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# Applications of multibeam echosounder data and video observations for biological monitoring on the south east Australian continental shelf

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## 1.0 Introduction

Understanding the distribution of marine biodiversity is essential for effective conservation and management (Last et al., 2010). However, to accurately sample an entire area of interest using traditional (e.g. grab sampling or diver surveys) *in situ* biological assessments in the marine environment is logistically difficult and prohibitively expensive. As a consequence, marine scientists are turning to technologies that allow the collection of detailed spatially-explicit information across broader geographic regions.

While multibeam echosounder (MBES) has been used predominantly for engineering and hydrographic purposes, it is increasingly being applied for biological applications. For example, biological characterisation of the seafloor (Ierodiaconou et al., 2011; Rattray et al., 2009; Rooper and Zimmermann, 2007), fisheries assessments (Kostylev et al., 2001; Nasby-Lucas et al., 2002), marine protected area planning (Jordan et al., 2005) and prediction of fish habitat suitability (Iampietro et al., 2005; Monk et al., 2011; Moore et al., 2009).

By deriving relationships between biological information (e.g. species, community or habitat) from *in situ* sampling, and physical characteristics of the acoustic return, predictions can be made concerning the spatial distribution of these biological entities in areas where direct measurements are not available. Presented in this paper are three case studies that integrate MBES information and video-derived biological datasets in the temperate marine environments of the southern Australia continental shelf. Specifically, this paper will highlight three applications of these datasets;

1. Habitat change detection: MBES bathymetry and backscatter information are integrated with *in situ* video observations to produce benthic biological habitat maps. Time series classified habitat maps are then analysed in order to identify systematic habitat changes.
2. Deriving biologically relevant acoustic signatures: A new approach of extracting information from MBES acoustic scattering to facilitate biological habitat mapping.
3. Habitat suitability modelling: Physical datasets derived from MBES are combined with video observations of a fish species to develop a high resolution habitat suitability map.

## 2.0 Methods

### 2.1 Descriptions of study sites

The study areas were located in three different regions in south-eastern Australia; Kennet River (case study 1), Discovery Bay (case study 2) and Hopkins (case study 3) as shown in Figure 1. These areas are 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). All sites encompassed different depth ranges from 9m to 54m (Kennet River), 11m to 80m (Discovery Bay) and 12m to 50m (Hopkins).

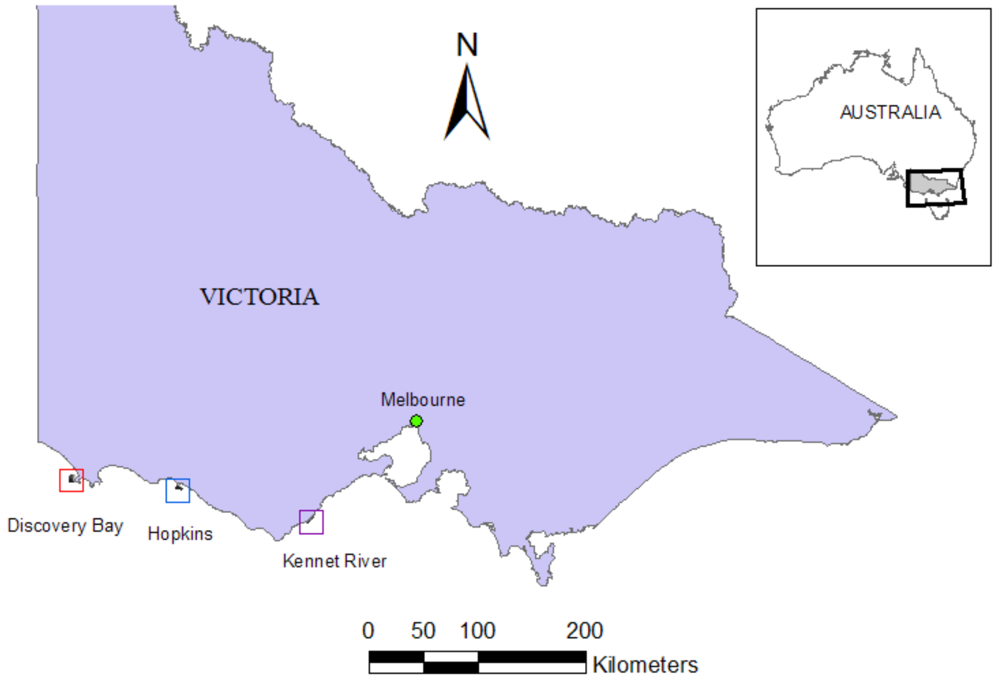


Figure 1: Location map of three study areas along the south east Australian continental shelf in Victoria Australia (Kennet River, Discovery Bay and Hopkins).

### 2.2 Acoustic data

The acoustic data were acquired aboard the Australian Maritime College research vessel *Bluefin*. The acquisition system consisted of hull-mounted Reson Seabat 8101 multibeam echosounder (MBES) leased from Fugro Survey Pty Ltd. Seabat 8101 operated at a frequency of 240 kHz, designed specifically for shallow water surveying purposes. This swath system consisted of 101 individual beams and each beam has beamwidth 1.5° (along and across track). Horizontal positioning was accomplished using Starfix HP Differential GPS system ($\pm$ 0.30 m), integrated with a POS MV (Positioning and Orientating System for Marine Vessels) for heave, pitch, roll and yaw corrections ($\pm$ 0.02° accuracy). Real-time navigation, data-logging, quality control and display were made possible using the Starfix suite 8.1 software (Fugro Survey Pty Ltd). Daily sound velocity profiles were collected to correct for water column sound speed variations. Two main data products were used in the case studies; depth and backscatter (intensity return). Starfix suite was also used to process the acoustic data in order to produce cleaned bathymetry and backscatter layer maps. The same vessel, sonar system and configuration were used to collect data for 2006 and 2008 that allowed the time series analysis (case study 1). The raw backscatter data was also processed using the CMST MB Process (Parnum, 2007) to generate backscatter imagery and to extract additional backscatter information (i.e. angular response) with their respective location (case study 2).

### 2.3 Underwater video observations

A georeferenced underwater video system (VideoRay microROV) was used to provide ground truth information for model building and evaluation. The video data were acquired aboard the Deakin University 8m research vessel *Courageous II*. Underwater acoustic positioning of video system was achieved using a Tracklink Ultra Short Base Line (USBL) acoustic tracking system, with vessel errors (roll, pitch and yaw) corrected using KVH motion sensor (Ierodiaconou et al., 2007a; Ierodiaconou et al., 2011; Rattray et al., 2009). Wide area Differential Global Positioning System (DGPS), Omnistar DGPS was used to fix the vessel location and apply corrections for the acoustically positioned video. The recorded video data was then classified according to the Victorian Towed Video Classification scheme to identify the benthic biota and substrata classes. The classification scheme followed the guidelines published by the Interim Marine and Coastal Regionalisation for Australia (IMCRA, 1998). All available reference data was randomly sampled for model development (70%) and for accuracy assessment (30%), and finally used for classification processes (case study 1 and 2). Accuracy assessments were based on the statistics (overall accuracy, kappa coefficient, user's and producer's accuracy) derived from error matrix (Congalton and Green, 2009).

For case study 3, baited video deployments were employed to determine the occurrence of specific fish species. A stratified random design was applied for sampling strategy to ensure good spatial coverage and adequate representation across the major structuring seafloor gradients. The baited video systems used comprised two Sony HC 15E video cameras mounted 0.7 m apart on a base bar inwardly converged at 8° to gain an optimized field of view with visibility of ~ 7 m distance (water clarity dependent; Harvey and Shortis, 1996). Each baited video system was deployed by boat and left to film on the seafloor for a period of 1 hour. At least 36 min of filming time is recommended to obtain measures for the majority of fish species, though 60 min is advisable to obtain measures of numerous targeted fish species (Watson, 2006). Each camera system was equipped with a synchronizing diode and ~ 800 grams of crushed pilchards (*Sardinops sagax*) in a closed plastic-coated wire mesh basket, suspended 1.2 m in front of the two cameras. Adjacent replicate drops were separated by at least 250 m to avoid overlap of bait plumes and reduce the likelihood of fish moving between sites within the sampling period (Cappo et al., 2001). All drops were deployed between 08:00 and 18:00 to minimize the effects of diurnal changes in fish behaviour (Willis et al., 2006). The fish data was randomly sampled into similar proportion as made in previous cases to be used in habitat suitability modelling technique.

### 2.4 Case study 1

In this study, the aim was to apply and create automated classification process using the high resolution MBES products (bathymetry and backscatter layers) and video observations from two time periods (summer 2007 & 2008) to classify benthic habitats. In order to observe in detail the variation of seabed, secondary derivatives were produced from the bathymetry and backscatter information. Six derivatives were generated from bathymetry (Jenness, 2004; Lundblad et al., 2006; Schmidt et al., 2003; Wilson et al., 2007); aspect, rugosity, maximum curvature, benthic position index (BPI), slope and complexity, while three from backscatter (Daily, 1983); Red, Green and Blue layer of Hue, Saturation and Intensity (HSI). These layers (including bathymetry and backscatter) were then used as the variables to run a decision tree supervised classification for each dataset. We used Quick, Unbiased, Efficient Statistical Tree (QUEST) decision tree (Loh and Shih, 1997) for creating decision rule using the available training data and subsequently produced classification maps. We compared benthic habitat maps using a post classification comparison change detection technique to quantify transitions between habitats. By using two time series of classification maps, systematic habitat transitions were identified by interrogating the traditional change detection matrix based on methods proposed by Pontius et al. (2004).

### 2.5 Case study 2

This section investigates the usefulness of the acoustic scattering process from MBES for classifying benthic biological habitat communities. Two types of backscatter data were used, the backscatter layer map (5m resolution) and the angular response of backscatter strength. Video ground truth data was used to assign benthic classes to angular response for model training. We integrate the low spatial resolution information from the angular response with the higher resolution backscatter layer map to maximise the habitat differentiating characteristics of both data sets. First, mean shift image segmentation (Christoudias et al., 2002; Comaniciu, 1999; Comaniciu and Meer, 2002) was applied to the backscatter map to segment adjacent pixels into homogenous regions. Secondly, we used supervised classification to classify angular response into 5 broad biota classes. Both of these results were combined using *k* nearest neighbour to create final habitat maps. Four different supervised classification methods were tested in this study to evaluate the angular response information used in the characterisation process; Maximum Likelihood Classification (MLC), QUEST decision tree (QUEST), Random Forest decision tree and Support Vector Machine (SVM).

### 2.6 Case study 3

The purpose of this case study was to generate two dimensional maps that provide information regarding habitat suitability for a fish species *Notolabrus fuciola*. Predictive modelling using Maximum Entropy (MAXENT) was used for assessing species habitat suitability (Phillips et al., 2006). This general-purpose machine learning approach is designed for modelling species distributions based on presence-only data to determine the largest spread (i.e. maximum entropy) in a geographic dataset of species presences in relation to a set of background environmental variables (Phillips et al., 2006). Ten variables were used for prediction where eight variables were similar as in case study 1 (bathymetry, backscatter and secondary derivatives) with the addition of Euclidean distance to Hopkins bank (a large geomorphic feature) and Euclidean distance to nearest reef. To reduce correlation between all variables, a spearman correlation coefficient of 0.5 was applied. Using the occurrence datasets that were set aside for model testing, model performance was evaluated using the threshold-independent AUC (area under the curve) of the ROC (receiver operating characteristic) (Fielding and Bell, 1997). An AUC value of 0.5 implies the model predicts species occurrence no better than random, and a value of 1.0 implies perfect prediction.

## 3.0 Results

### 3.1 Case study 1

The decision tree classification produced high resolution habitat maps representing the distribution of four broad biological habitats. Classification accuracies for each year were derived using an error matrix approach (Congalton and Green, 2009) and were estimated at 92% overall accuracy for the 2007 classification and 93% for the 2008 classification (Table 1). The distribution of biological habitats shows a strong relationship with depth, driven by attenuation of light in the water column and also reduction in exposure to wave energy with increasing depth. Kelp dominated habitats were found in depths <40m, whereas for depths >50m the areas were replaced by sponge dominated habitats. A zone of transition between algal dominated shallow reefs and invertebrate (sponge) dominated deeper reefs was identified between these depths.

Table 1: Error matrices for classification years 2007 and 2008. Values in the major diagonal of each matrix (italicised) indicate agreement of reference data with classified maps, values in the off-diagonal show confusion between classes. Habitat categories are: NB – Unconsolidated sediments; ALGDOM - Algal dominated (kelp habitat); INVDOM – Invertebrate dominated (sponge habitat); ALG/INV – Mixed algae and invertebrates (transition zone between kelp and sponge habitats).

| | **Reference** | | | | | **%Producers** | **%Users** |
|---|---|---|---|---|---|---|---|
| | **NB** | **ALGDOM** | **ALG/INV** | **INVDOM** | **Total** | **Accuracy** | **Accuracy** |
| 2007 (overall accuracy = 93%; KHAT = 0.83 ) | | | | | | | |
| NB | *1020* | 1 | 12 | 37 | 1070 | 96 | 95 |
| ALGDOM | 11 | *111* | 2 | - | 124 | 97 | 89 |
| ALG/INV | 6 | 2 | *24* | 3 | 35 | 56 | 69 |
| INVDOM | 31 | 1 | 5 | *219* | 256 | 85 | 86 |
| Total | 1068 | 115 | 43 | 259 | 1485 | | |
| | | | | | | | |
| 2008 (overall accuracy = 92%; KHAT = 0.83) | | | | | | | |
| NB | *1070* | 8 | 1 | 36 | 1115 | 94 | 96 |
| ALGDOM | 11 | *116* | 5 | 3 | 135 | 91 | 86 |
| ALG/INV | 4 | 4 | *21* | - | 29 | 62 | 72 |
| INVDOM | 52 | - | 7 | *277* | 336 | 88 | 82 |
| Total | 1137 | 128 | 34 | 316 | 1615 | | |

Time series classified maps were compared to assess how dominant biological habitats had changed between the two dates. Results demonstrate a dynamic link between the three biological classes examined in this study. Concurrent incidences of systematic gains and losses between classes show a clear positive depth shift of the transition zone between algal dominated and invertebrate dominated habitats between time series classified maps (Figure 2). Systematic habitat transitions defined by the study show a pattern consistent with inter-annual thinning of kelp beds at the site resulting in retraction of kelp cover at the deeper end of its depth range and subsequent replacement by adjacent habitat categories.

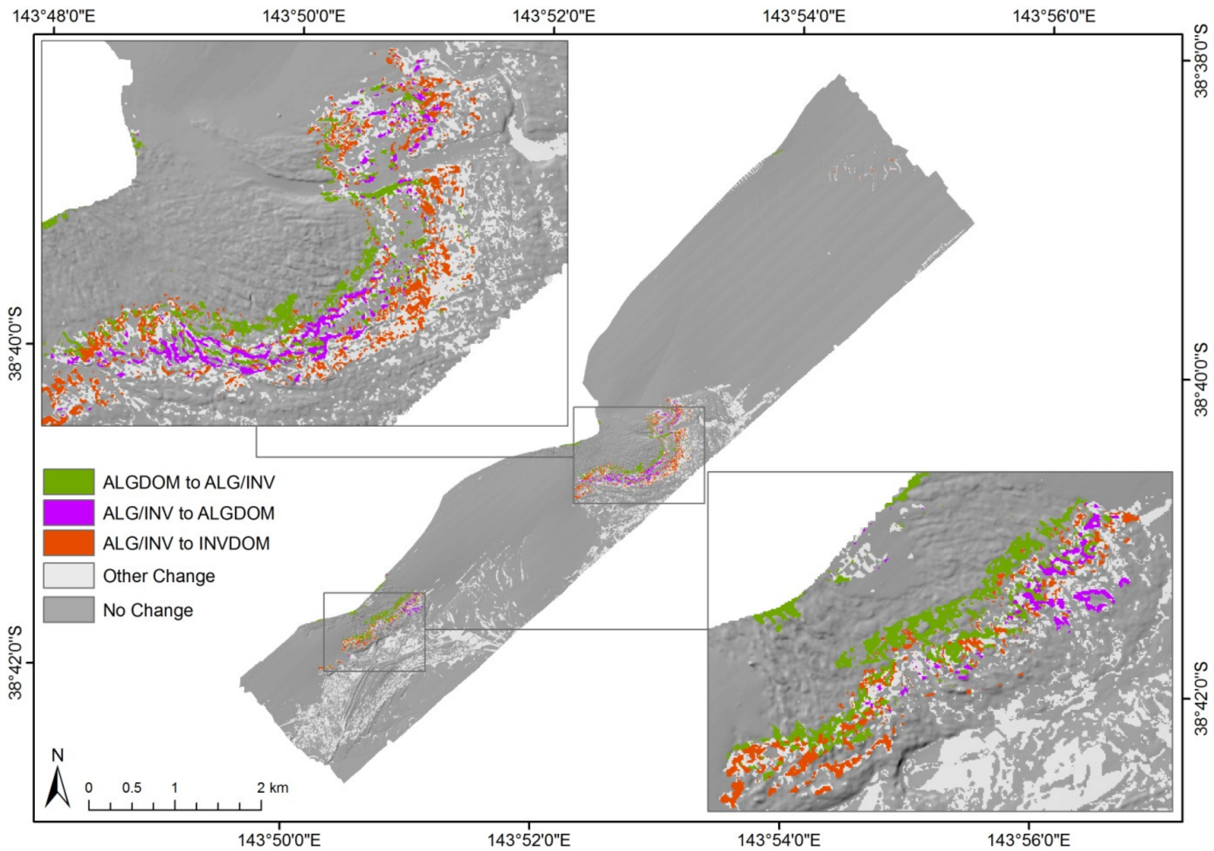


Figure 2: Spatial representation of systematic habitat changes between the years 2007 and 2008. Habitat categories are: ALGDOM - Algal dominated (kelp habitat); INVDOM – Invertebrate dominated (sponge habitat); ALG/INV – Mixed algae and invertebrates (transition zone between kelp and sponge habitats).

### 3.2 Case study 2

Analysis of mean angular response of backscatter (Figure 3) from different biological benthic habitats illustrates that each habitat produced different characteristic of response curves. Significant different was noticeable between NVB (No Visible Biota) and other classes. On the other hand, small separation was observed between MB (Mixed Brown algae) and MBI (Mixed Brown and

Invertebrate). Aided by class information from underwater video observations, supervised classification has been successfully applied. Automated image segmentation of backscatter map has successfully produced polygons with homogeneous regions. The integration of the segmented polygons and the angular response classification results enabled the construction of habitat maps with original resolution as in the backscatter imagery (5m) (Figure 4). Overall accuracy achieved using four different classifier methods shows that the accuracy varies from 69.9% to 83.8% with Random Forest decision tree producing best results and Maximum Likelihood Classifier lowest (Table 2).

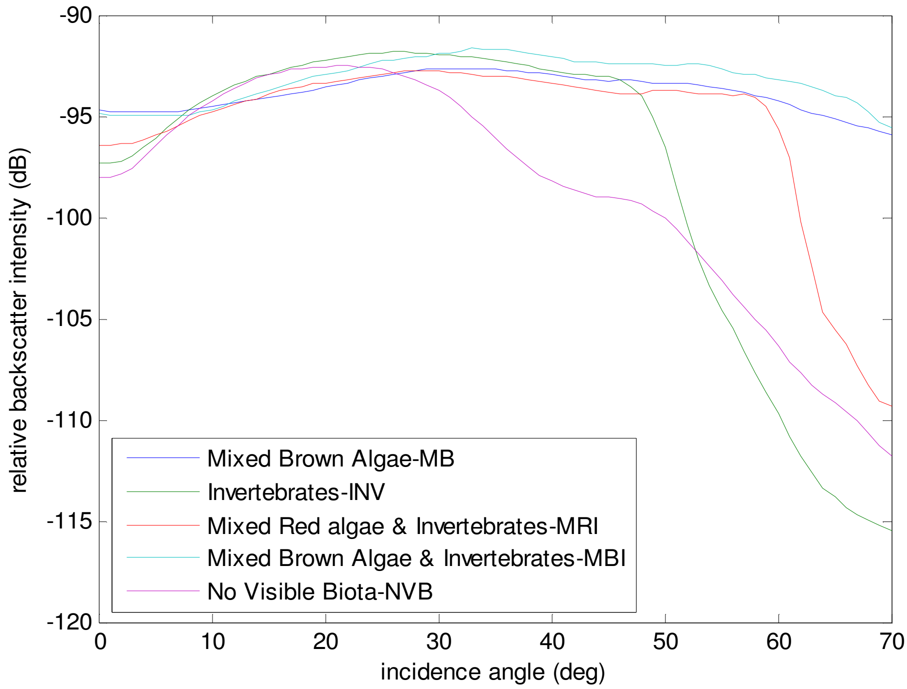


Figure 3: Summary of mean angular response of backscatter from different benthic biological habitats (Discovery Bay)

Table 2: Accuracy assessment from four different classifiers using angular response information

| **Classifiers** | **Overall accuracy (%)** | **Kappa Coefficient** |
|---|---|---|
| Maximum Likelihood Classifier | 69.9 | 0.51 |
| QUEST decision tree | 79.6 | 0.66 |
| Random Forest decision tree | 83.8 | 0.73 |
| Support Vector Machine | 81.9 | 0.70 |

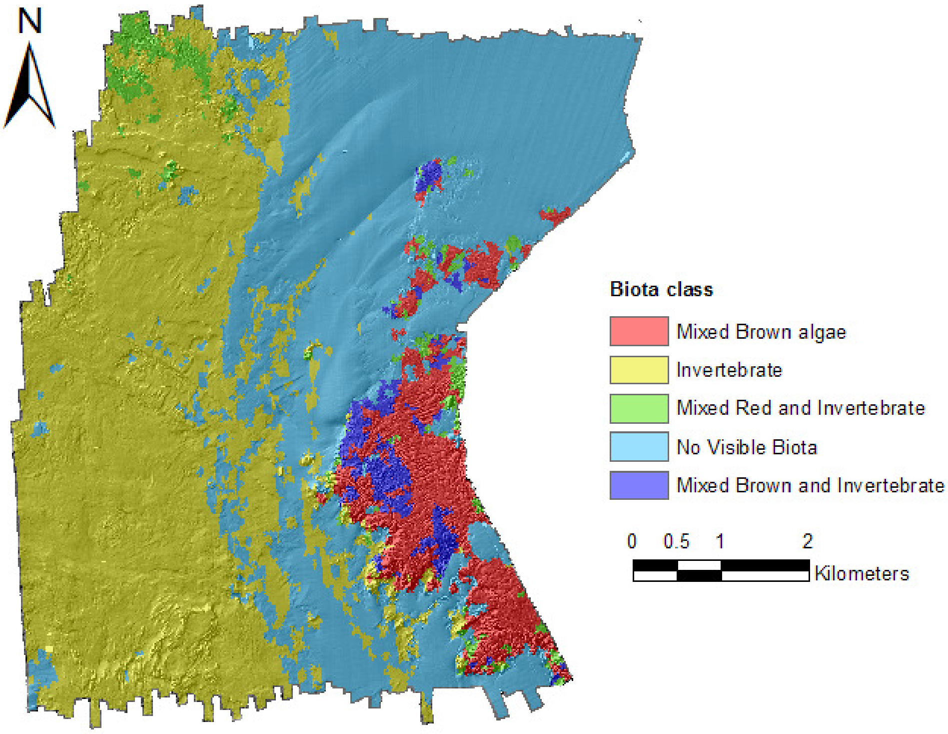


Figure 4: Classification map derived from best model run in case study 3 (Random Forest decision tree)

### 3.3 Case study 3

Maxent model provided an excellent prediction of habitat suitability for *Notolabrus fuciola*; as reflected by an AUC value of 0.89. Of the ten least correlated variables, Euclidean distance to Hopkins bank and rugosity were the most important (Table 3) in predicting the habitat suitability of this species (73 % and 11 %, respectively). The remaining eight variables contributed a combined total of 16 % to the model. The suitability map (Figure 5) shows areas that were predicted as the most suitable location for the species. As to be expected the most suitable habitat of this reef dwelling species was confined to highly rugose macroalgal dominated reef system in the shallowest extent of the size between depths of 12 to 20 metres.

Table 3: Percent contribution of variables used to predict fish habitat suitability using Maxent (case study 3)

| **Variable** | **Cumulative Percent contribution** |
|---|---|
| Euclidean distance to Hopkins bank | 73.3 |
| Rugosity | 11 |
| Aspect (Northness) | 5.4 |
| HSI (Red) | 2.8 |
| Benthic Position Index | 2.4 |
| Euclidean distance to nearest reef | 1.9 |
| Aspect (Eastness) | 1.5 |
| Complexity | 1 |
| Bathymetry | 0.4 |
| Maximum curvature | 0.3 |

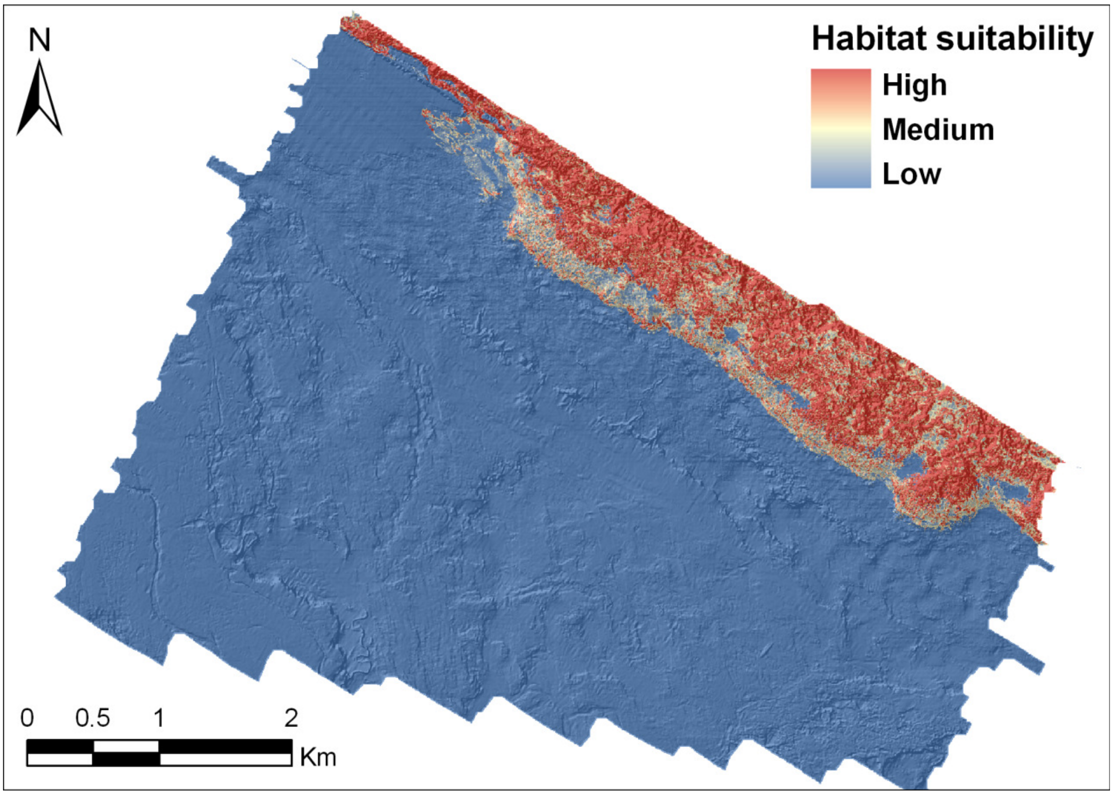


Figure 5: Prediction of habitat suitability for *Notolabrus fuciola*. Red indicates high suitability; blue low suitability.

## 4.0 Discussion

MBES has been widely accepted as an important tool for hydrographic surveying, nautical charting, inspection works (such as underwater cable routing) and various geological applications such as seafloor engineering geomorphology (Prior and Hooper, 1999), submarine geomorphology structure (Gardner et al., 2003), surface morphology of glacial deposits (Shaw et al., 1997) and bedrock mapping (Courtney and Shaw, 2000). However, over the past decades data from MBES has been explored to be used and facilitate the benthic habitat mapping process (for a review see; Brown et al., 2011). This is driven by interest from marine ecologists and scientists to create spatially-explicit habitat maps that are crucial for explaining habitat structure, species distribution and abundance. To accomplish this, application of a seascape terrain analysis (bathymetry derivatives) in habitat characterisation process provides new feature in explaining how species are located and distributed. By adding habitat information through video observations and applying proper predictive models, MBES application is been prolonged as useful tool for biological monitoring.

Monitoring of shallow (<20m) sub-littoral habitats such as seagrass, corals and surface kelps has been realised using time-series datasets derived from optical sensors (Agostini et al., 2002; Dekker et al., 2005; Ferguson and Korfmacher, 1997). The ability to quantitatively define change in biological habitats beyond the range of optical sensors remains a major challenge for the marine ecological community. In case study 1, small scale inter-annual variation in the distribution of kelp and sponge dominated habitats in depths to 60m was successfully captured using high resolution MBES information coupled with video reference data demonstrating the utility of habitat monitoring using acoustic means. Accurate definition of areas susceptible to change provides a framework for future habitat mapping and monitoring projects.

The use of angular response (case study 2) provides additional information to identify benthic biological habitats and its use is highlighted in a benthic habitat characterisation process. The key to the identification of biological habitats is made through the video observations. The advantage is that users do not have to understand how the scattering process of backscatter occurred, rather only use this as the model input for different supervised classification methods. The usefulness of using angular response information for seafloor characterization has been demonstrated by the geo-acoustic inversion process (Fonseca et al., 2009; Fonseca and Mayer, 2007). This method extracts parameters from angular response and uses this as input to mathematical models that link to acoustic scattering properties of the seafloor. The present method uses signatures derived from the video to translate the classification model into a meaningful ecological application. The accuracy of the classification model depends how well the classifiers handle or treat the training data and relationships between the biological and physical attributes that can be defined. Further investigation is required to integrate depth and its derived landscape metrics (applied in case study 1) with angular response in explaining benthic biological habitat distribution.

*Notolabrus fuciola* is a common species of wrasse in south-east Australia. It is known to inhabit shallow reef systems; particularly highly rugose kelp dominated areas (Edgar, 1997). This ecology is reflected by the importance of Euclidean distance to Hopkins bank in the model. This bank feature supports dense stands of canopy-forming kelps (e.g. *Phyllospora comosa;* Ierodiaconou et al. (2007a). Although originally used for prediction of terrestrial species' distributions, incorporating MBES-derived datasets has enabled these 'terrestrial' techniques to be applied to predict the habitat suitability of marine species over large regions of seafloor. The present technique of producing suitability maps provides marine managers with high-resolution, spatially-continuous information that is in stark contrast to the limited, coarse-resolution predictions that have historically been relied upon.

## 5.0 Conclusion

This paper presents three case studies that demonstrate how we derive benthic habitat information using MBES data, video observations and predictive modelling techniques. The techniques applied in this study provide advantages compared to the conventional method of acquiring biological information over broad geographic regions that are often sparsely located. The maps constructed from these prediction techniques are not only capable of explaining flora and fauna distributions, but also their relationships with the physical structure of the seafloor. Although MBES provide 100%

coverage of the seafloor, there are limitations when acquiring acoustic data for very shallow water (<10m). Other data collection techniques are needed to assist and filling the gap that is not possible with hydro-acoustic method. Potential approach for this purpose (i.e. habitat mapping for shallow water) is the application of optical and laser sensors such as Light Detection and Ranging (LIDAR) (Chust et al., 2010; Wedding et al., 2008), multispectral (Kutser et al., 2006b), or hyper spectral remote sensing (Fearns et al., 2011; Holden and LeDrew, 2002; Kutser et al., 2006a; Vahtmäe et al., 2006). In addition, data observed from overlapping areas between acoustic and remotely sensed techniques could also provide direct habitat map comparisons as well as data assimilation and integration. Wide area coverage and variation techniques of collecting physical data for species identification and monitoring have giving scientists more flexibility and feasibility to understand thoroughly species characteristics and uniqueness in a broader geographic scale.

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## References

Agostini, S., Marchand, B., and Pergent, G., 2002, Temporal and spatial changes of seagrass meadows in a Mediterranean coastal lagoon: *Oceanologica Acta*, v. 25, p. 297-302.

Brown, C.J., Smith, S.J., Lawton, P., and Anderson, J.T., 2011, Benthic habitat mapping: A review of progress towards improved understanding of the spatial ecology of the seafloor using acoustic techniques: *Estuarine, Coastal and Shelf Science*, v. 92, p. 502-520.

Cappo, M., Speare, P., Wassenberg, T.J., Harvey, E., Rees, M., Heyward, A., and Pitcher, R., 2001, Use of baited remote underwater video stations (BRUVS) to survey demersal fish-how deep and meaningful?, *in* Harvey, E.S., and Cappo, M., eds., Video sensing of the size frequency and abundance of target and non-target fauna in Australian fsheries-a national workshop., Fisheries Research and Development Corporation, Australia, p. 63-71.

Christoudias, C.M., Georgescu, B., and Meer, P., 2002, Synergism in low level vision, Pattern Recognition, 2002. Proceedings. 16th International Conference on, Volume 4, p. 150-155 vol.4.

Chust, G., Grande, M., Galparsoro, I., Uriarte, A., and Borja, Á., 2010, Capabilities of the bathymetric Hawk Eye LiDAR for coastal habitat mapping: A case study within a Basque estuary: *Estuarine, Coastal and Shelf Science*, v. 89, p. 200-213.

Comaniciu, D., 1999, Mean Shift Analysis and Applications, *in* Peter, M., ed., Volume 2, p. 1197-1197.

Comaniciu, D., and Meer, P., 2002, Mean shift: a robust approach toward feature space analysis: *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, v. 24, p. 603-619.

Congalton, R.G., and Green, K., 2009, Assessing the accuracy of remotely sensed data: Boca Raton, FL, CRC Press.

Courtney, R., and Shaw, J., 2000, Multibeam Bathymetry and Backscatter Imaging of the Canadian Continental Shelf: *Geoscience Canada*, v. 27, p. 31-42.

Daily, M., 1983, Hue-saturation-intensity split-spectrum processing of Seasat radar imagery: *Photogrammetric Engineering & Remote Sensing*, v. 49, p. 349-355.

Dekker, A.G., Brando, V.E., and Anstee, J.M., 2005, Retrospective seagrass change detection in a shallow coastal tidal Australian lake: *Remote Sensing of Environment*, v. 97, p. 415-433.

Edgar, G.J., 1997, Australian Marine Life: *Reed Books, Melbourne, Victoria (1997)*, p. 544 pp.

Fearns, P.R.C., Klonowski, W., Babcock, R.C., England, P., and Phillips, J., 2011, Shallow water substrate mapping using hyperspectral remote sensing: *Continental Shelf Research*, v. 31, p. 1249-1259.

Ferguson, R.L., and Korfmacher, K., 1997, Remote sensing and GIS analysis of seagrass meadows in North Carolina, USA: *Aquatic Botany*, v. 58, p. 241-258.

Fielding, A.H., and Bell, J.F., 1997, A review of methods for the assessment of prediction errors in conservation presence/absence models: *Environ. Conserv.*, v. 32, p. 614-623.

Fonseca, L., Brown, C., Calder, B., Mayer, L., and Rzhanov, Y., 2009, Angular range analysis of acoustic themes from Stanton Banks Ireland: A link between visual interpretation and multibeam echosounder angular signatures: *Applied Acoustics*, v. 70, p. 1298-1304.

Fonseca, L., and Mayer, L., 2007, Remote estimation of surficial seafloor properties through the application Angular Range Analysis to multibeam sonar data: *Marine Geophysical Researches*, v. 28, p. 119-126.

Gardner, J.V., Dartnell, P., Mayer, L.A., and Hughes Clarke, J.E., 2003, Geomorphology, acoustic backscatter, and processes in Santa Monica Bay from multibeam mapping: *Marine Environmental Research*, v. 56, p. 15-46.

Harvey, E., and Shortis, M., 1996, A system for stereo-video measurement of subtidal organisms: *Marine Technology Society Journal*, v. 29, p. 10-22.

Holden, H., and LeDrew, E., 2002, Measuring and modeling water column effects on hyperspectral reflectance in a coral reef environment: *Remote Sensing of Environment*, v. 81, p. 300-308.

Iampietro, P.J., Kvitek, R.G., and Morris, E., 2005, Recent Advances in Automated Genus-specific Marine Habitat Mapping Enabled by High-resolution Multibeam Bathymetry: *Marine Technology Society Journal*, v. 39, p. 83-93.

Ierodiaconou, D., Burq, S., Reston, M., and Laurenson, L., 2007a, Marine benthic habitat mapping using multibeam data, georeferenced video and image classification techniques in Victoria, Australia: *Journal of Spatial Science*, v. 52, p. 93-104.

Ierodiaconou, D., Monk, J., Rattray, A., Laurenson, L., and Versace, V.L., 2011, Comparison of automated classification techniques for predicting benthic biological communities using hydroacoustics and video observations: *Continental Shelf Research*, v. 31, p. S28-S38.

Ierodiaconou, D., Rattray, A., Laurenson, L., Monk, J., and Lind, P., 2007b, Victorian marine habitat mapping project: *Deakin University*.

IMCRA, 1998, Interim Marine and Coastal Regionalisation for Australia: An ecosystem-based classification for marine and coastal environments (Version 3.3): *Environment Australia, Commonwealth Department of the Environment, Canberra*.

Jenness, J.S., 2004, Calculating landscape surface area from digital elevation models: *Wildlife Society Bulletin*, v. 32, p. 829-839.

Jordan, A., Lawler, M., Halley, V., and Barrett, N., 2005, Seabed habitat mapping in the Kent Group of islands and its role in marine protected area planning: *Aquatic Conservation-Marine and Freshwater Ecosystems*, v. 15, p. 51-70.

Kostylev, V.E., Todd, B.J., Fader, G.B.J., Courtney, R.C., Cameron, G.D.M., and Pickrill, R.A., 2001, Benthic habitat mapping on the Scotian Shelf based on multibeam bathymetry, surficial geology and seafloor photographs: *Marine Ecology-Progress Series*, v. 219, p. 121-137.

Kutser, T., Miller, I., and Jupp, D.L.B., 2006a, Mapping coral reef benthic substrates using hyperspectral space-borne images and spectral libraries: *Estuarine, Coastal and Shelf Science*, v. 70, p. 449-460.

Kutser, T., Vahtmäe, E., and Martin, G., 2006b, Assessing suitability of multispectral satellites for mapping benthic macroalgal cover in turbid coastal waters by means of model simulations: *Estuarine, Coastal and Shelf Science*, v. 67, p. 521-529.

Last, P.R., Lyne, V.D., Williams, A., Davies, C.R., Butler, A.J., and Yearsley, G.K., 2010, A hierarchical framework for classifying seabed biodiversity with application to planning and managing Australia's marine biological resources: *Biological Conservation*, v. 143, p. 1675-1686.

Loh, W.Y., and Shih, Y.S., 1997, Split selection methods for classification trees, Volume Vol. 7, Statistica Sinica, p. 815 - 840.

Lundblad, E.R., Wright, D.J., Miller, J., Larkin, E.M., Rinehart, R., Naar, D.F., Donahue, B.T., Anderson, S.M., and Battista, T., 2006, A Benthic Terrain Classification Scheme for American Samoa: *Marine Geodesy*, v. 29, p. 89-111.

Monk, J., Ierodiaconou, D., Bellgrove, A., Harvey, E., and Laurenson, L., 2011, Remotely sensed hydroacoustics and observation data for predicting fish habitat suitability: *Continental Shelf Research*, v. 31, p. S17-S27.

Moore, C.H., Harvey, E.S., and Van Niel, K.P., 2009, Spatial prediction of demersal fish distributions: enhancing our understanding of species–environment relationships: *ICES Journal of Marine Science: Journal du Conseil*, v. 66, p. 2068-2075.

Nasby-Lucas, N.M., Embley, B.W., Hixon, M.A., Merle, S.G., Tissot, B.N., and Wright, D.J., 2002, Integration of submersible transect data and high-resolution multibeam sonar imagery for a habitat-based groundfish assessment of Heceta Bank, Oregon: *Fishery Bulletin*, v. 100, p. 739-751.

Parnum, I.M., 2007, Benthic Habitat Mapping Using Multibeam Sonar Systems: *PhD Thesis, Curtin University of Technology, Australia*.

Phillips, S.J., Anderson, R.P., and Schapire, R.E., 2006, Maximum entropy modeling of species geographic distributions: *Ecological Modelling*, v. 190, p. 231-259.

Pontius, R.G., Shusas, E., and McEachern, M., 2004, Detecting important categorical land changes while accounting for persistence: *Agriculture, Ecosystems & Environment*, v. 101, p. 251-268.

Prior, D.B., and Hooper, J.R., 1999, Sea floor engineering geomorphology: recent achievements and future directions: *Geomorphology*, v. 31, p. 411-439.

Rattray, A., Ierodiaconou, D., Laurenson, L., Burq, S., and Reston, M., 2009, Hydro-acoustic remote sensing of benthic biological communities on the shallow South East Australian continental shelf: *Estuarine, Coastal and Shelf Science*, v. 84, p. 237-245.

Rooper, C.N., and Zimmermann, M., 2007, A bottom-up methodology for integrating underwater video and acoustic mapping for seafloor substrate classification: *Continental Shelf Research*, v. 27, p. 947-957.

Schmidt, J., Evans, I.S., and Brinkmann, J., 2003, Comparison of polynomial models for land surface curvature calculation: *International Journal of Geographical Information Science*, v. 17, p. 797-814.

Shaw, J., Courtney, R.C., and Currie, J.R., 1997, Marine geology of St. George's Bay, Newfoundland, as interpreted from multibeam bathymetry and back-scatter data: *Geo-Marine Letters*, v. 17, p. 188-194.

Vahtmäe, E., Kutser, T., Martin, G., and Kotta, J., 2006, Feasibility of hyperspectral remote sensing for mapping benthic macroalgal cover in turbid coastal waters--a Baltic Sea case study: *Remote Sensing of Environment*, v. 101, p. 342-351.

Watson, D.L., 2006, Use of underwater stereo-video to measure fish assemblage structure, spatial distribution of fishes and change in assemblages with protection from fishing [PhD Thesis thesis], The University of Western Australia.

Wedding, L.M., Friedlander, A.M., McGranaghan, M., Yost, R.S., and Monaco, M.E., 2008, Using bathymetric lidar to define nearshore benthic habitat complexity: Implications for management of reef fish assemblages in Hawaii: *Remote Sensing of Environment*, v. 112, p. 4159-4165.

Willis, T.J., Badalamenti, F., and Milazzo, M., 2006, Diel variability in counts of reef fishes and its implications for monitoring: *Journal of Experimental Marine Biology and Ecology*, v. 331, p. 108-120.

Wilson, M.F.J., O'Connell, B., Brown, C., Guinan, J.C., and Grehan, A.J., 2007, Multiscale Terrain Analysis of Multibeam Bathymetry Data for Habitat Mapping on the Continental Slope: *Marine Geodesy*, v. 30, p. 3-35.