

Combining angular response classification and backscatter imagery segmentation for benthic biological habitat mapping

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ABSTRACT

Backscatter information from multibeam echosounders (MBES) have been shown to contain useful information for the characterisation of benthic habitats. Compared to backscatter imagery, angular response of backscatter has shown advantages for feature discrimination. However its low spatial resolution inhibits the generation of fine scale habitat maps. In this study, angular backscatter response was combined with image segmentation of backscatter imagery to characterise benthic biological habitats in Discovery Bay Marine National Park, Victoria, Australia. Angular response of backscatter data from a Reson Seabat 8101 MBES (240 kHz) was integrated with georeferenced underwater video observations for constructing training data. To produce benthic habitat maps, decision tree supervised classification results were combined with mean shift image segmentation for class assignment. The results from mean angular response characteristics show effects of incidence angle at the outer angle for invertebrates (INV) and mixed red and invertebrates (MRI) classes, whilst mixed brown algae (MB) and mixed brown algae and invertebrates (MBI) showed similar responses independent from incidence angle. Automatic segmentation processing produce over segmented results but showed good discrimination between heterogeneous regions. Accuracy assessment from habitat maps produced overall accuracies of 79.6% (Kappa coefficient = 0.66) and 80.2% (Kappa coefficient = 0.67) for biota and substratum classifications respectively. MRI and MBI produced the lowest average accuracy while INV the highest. The ability to combine angular response and backscatter imagery provides an alternative approach for investigating biological information from acoustic backscatter data.

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1. Introduction

Seabed habitat mapping is key to understanding the distribution of habitats in marine environments since it provides baseline knowledge for sustainable management (Bax et al., 1999) and is essential for planning of Marine Protected Areas (Jordan et al., 2005). In an environment with increasing anthropogenic activities, there is a need to map and quantify seafloor habitats and associated biological benthic communities (Kostylev et al., 2001; Beaman et al., 2005; Brown and Collier, 2008). Benthic habitats, particularly the biological communities have been shown to have important biodiversity roles in a variety of marine systems (Snelgrove, 1997).

The development of underwater acoustic technology, particularly multibeam echosounder systems (MBES) has revolutionised tools for seabed habitat mapping (Hughes Clarke et al., 1996). The

wide swath of MBES provides complete and full seabed acoustic coverage compared to single beam echosounders. In addition to acquiring depth information, backscatter (intensity of acoustic return) from MBES systems has also been used for a variety of applications such as geological analysis (Gardner et al., 2003; Le Gonidec et al., 2003; Dartnell and Gardner, 2004) and more recently benthic habitat characterisation (Ierodiaconou et al., 2007a, 2011; McGonigle et al., 2009; Ratray et al., 2009; De Falco et al., 2010; McGonigle et al., 2011).

While MBES bathymetry and backscatter imagery maps are being increasingly used for habitat mapping, analysis of angular dependent backscatter (i.e. angular backscatter response) has also been shown to contain important information on seafloor characteristics (Hughes Clarke, 1994; Fonseca and Calder, 2007; Fonseca et al., 2009). Incidence angle affects backscatter intensity (de Moustier and Alexandrou, 1991) and thus has the potential to be used as an important characteristic for classification processes. The use of parameter extractions and inversion models using angular response information has been extensively applied to discriminate

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between different sediment types (Hughes Clarke, 1994; Hughes Clarke et al., 1997; Chakraborty et al., 2000, 2002; Canepa and Berron, 2006; Fonseca and Mayer, 2007; Fonseca et al., 2009; Lamarche et al., 2010). Efforts have been made to relate angular response to benthic biological communities using unsupervised clustering (Hamilton and Parnum, 2011). The results (presented as point sample characterisations) demonstrate some similarities with the biological habitats such as rhodolith and seagrass areas previously mapped (Ryan et al., 2007). Additionally, the mean angular response from seagrass was found to be higher than sand and mud (Siwabessy et al., 2006) but similar to gravelly sand (De Falco et al., 2010). However to date there has been limited work investigating information contained within angular response to characterise benthic communities such as macro-algae communities typical in cool temperate waters of Australia (Phillips, 1998; James et al., 2001; Wernberg et al., 2003).

Whilst angular response is applicable for the discrimination process, its spatial resolution is limited to the MBES swath width (Hughes Clarke, 1994; Hughes Clarke et al., 1997) and inhibits the construction of fine resolution habitat maps. Fonseca et al. (2009) demonstrates that fine resolution benthic sediment maps can be constructed by integrating high resolution backscatter imagery with angular response analysis. They apply a manual segmentation method to the backscatter imagery to define areas that have similar angular response characteristics and recommend that automated image segmentation could be a more systematic approach. Automated image segmentation serves as a first stage in the object

oriented classification approach and has been successfully applied to side-scan sonar backscatter imagery for reef based classifications (Lucieer, 2007, 2008). Meanwhile, automated feature extraction has been applied to MBES backscatter imagery to perform automated image classification (Cutter et al., 2003; Preston, 2009). This study will investigate whether automated image segmentation of backscatter imagery can be combined with the supervised classification of angular response to produce benthic biological habitat maps.

2. Methods

2.1. Study area

The study area is located in Discovery Bay, south-eastern Australia and covers a total area of 39.8 km², with 26.3 km² situated in the Discovery Bay Marine National Park (Fig. 1). The site ranges in depth from 12 to 80 m. Vertical basalt reef structures rise up to 20 m from the seafloor, reflecting the region's dynamic volcanic history (Boutakoff, 1963). This area is covered in a rich array of temperate southern Australian flora and fauna. The shallow reef structures support diverse assemblages of red algae and kelps (dominated by *Ecklonia radiata*, *Phyllospora comosa* and *Durvillaea potatorum*), while the deeper regions are covered in sponges, ascidians, bryozoans and gorgonian corals (Ierodiaconou et al., 2007b). The variety of temperate marine habitats present in this site makes it ideal for testing the association of acoustic response with habitat classes.

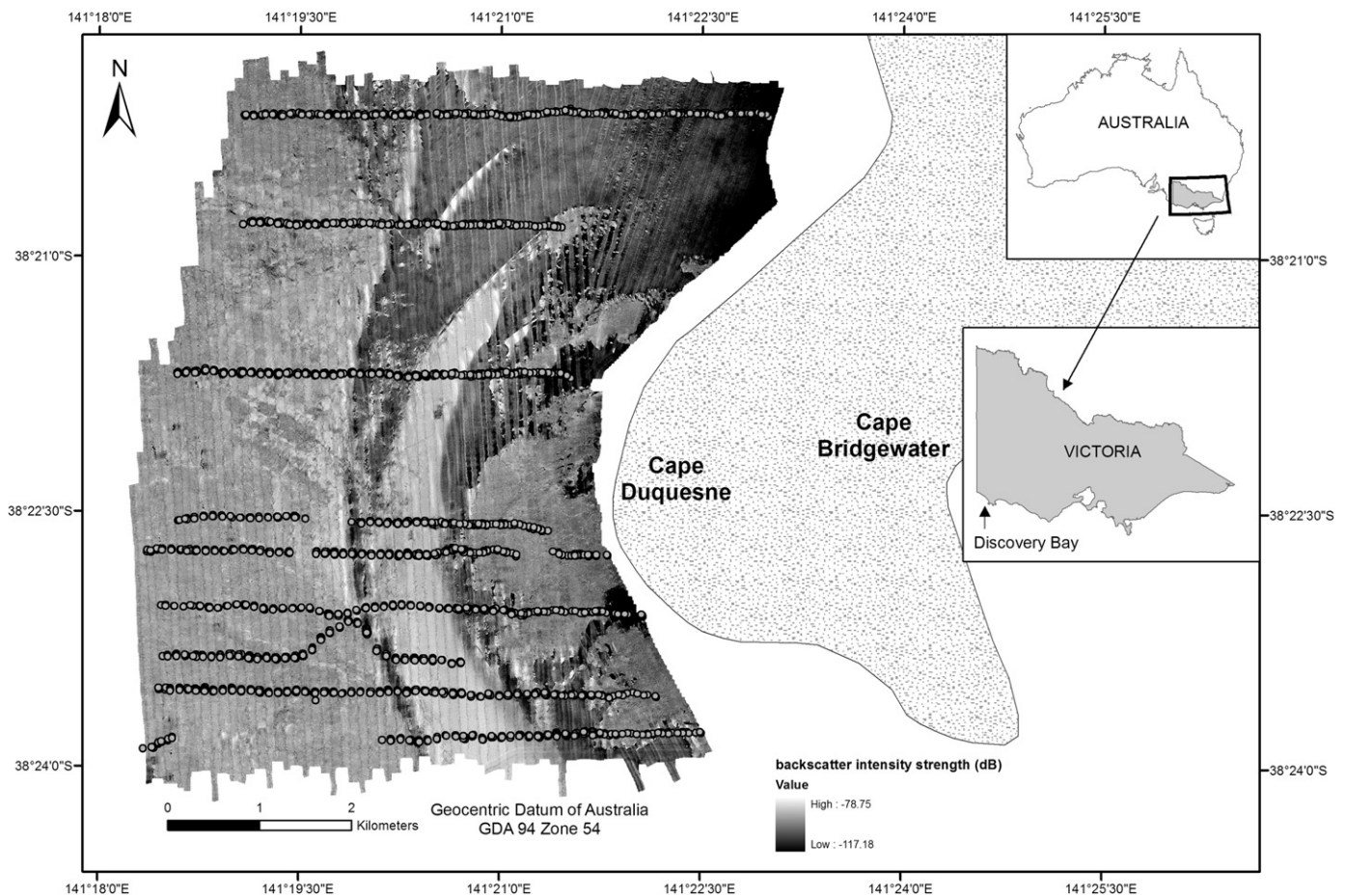


Fig. 1. Location map of Discovery Bay and backscatter imagery of study area together with the location of underwater georeferenced video data (intersected with angular response position) represented by white circles.

2.2. MBES acoustic data

The acoustic data was collected using a Reson Seabat 8101 multibeam echo sounder (MBES) from 6 to 7 November 2005 with an operating frequency of 240 kHz, designed specifically for shallow water surveying purposes. This swath system consists of 101 individual beams and each beam has a beamwidth of 1.5° (along and across track). Horizontal positioning was accomplished using a Starfix HP Differential GPS system (± 0.30 m), integrated with a POS MV (Positioning and Orientating System for Marine Vessels) for heave, pitch, roll and yaw corrections ($+0.02^\circ$ accuracy). Daily sound velocity profiles were collected to correct for water column sound speed variations (deepest at 73 m).

The uncorrected backscatter amplitudes (snippets) were recorded from the Seabat 8101 and archived for subsequent post processing. We employed the Centre for Marine Science and Technology's (CMST) multibeam sonar processing toolbox, written in Matlab® to process the amplitude data (Parnum, 2007). The CMST tool corrects for the time variable gain (TVG) in order to estimate the backscatter intensity strength. At this stage, the backscatter intensity strength is affected by the incidence angle, hence it is known as the angular backscatter intensity. To generate a backscatter map (backscatter imagery), first angular backscatter intensity needs to be compensated for the angular variation (Parnum, 2007), then it is gridded (5 m). We produced the angular response curve that is the average of angular backscatter intensity from stacks of 25 consecutive pings, defined by one spatial coordinate with port and starboard sides treated separately. The detailed description of CMST tool processing stage and algorithms can be found in Parnum (2007). The tool has been applied to study the relationship between backscatter and seagrass distribution (De Falco et al., 2010) and differentiate between benthic biological habitats using the unsupervised clustering of angular response curves (Hamilton and Parnum, 2011).

2.3. Ground truth data

To determine benthic habitat associations with angular response, a training dataset was required to label angular response with defined user classes. Georeferenced underwater video data were collected and classified as part of the Victorian Habitat Mapping Project to investigate the distribution of benthic biological habitats in coastal waters of Victoria. The underwater video was collected using a Remotely Operated Vehicle (ROV) and positioned using DGPS and Tracklink Ultra Short Base Line (USBL) underwater acoustic system, with vessel errors (roll, pitch and yaw) corrected using a KVH (KVH Industries, Inc.) motion sensor (Rattray et al., 2009). The classified video produced five broad biota classes; Mixed Brown algae (MB), Invertebrates (INV) – sponges, Mixed Red algae and Invertebrates (MRI), Mixed Brown algae and Invertebrates (MBI) and No Visible Biota (NVB) and three substratum classes; Reef (R), Sediment (S) and Reef/Sediment (RS). We identified the nearest groundtruth locations to angular response positions by using an approximate intercept method which selects the most frequent class within a 10 m radius of each angular response position. Approximately 70% of the ground data provided a training label for angular response used in the classification process while the remaining 30% was selected for accuracy assessment (Table 1).

2.4. Decision tree classification

A decision tree approach was used to create a decision rule from the predictor variables (i.e. angular response curve with known class signature). The predictor variables were the angular response of backscatter strength values from 0° to 70° incidence angles (at

Table 1

The distribution of angular response data used for training and for accuracy assessment (biota and substratum). For accuracy assessment process, only the position and class of angular response are used.

	Number of angular response used for training	Number of angular response used for accuracy assessment
<i>Biota Class</i>		
Mixed Brown algae	66	26
Invertebrates	556	233
Mixed Red algae and Invertebrates	66	28
No Visible Biota	432	183
Mixed Brown and Invertebrates	25	11
Sum	1145	481
<i>Substratum Class</i>		
Reef	171	72
Sediment	589	252
Reef/Sediment	423	177
Sum	1183	501

one degree intervals). The decision rules generated using the training data then were used to classify the angular response curves from the remaining locations for class assignment. A decision tree is defined as a classification procedure that recursively partitions a dataset into smaller subdivisions on the basis of a set of tests defined at a branch or node in the tree (Friedl and Brodley, 1997). A widely known decision tree technique is the Classification and Regression Tree (CART) (Breiman et al., 1984). CART has been used to classify substratum types (Rooper and Zimmermann, 2007) and to predict benthic biological distributions (Holmes et al., 2008). Several methods have been developed to improve CART decision trees to avoid over fitting in searching for splitting rules (Gray and Fan, 2008). Quick, Unbiased and Efficient Statistical Tree (QUEST) was selected to classify the angular response data. QUEST generates a similar decision tree to CART but it does not use an exhaustive variable search routine and is unbiased in choosing variables which afford more splits (Loh and Shih, 1997). QUEST has been used to predict the biological benthic habitat communities using MBES data (bathymetry, backscatter and their derivatives) and georeferenced underwater video (Rattray et al., 2009; Ierodiaconou et al., 2011). We used the QUEST executable program available from <http://www.stat.wisc.edu/~loh/quest.html>.

2.5. Image segmentation

Image segmentation techniques were used to group pixels with similar characteristics in the backscatter imagery. We applied the mean shift image segmentation technique (Comaniciu and Meer, 2002) through the Edge Detection and Image Segmentation System (EDISON) tool (<http://coewww.rutgers.edu/riul/research/code/EDISON/index.html>). Although mean shift image segmentation is not designed for object oriented classification, a comparison of segmentation quality between mean shift and other segmentation techniques (mostly used in remote sensing applications) shows that it can produce promising results (Neubert et al., 2008).

Mean shift segmentation is based on nonparametric feature space analysis and uses a kernel density estimation. The spatial parameter is used to define the radius of the density estimation search process in feature space until the mean shift vector is converged (Comaniciu, 1999; Christoudias et al., 2002; Comaniciu and Meer, 2002). The mean shift segmentation algorithm used five-dimensional feature space consisting of three colour space such as RGB (Red, Green and Blue) and two lattice coordinates (X and Y). If the image is greyscale, the segmentation performs

similarly except the feature space consists of only three dimensions; the grey value and the lattice coordinates. Since the segmentation tool (i.e. EDISON) cannot handle an intensity image (floating point image) directly, we applied a pseudo colour image transformation (RGB) in Matlab. A pseudo colour image offers more than one colour parameter and has been shown to provide additional information for the segmentation process when compared to greyscale imagery (Cheng et al., 2001, 2002). Pseudo colour image transformations have been applied in remote sensing applications such as change detection and have shown to provide rich and informative attribute from analogue maps (Saraf, 2003). We ran segmentation using the three main parameters, spatial resolution = 7, colour resolution = 6.5 and minimum region = 100 pixels. All parameters were default except for the minimum region that was changed from 20 to 100 pixels to avoid generating too many small regions.

2.6. *k* nearest neighbour

The segmented regions (polygons) were joined with the spatial information of angular response and the predicted class (from the supervised classification process) so that all the polygons were assigned class information. This was done by computing the polygon centroid and using *k* nearest neighbour ($k = 7$) to search the nearest majority angular response class and assign class names to polygon centroid. We employed nearest neighbour algorithm as described in Theodoridis et al. (2010). The maps produced using the above methods were evaluated using the independent ground truth class information. We use an error matrix to measure individual class accuracy (user and producer accuracy), overall accuracy and Kappa coefficients (Congalton, 1991).

3. Results

3.1. Angular response characteristic from ground truth

The shape of mean angular response from the biota class showed that MB and MBI produced a similar profile (Fig. 2a), with MBI slightly higher than MB (Fig. 3a), especially from 20° to over 60° incidence angle. The differences of mean angular response between MBI and MB consistently increased with incidence angle (maximum differences = 1.3 dB at 63°) (Fig. 3b). These responses indicate that the presence of invertebrate (sponge dominated habitat) could produce a small increment of backscatter intensity in MBI compared to MB class (brown algae). INV and MRI show good separation in backscatter intensity as the incidence angle increased above 50° (Fig. 2a) with the curves reducing drastically at 50° (INV) and 60° (MRI). These results show that the outer angle (55–70°)

has strong discrimination characteristic for INV and MRI compared to the near (0–15°) and moderate incidence angle (15–55°).

Substratum classes were more easily distinguished compared to biota from the mean angular response (Fig. 2b). Although they have similar curve responses from 0° to 30°, the moderate and outer angles provide separation for all classes. Reef class was found to have the highest backscatter intensity at the outer angle. Sediment and Reef/Sediment classes differed significantly from 30° to 50° and produced almost similar backscatter intensity towards 70°. The mean angular response from substratum class shows that Reef/Sediment response was the combination of responses between Sediment and Reef classes, particularly from 30° to 70°. The effect of incidence angle for substratum classes was more pronounced compared to biota.

3.2. Segmentation of backscatter imagery

Segmentation of the backscatter imagery shows that the size of polygons varies according to the homogeneity of the texture in the backscatter imagery and was capable of delineating between regions of differing backscatter characteristics (Fig. 4a). The segmentation process produced 5323 segmented regions with an average 365 pixels per segment. Nadir artefacts from individual survey lines appeared to affect some of the polygon boundary and shapes. Small polygons were also observed and produced over segmentation results. However, by performing the *k* nearest neighbour analysis, most of the smaller polygons were grouped into the majority surrounding class, minimising the effect of over segmentation in the final habitat map and reduced nadir boundary artefacts (Fig. 4c).

3.3. Accuracy assessment

The integration of the image segmentation of backscatter imagery and the supervised classification of the angular response enabled the construction of habitat maps for biota and substratum presented in Fig. 5. For biota, the accuracy was 79.6% with Kappa coefficient 0.66 (Table 2). The average value between user and producer's accuracy indicated that MRI has the lowest accuracy (35%), while INV produced the highest (84%). The results also show that most of the MRI class was misclassified as INV. MB on the other hand shows a better accuracy (78%) compared to MRI even though these classes were similar in sample size for training data. MBI has the smallest number of sample size (25 for training) producing a poor accuracy (44%).

The substratum classification produced an overall accuracy of 80.2% and Kappa coefficient 0.67 (Table 3). Average accuracy indicates that all three classes achieved accuracies of more than 77%.

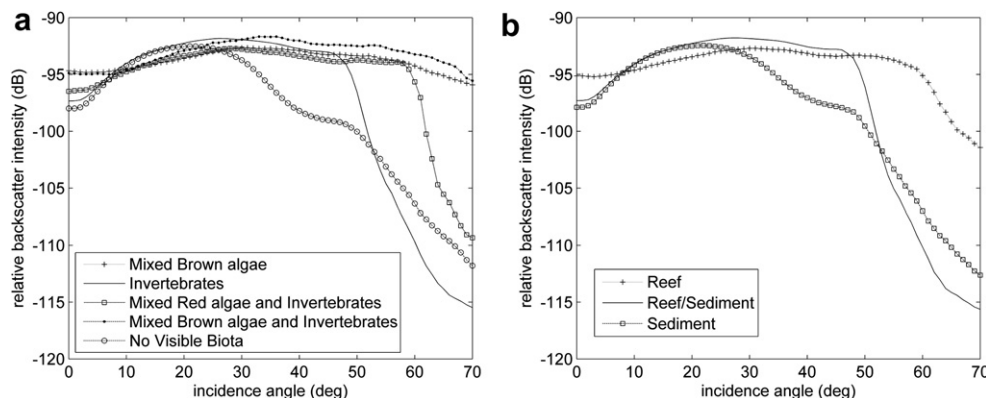


Fig. 2. Mean angular response curves for biota class (a) and substratum class (b).

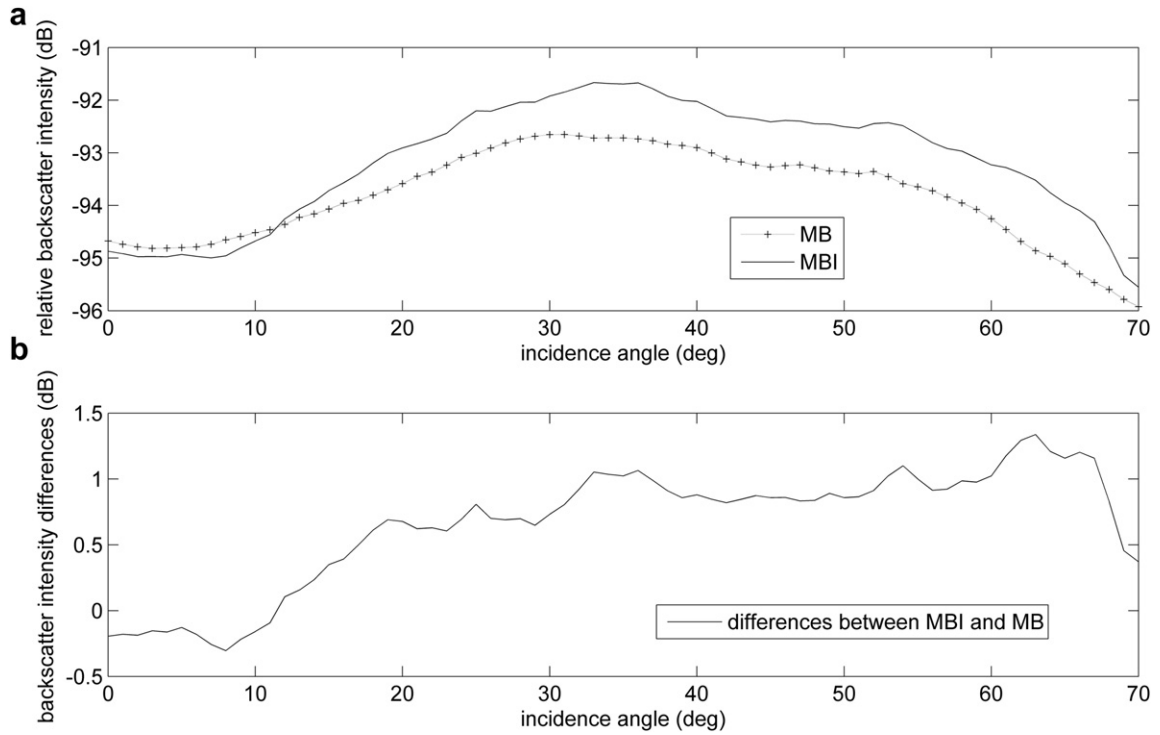


Fig. 3. Mean angular response curves (a) and their differences (b) between MBI and MB. MB = Mixed Brown algae, MBI = Mixed Brown algae and Invertebrates.

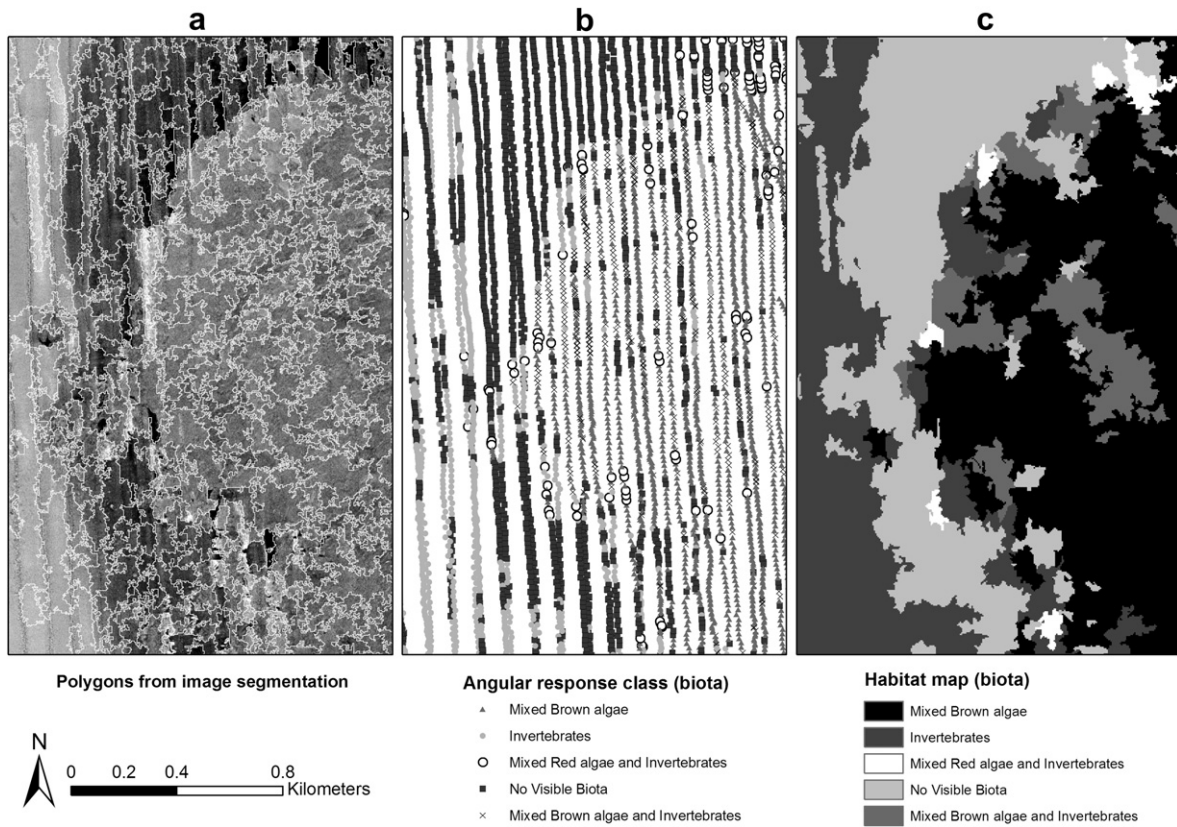


Fig. 4. Segmented image and angular response classification for generating the habitat map; (a) Polygons produced from mean shift image segmentation overlaid with the original backscatter imagery, (b) angular response classification results that are represented by angular response position as single point for port or starboard side with different shapes denote different class, (c) habitat map results from k nearest neighbour process between polygons in 4a and class positions in 4b, with different colours represent different habitat class.

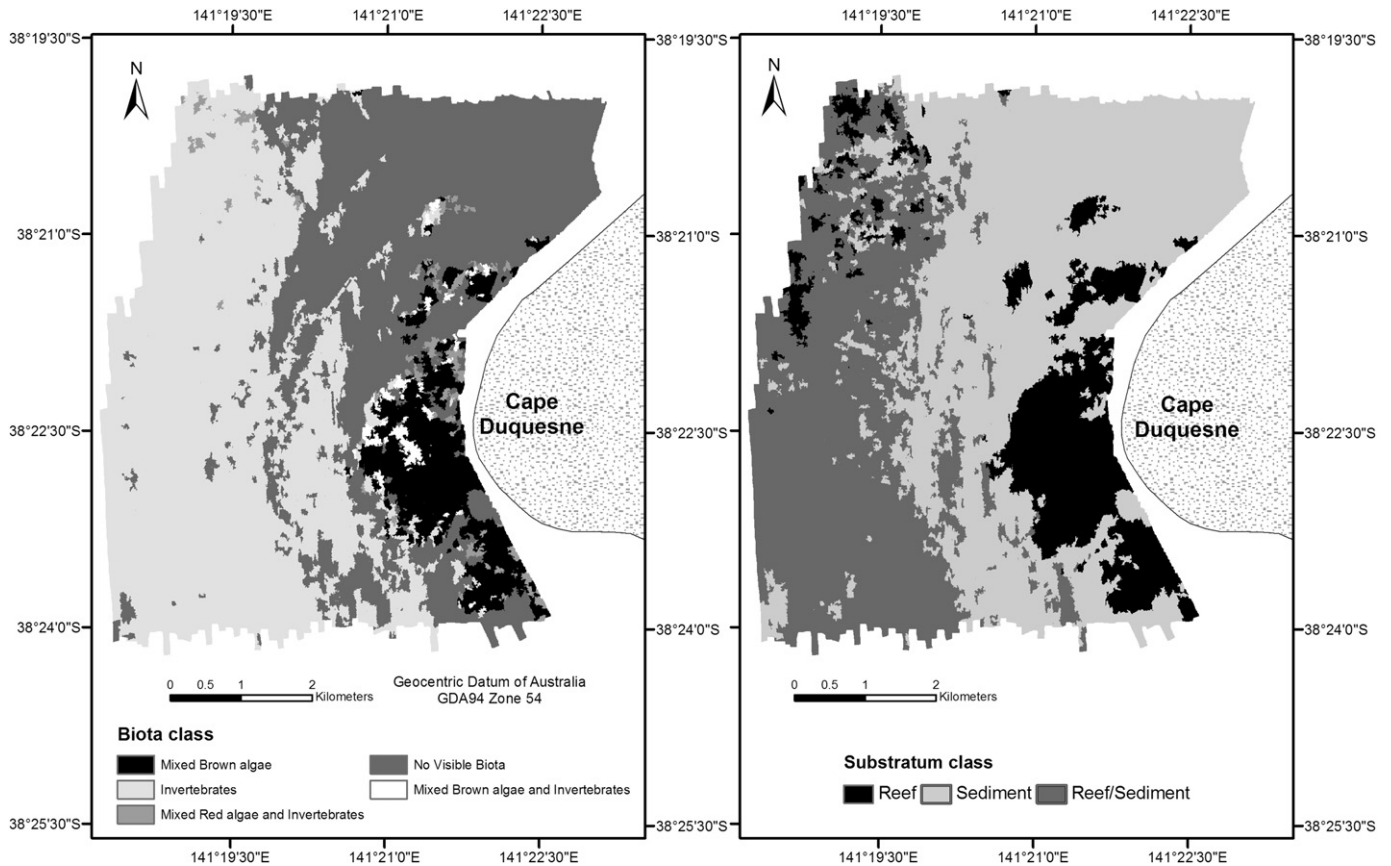


Fig. 5. Habitat maps of biota (left) and substratum (right).

The error matrix shows that Reef was well classified with less confusion with the other two classes. Despite Reef having the smallest sample size, it still produced good accuracy (81%). Although some confusion occurred between Sediment and Reef/Sediment, the proportions of uncorrected classes were small and both classes showed good accuracies (83% and 77% respectively).

4. Discussion

This study used angular response and backscatter imagery from MBES to examine whether they can be integrated to provide useful information that can be used to predict the distribution of benthic biological communities. We demonstrate how angular response is classified using a decision tree classification and automated image

segmentation of the backscatter imagery and how these two techniques can be integrated to produce habitat maps for benthic biological communities. This technique has the advantage of preserving the spatial resolution from the backscatter imagery, whilst taking advantage of the valuable information contained with the angular response. This information has been effectively used to discriminate different macro-algae habitats and invertebrate (sponge) from sediment class (no visible biota). This signifies that the present approach is capable of distinguishing between hard (reef based habitats) and soft classes (non reef).

Previous applications of angular response classifications have mostly concentrated on sediment characterisation (Hughes Clarke, 1994; Hughes Clarke et al., 1997; Canepa and Berron, 2006; Fonseca and Mayer, 2007; Fonseca et al., 2009; Lamarche et al., 2010) with

Table 2
Accuracy assessment for biota classification.

		Error matrix					
		Ground truth data					
	Biota class	MB	INV	MRI	NVB	MBI	Sum
Classified data	MB	26	6	6	3	8	49
	INV	0	208	17	37	0	262
	MRI	0	2	3	0	0	5
	NVB	0	17	0	143	0	160
	MBI	0	0	2	0	3	5
	Sum	26	233	28	183	11	481
	User's accuracy (%)	53	79	60	89	60	
	Producer's accuracy (%)	100	89	11	78	27	
	Average accuracy (%)	77	84	35	84	44	
	Overall accuracy (%)	79.6					
	Kappa coefficient	0.66					

MB = Mixed Brown algae, INV = Invertebrates, MRI = Mixed Red algae and Invertebrates, NVB = No Visible Biota, MBI = Mixed Brown algae and Invertebrates.

Table 3
Accuracy assessment for substratum classification.

		Error matrix				
		Ground truth data				
		Substratum class	R	S	RS	Sum
Classified data	R		59	8	7	74
	S		5	202	29	236
	RS		8	42	141	191
	Sum		72	252	177	501
User's accuracy (%)			80	86	74	
Producer's accuracy (%)			82	80	80	
Average accuracy (%)			81	83	77	
Overall accuracy (%)			80.2			
Kappa coefficient			0.67			

R = Reef, S = Sediment, RS = Reef/Sediment.

recent work applying these methods to biological communities. Hamilton and Parnum (2011) demonstrated the usefulness of angular response information for biological habitats (seagrass and rhodolith) using unsupervised statistical clustering. This study shows that angular response is capable of differentiating between different biological habitats on reef structures. The low spatial resolution of angular response classification can be overcome with automated segmentation procedures which provide advantages in terms of repeatability compared to manual digitising methods previously demonstrated (Fonseca et al., 2009). With the increasing amount of acoustic backscatter data and coverage that can be collected through MBES systems (Hughes Clarke et al., 1996), it is essential that the primary data should be studied and explored in different ways to determine its full capability and whether it is useful for alternative applications.

The comparison of mean angular response between biological habitats in this study provides some information about their acoustic characteristics. Angular response is a complicated process derived from the geological and biological nature and upper morphology of the seabed; factors such as the water/sediment interface, roughness and the sediment volume structure influence the response (Canepa and Berron, 2006). In some studies, the presence of biological habitat (such as seagrass) has been shown to increase backscatter intensity when compared to sand (Siwabessy et al., 2006; Parnum, 2007; De Falco et al., 2010) and reef structures often show higher backscatter intensity than sediment (Hamilton and Parnum, 2011). Angular response curves for biota (except MB and MBI) and substratum decreased as the incidence angle increased, matching the typical shape of the angular response curve (Hughes Clarke, 1994; Hughes Clarke et al., 1997), particularly for sediment. Despite the effect from sediment, INV and MRI (mostly distributed on Reef/Sediment) had angular response curves similar to sediment at the outer angle while the mean angular response from biological habitats on reef structures (MB and MBI) seemed to be independent of the incidence angle. When comparing these habitats with other biota classes, the angular response curve was almost horizontal. The results presented here are similar to those of Siwabessy et al. (2006) who reported that the slope of mean angular response (between 10° and 35° incidence angle) from algae on reefs was likely to be small and flat. This shows that the combination of substratum and biota habitats influences the angular response characteristic. However, there will be difficulties in determining which layer contributes most to the scattering process. A further study using water column data extracted from MBES backscatter (McGonigle et al., 2011) could be combined with angular response data to investigate this issue.

The use of decision tree supervised classification has allowed the production of thematic habitat maps with moderate accuracy (Congalton and Green, 2009). The accuracy assessment is

a summative process derived from training data, the decision tree model, image segmentation and joining processes between angular response classification and the segmented polygons. The accuracy assessment shows misclassification occurring between MB with MBI, and MRI with INV. These classes were most likely to be in the same acoustic group because they share similar species composition and substratum types and are often differentiated based on changes in canopy density. Low classification accuracy has been observed with algal classes that have similar characteristics using bathymetry, backscatter and their derivatives (Ratray et al., 2009).

The use of mean shift image segmentation in the present study has been shown to be a useful technique for integration with angular response classifications to produce benthic habitat maps. Spatial clustering in the segmentation provides polygons that serve as base maps for point class information. Segmentation approaches combined with other classification techniques such as object oriented classification have been shown to be useful for differentiating sand and reef classes using backscatter from side-scan sonar (Lucieer, 2007, 2008). By creating polygons from similar adjacent pixels, the final classification maps can reduce the 'salt and paper' effect that commonly appears in pixel based classifications. The main drawback of image segmentation is that it is easily affected by under or over segmenting depending on the technique used. Under segmentation produces large polygons whereas over segmentation will generate too many smaller polygons. Although over segmentation is observed with mean shift image segmentation in the present study, their effects have been decreased by taking the nearest neighbour for angular response class labelling.

The angular response classification presented here (e.g. Fig. 4b) is useful even when not combined with backscatter image segmentation. The class information can be mapped as single point features for the study area at a scale of half the swath width (port and starboard sides) (Hamilton and Parnum, 2011) and spatial distribution of each habitat can be recognised and determined. However, there will be limitations where the results are to be combined or compared with other small scale map information such as from the high resolution bathymetric maps. Depth has been shown to influence the distribution of benthic biological habitat communities and provides useful information to the habitat classification using MBES data (Brown et al., 2011). Further investigation is required to determine whether depth and its derived seascape metrics can be integrated with angular response classification in explaining benthic biological habitat distributions.

The construction of angular response of backscatter is generated from a number of consecutive sonar pings (port and starboard are handled separately) which assumes that the seafloor habitat within this range is homogeneous, which often is not the case as the variability of seafloor habitats occurs between swaths (Hamilton and Parnum, 2011). Moreover only single spatial information is given to each side of the swath to represent the position of the angular response curve that causes uncertainty when the merging process is carried out between the angular response position and the segmented polygons. Some adjacent angular response positions will overlap which initially should be filtered, since the swath coverage from the original MBES survey lines is targeted to be at least 50% overlap. Ambiguity is also caused when assigning video observation classes to the angular response positions within its 10 m radius. Computing the angular response curve only from homogeneous segmented regions rather than across the sonar swath may also improve class differentiation. Techniques of combining angular response classification with its similar acoustic region from backscatter imagery such as the acoustic theme method could be essential in minimising the errors occurred with angular response position (Fonseca et al., 2009). The segmentation algorithm used in this study also has limitations because of high

computational complexity limiting its application for processing large volumes of data (Wan and Deng, 2011). We found a 5 m pixel resolution appropriate for our dataset to avoid memory limitations.

5. Conclusion

This study provides techniques to produce benthic biological habitat maps using the combination of angular response and backscatter imagery. The use of angular response for supervised classification is important because backscatter intensity from different habitats on the seabed is presented at different angles and provides more information than a single normalised backscatter value (i.e. backscatter imagery). By combining with mean shift image segmentation, habitat maps have been successfully generated. The ability to use angular response and backscatter imagery to produce habitat maps has improved our understanding of the level of benthic biological information that can be extracted from MBES acoustic backscatter. Results from this study have extended angular response applications from seafloor substrate classifications to biological habitat mapping. The quantitative analysis of angular response is not limited to the decision tree technique presented in this study, with scope to test the performance of other supervised approaches. Additionally, the role of image segmentation is recognised as an important tool in the identification of homogeneous areas to be used for further analysis (i.e. classification process). This study provides a framework for linking backscatter data with benthic biological identities and overcomes low spatial resolution of angular response data for benthic habitat mapping using acoustic techniques. With a variety of techniques and data available to generate marine habitat maps, the integration and assimilation of these datasets allows the extraction of more information to further understand marine ecosystem processes and provides a more systematic approach to managing and preserving marine biodiversity.

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