoustic signal (volume backscatter; Sv) between the canopy top and the

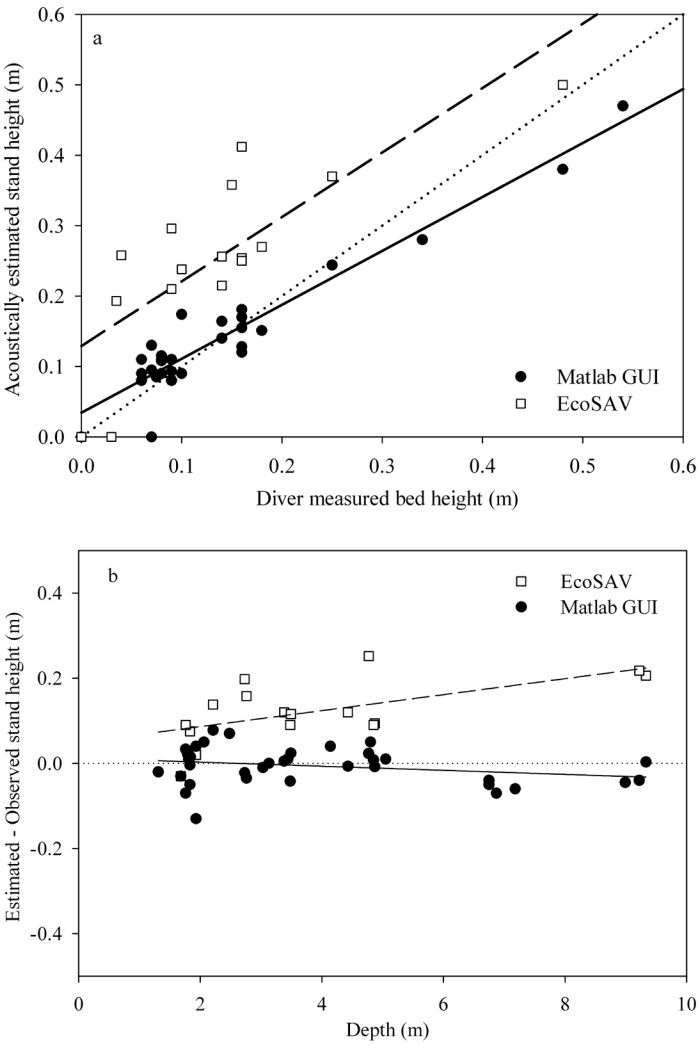

Fig. 4. (a), Relationship between algal stand height estimated from acoustic data and diver-measured stand height from the corresponding ground truth samples. Note: Data recorded as zero acoustic height along the *x*-axis indicate measurable height in situ, but were not detected by EcoSAV or the GUI because they failed to meet the minimum height requirements. Dotted line, 1:1 line; solid regression line, $\text{StandHeight}_{GUI} = 0.014 \pm 0.009 + 0.83 \pm 0.056[\text{StandHeight}_{Diver}]$, $r^2 = 0.87$, $P < 0.0001$; dashed regression line, $\text{StandHeight}_{EcoSAV} = 0.13 \pm 0.02 + 0.92 \pm 0.11[\text{StandHeight}_{Diver}]$, $r^2 = 0.75$, $P < 0.0001$. Samples with stand height <7.5 cm were excluded from regression. (b), Plot of acoustically estimated – observed stand height from ground truth samples as a function of site depth. Dashed line, regression for EcoSAV-generated residuals ($y = 0.05 \pm 0.019 + 0.018 \pm 0.01[\text{Depth}]$, $r^2 = 0.37$, $P < 0.05$); solid line, regression for GUI residuals ($y = 0.012 \pm 0.014 - 0.005 \pm 0.003[\text{Depth}]$, $r^2 = 0.04$, $P = 0.12$). Note: The depth values (*x*-axis) are taken as the reported depth from the GUI output.

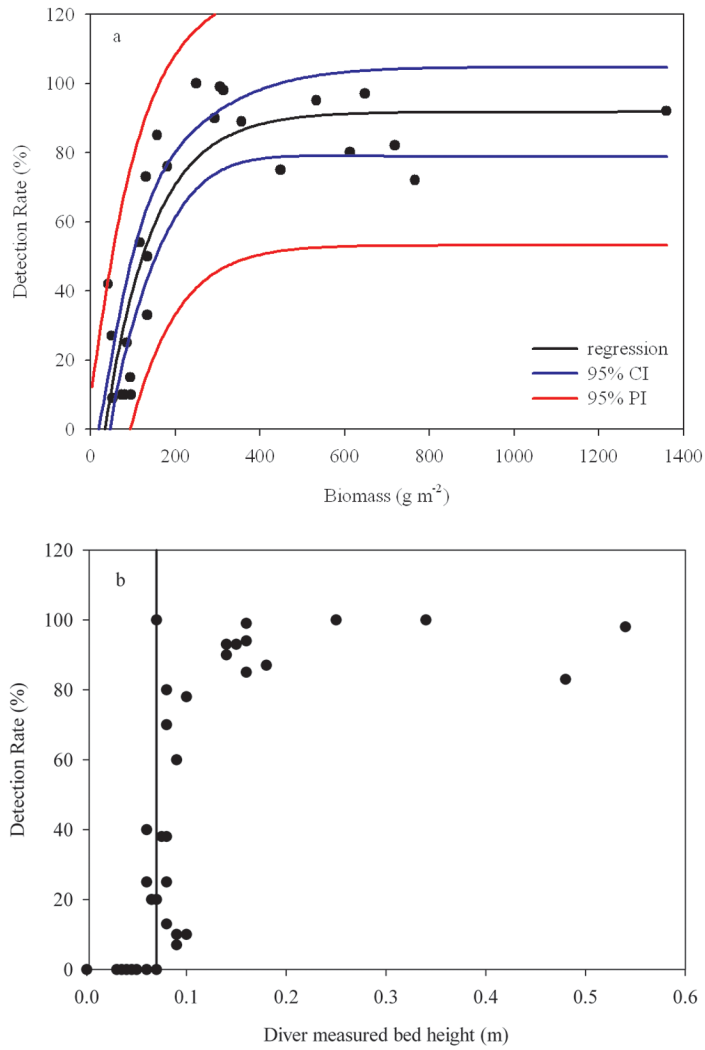

Fig. 5. (a), Detection rate versus dry biomass of *Cladophora* sp. Regression line ($\text{DetectionRate} = -31.88 + 123.55 \pm 10.15[1 - e^{(-0.0089 \pm 0.001 \times \text{Biomass})}]$), $r^2 = 0.72$, $P < 0.0001$) and 95% confidence intervals (CIs) and 95% prediction intervals (PIs) are also shown. (b), Detection rate versus in situ stand height as measured by divers. The solid line denotes the height threshold of 7.5 cm.

declared bottom is considerably worse, showing differences only for the two highest biomass samples (Fig. 6b). Subsetting the data into classes of biomass (low <100 g m^{-2}, medium 100–300 g m^{-2}, moderate 300–500 g m^{-2}, and high >500 g m^{-2}) did not yield much improvement, as significant differences in average backscatter intensity were observed only for the high bin (ANOVA, $F_{3,22} = 8.413$, $P < 0.05$; Tukey-Kraemer post hoc test $P < 0.05$).

Discussion

Detection of algal presence—Acoustic detection of *Cladophora* sp. at the two study sites was especially challenging because the areas are characterized by uneven rocky and boulder bottoms. For example, during early spring surveys at the Oakville location, *Cladophora* sp. was confirmed with the use of an underwater drop video camera to be either absent or growing only in very short (<5 cm) tufts. When the echograms were inspected, however, we noticed a short, weak echo directly above the stronger bottom return in the range of –55 to –60 dB when

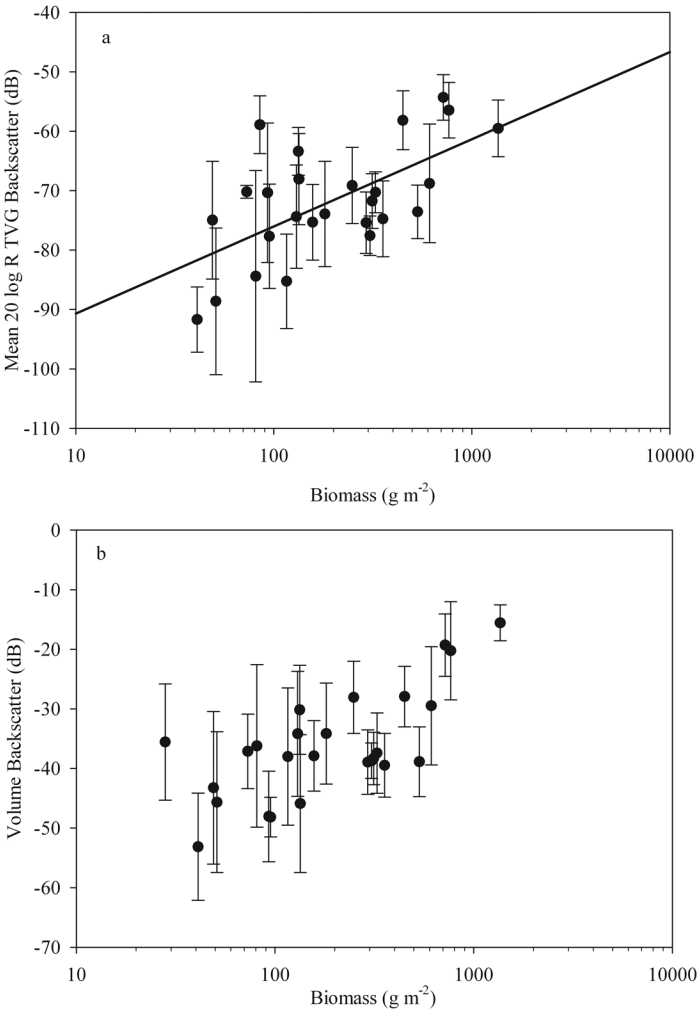

Fig. 6. Average backscatter intensity (dB) (a) and volume backscatter intensity (Sv; dB) (b) of the echo envelope between the declared canopy top and the lake bottom versus dry biomass of *Cladophora* sp. Error bars represent the average SD computed from each ping in the cycle.

passing over moderately rough cobble (Fig. 2, pings 2850–2900). This feature is not observed over flat rocky bottoms (Fig. 2, pings 2800–2850) or over softer depositional substrata (e.g., sand or silts; data not shown). We believe this is related to the varying perturbations of the echo associated with the highly variable surface orientation common on rocky bottoms (Hamilton 2001). Additional problems were encountered with reflection of side lobe energy. Boulders and other vertically distinct substrata not directly in the transducer beam path often returned an echo characterized by backscatter intensity similar to that of algae, causing the unsupervised EcoSAV algorithm to falsely classify these areas as vegetated. During supervised classification with the GUI, the rocky areas were easily distinguished by a trained analyst from the algal signal based on their curved shape and obvious height difference compared to the algal canopy and/or bottom.

Estimation of algal stand height—Estimation of algal stand height was significantly better with the use of the GUI compared to estimated stand heights from EcoSAV. Whereas the GUI underestimated stand heights by and average of 0.2 ± 3.9 cm, EcoSAV overestimated stand heights by an average of 12.5 ± 7.0 cm. This is far greater than the overestimation reported by Sabol et al. (2002a) of 1 ± 4.8 cm. Other studies have found larger and more variable disagreements between acoustically estimated and in situ plant heights, but these discrepancies are likely the result of different methods of comparison between ground truth data and acoustic data, in addition to differences in canopy structure provided by monospecific stands and mixed species stands (Valley and Drake 2005).

The overestimation of stand height reported by EcoSAV is almost entirely due to the differences in algorithm logic in defining the bottom depth. Although the signal-processing algorithms used in EcoSAV and the GUI are based on the rationale described in Sabol et al. (2002a), EcoSAV was primarily built to work in shallow, soft-bottom estuaries and systems that would be conducive for the growth of seagrasses and macrophytes (Sabol et al. 2002a). In systems with soft substrate and strongly scattering vascular vegetation, the strongest scattering may occur in the plant canopy rather than at the substrate–water column interface (Sabol et al. 2002a). Therefore, to correctly track the bottom, a two-feature bottom tracking algorithm was implemented in EcoSAV so that the declared bottom depth did not occur within the plant canopy (Sabol et al. 2002a,b). Simply speaking, the EcoSAV algorithm associates the sharpest rise in acoustic backscatter with the bottom unless the sharpest rise occurs well above the trailing edge of the bottom echo envelope. In the latter case, EcoSAV assumes that the sharpest rise occurs within the plant canopy, and not at the water column–substrate interface, and implements a depth adjustment to place the bottom depth deeper in the water column (BioSonics 2004a).

In contrast to EcoSAV, the GUI was configured to place the bottom at a user-specified backscatter intensity threshold. This configuration was chosen for two reasons. First, because all data were collected over rocky substrate with an overlying canopy of weakly scattering algal stands, the strongest backscatter intensity always occurred at the water column–substrate interface. Second, the presence of rocks and uneven substrate may generate a wide echo envelope that exceeds the threshold for positive classification, even if there is no growth of algae on the substratum, and in an unsupervised mode, generates a false positive. To illustrate this, an echogram and associated classification results are provided in Fig. 7. The MATLAB GUI classification is provided in Fig. 7a. Here, data were collected while moving slowly over a relatively shallow area (depth ~2 m). Variability in algal stand height is observed in addition to large variations in the GUI declared bottom depths, primarily due to the rocky substrate. Both EcoSAV and the GUI track the bottom reasonably well (Fig. 7b), but EcoSAV always places

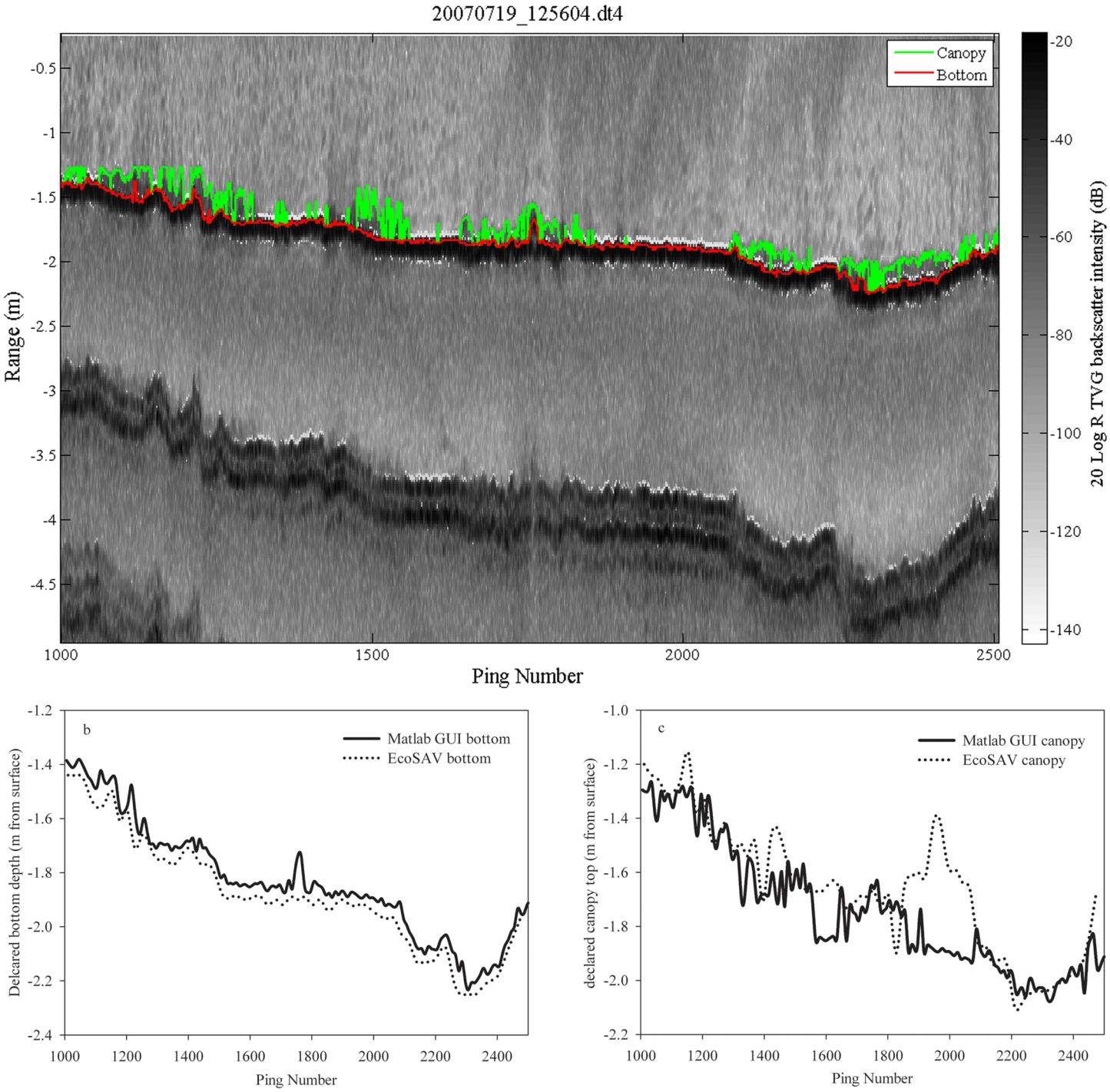

Fig. 7. (a), Sample echogram showing classification of bottom and canopy top as done in MATLAB GUI. (b), Plot of declared bottom depth from EcoSAV and the MATLAB GUI classification in panel (a). (c), Plot of the depth of the algal stand canopy top from EcoSAV and the MATLAB GUI classification of the data in panel (a). The depth of the algal canopy top was computed by adding the estimated algal stand height to the declared bottom depth.

the bottom depth deeper than the GUI. This is likely caused by the two-point bottom tracking feature (*see* above). Although the depth of the algal canopy is generally correctly identified by both platforms (Fig. 7c; but note that EcoSAV appears to classify excessive surface noise as plant canopy; pings 1850–2100), the deeper placement of the bottom depth by EcoSAV (mean 0.08 ± 0.06 m) results in the subsequent overestimation of algal canopy height by EcoSAV because canopy height is computed as top of plant canopy minus the declared bottom depth (BioSonics 2001).

The tendency for EcoSAV to increase the overestimation of algal stand height as depth increases likely results from the use of non-normalized echo envelopes. The time to ensonify to a given angle increases with depth, causing a lengthening of the echo signal (Hamilton 2001). This phenomenon has been observed to influence substrate classification accuracy (Hamilton 2001; Dommisse et al. 2005) and is most simply described as a thickening of the echo envelope as depth increases. The width of the echo envelope associated with the bottom is a function of pulse length, spreading time of the wave front, and the travel time in the substrate. On hard substrate at our working frequency, there should be negligible penetration of the acoustic wave into the substrate (Hamilton 2001). Since the pulse length is constant (0.1 ms), the spreading time of the wave front is the only quantity that can influence the width of the returned echo. Because the BioSonics system samples the returned echo at a constant rate (41.67 kHz; BioSonics 2004b), the width of a returned echo envelope from a ping in deep water will appear thicker than an echo envelope from a ping in shallow water. Although newer bottom classification software (e.g., QTCView®) can correct this by normalizing the echoes to a reference depth, this feature is not implemented in EcoSAV, perhaps because it is not useful when surveying shallow estuaries for submerged vegetation.

Based on the processing algorithm in EcoSAV, such errors will increase on structurally complex bottoms where large boulders or other debris are present, as the trailing edge of the echo envelope will determine the placement of the bottom rather than the sharpest rise feature. This will lead to increasingly worse performance over very rocky bottoms, or those that produce thick echo envelopes (e.g., very soft silt; Valley and Drake 2005). Although we did not routinely measure the distance from the transducer to the lake bottom, and so cannot comment on the agreement between depths predicted by EcoSAV or the GUI in relation to the true bottom depth, the deeper bottom depth placement by EcoSAV is the most likely cause for the disagreement between the two platforms when determining the height of the algal canopy.

Estimation of percent cover—We observed poor correlations between percent cover estimated by acoustic methods and percent cover as measured by divers in the quadrats. Percent cover as computed by the algorithms is based on the number of plant pings divided by the total number of pings in the summary cycle. This is obviously a different quantity than percent of a quadrat that is covered by *Cladophora* sp. Furthermore, the range of percent cover values in our ground truth data set (80%–100%; typical conditions in our study areas) were not likely of sufficient range to rigorously evaluate the ability of the acoustic method to assess percent cover. Prior work with acoustic methods and assessments of percent cover has mainly used towed underwater georeferenced video, and indicates that reliable estimates of percent cover are computed over short distances (Sabol et al. 2002a; Stevens et al. 2008) or longer transects (Winfield et al. 2007) across a range of acoustic frequencies (e.g., 200–420 kHz). Because we lack access to a video system comparable to those used in previous studies, and because the nature of our ground truth data set (80%–100% quadrat coverage) makes comparisons against previous studies difficult, future work should incorporate a similar means of assessing percent cover that better relates to the nature of percent cover as computed by the algorithm. Nevertheless, the GUI proved to be robust at characterizing the algal stand height on rocky substrate, and by extension, the estimation of percent cover should achieve a similar level of sensitivity, since a ping must be classified as plant before the stand height is computed.

Estimation of biomass—Estimation of biomass or standing crop is a frequently desired endpoint in many surveys and management programs (Vis et al. 2003). Previous studies have found a linear relationship between backscatter strength and biomass (Sabol et al. 2002a), but the predictive capacity tends to be poor due to high variability of lacunae in different species of vascular plants and the presence of epiphytic algae and/or organisms (Sabol et al. 2002a). Summation of backscatter has also been examined, but appears to suffer from a saturation effect at high biomass values (Haga et al. 2007). It is probable that for high densities of strongly scattering vegetation, acoustic shadowing becomes a factor, making the accurate determination of biomass a difficult task (Simmonds and MacLennan 2005).

Our comparison of the average backscatter and biomass (Fig. 6a) and volume backscatter and biomass (Fig. 6b) yielded poor relationships. Variability is particularly high at the low-to-moderate biomass levels, which are most commonly observed in the Great Lakes (e.g., Higgins et al. 2005); thus such relationships are not likely to be of any practical value. The high variability in both the average backscatter and volume backscatter may be due to several factors. First, although much care was taken to exclude backscatter from the substrate, the high degree of bottom roughness and the vertical resolution of the sampled echo (~1.8 cm) may have nonetheless included some contribution from the substratum (Ona and Mitson 1996). Second, stands of *Cladophora* sp. are often inhabited by benthic invertebrates such as amphipods (e.g., *Echinogammarus ischnus* and *Gammarus fasciatus*) and midge larvae (Chironomidae) (Barton et al. 2005). These invertebrates are characterized by target strengths (TS) that are strong enough to produce backscatter within the range used to classify *Cladophora* sp. (–76 to –65 dB TS for chironomids [Kubecka et al. 2000] and –76 dB TS for a single amphipod [Wiebe et al. 1990]). Furthermore, the areal abundances of these organisms in stands of *Cladophora* sp. can be appreciable (*E. ischnus* at up to 2900 m^{-2} [Dermott et al. 1998], *G. fasciatus* up to 680 m^{-2} [Haynes et al. 2005], and chironomids from 2 to 12,000 m^{-2} [Barton et al. 2005]). Because we did not attempt to quantify the numbers or types of invertebrates in the ground truth samples, the possible contribution (if any) of these animals to the backscatter we measured from *Cladophora* sp. is not known.

Third, *Cladophora* sp. growing in the lower Great Lakes is commonly encrusted with epiphytic diatoms (Stevenson and Stoermer 1982; Malkin et al. 2009). Because the density of diatom silica is ~2.6 g cm^{-3} (Blanc et al. 2000), it is likely that the epiphytic coating acts to increase the acoustic impedance of the *Cladophora* sp. filaments, leading to an increase in measured acoustic backscatter. The degree to which this may have affected our measures of acoustic backscatter is not easily assessed, since our ground-truth data were collected during the growing season (June–August), and we did not collect data on the abundance of epiphytic diatoms in our ground-truth samples. Last, as mentioned in the "Introduction," production of oxygen bubbles during photosynthesis (Hermand 2006) may significantly affect the measured backscatter, particularly at depths where light saturation is sufficient.

Comments and recommendations

Acoustic methods have proven to be effective tools for estimating the abundance and cover of submerged aquatic vegetation in various habitats (Sabol et al. 2002a,b; Valley and Drake 2005; Zhu et al. 2006; Warren and Peterson 2007; Winfield et al. 2007) using frequencies ranging from 70 kHz (Zhu et al. 2006) to 600 kHz (Warren and Peterson 2007). Here, we show that detection and estimation of nuisance filamentous algal stand height was successful for algal stands that exceeded 7.5 cm in height, suggesting that this approach could be useful in environments previously thought to be incompatible with acoustic surveys (Sabol et al. 2002b). There are, however, some shortcomings of the acoustic method that must be noted. First, in areas where *Cladophora* sp. is present, but at low biomass or insufficient stand height, acoustic methods will fail because of the inability to detect algal stands shorter than 7.5 cm. Whereas this would undoubtedly be problematic for surveys designed to examine absolute presence or absence of *Cladophora* sp., it is far less of a problem for those designed to characterize the distribution of nuisance growths where stand heights often exceed 7.5 cm. In the Laurentian Great Lakes, much of the algal fouling problems occur when algal biomass accrues to nuisance levels (e.g., Higgins et al. 2005). A tool, therefore, that has the ability to characterize the distribution of nuisance *Cladophora* sp. (or other macroalgal) stands would be of great value for monitoring programs. Second, the nature of the algorithm in the GUI is based on interpretation of vegetated and unvegetated surfaces, and therefore requires a trained operator to interpret the collected echograms and supervise the classification procedure. Although this may seem an onerous task, the visualization of the acoustic data and classification in the GUI provides a functionality not yet available in commercial software. The analyst can observe the classification and adjust relevant parameters to achieve the best possible classification. The GUI additionally contains the ability to manually remove improperly classified data (for example schools of fish, large boulders, logs, or steep bottom slopes) much in the same manner as other acoustic analysis programs (e.g., SonarView®) can do for data collected during fisheries surveys.

Despite the challenges of acoustic detection of *Cladophora* sp., we believe that this method can be a valuable addition to current research and monitoring programs. The combination of robustly characterized acoustic signals and georeferenced position data allows for rapid mapping of the spatial distribution of nuisance algal growth, information that is important for designing and assessing effective management strategies. Although in situ sampling is still needed for species identification and ground truthing, acoustic survey data provide much better spatial resolution than can be obtained from more laborious manual methods. The combination of acoustic and in situ methods will ultimately provide a much better tool for characterizing benthic algal growth in shallow water environments than has been available previously.

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