Remote sensing of kelp: novel methods for mapping and monitoring wild kelp resources

Matthew Bennion, Chris Yesson, Juliet Brodie

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Authors

Matthew Bennion\textsuperscript{1,2}, Chris Yesson\textsuperscript{1}, Juliet Brodie\textsuperscript{2}

\textsuperscript{1}Institute of Zoology, Zoological Society of London, Regent's Park, London, NW1 4RY
\textsuperscript{2}Department of Life Sciences, Natural History Museum, Cromwell Road, London SW7 5BD

Email for correspondence: j.brodie@nhm.ac.uk

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1. Executive Summary

Kelp (Laminariales) are large brown, habitat-forming macroalgal (seaweed) species. Their large biogenic structure and ‘forest-like’ nature provide nursery and feeding grounds for a rich diversity of associated flora and fauna, many of which are critical to ecosystem functioning and commercial fisheries. Kelps, like many other macroalgal species worldwide are under threat: climate change, ocean acidification, anthropogenic pollution, overfishing and invasive species are just some of the pressures that have been reported to negatively impact these and other macroalgae.

Kelps are also under an old, but growing threat: wild harvesting. Harvesting of seaweeds from natural populations has been in practice for hundreds of years, particularly in the northeast Atlantic. Now, however, the rate at which kelps are harvested from the wild is increasing due to rising consumer demand for seaweed and seaweed derived products.

Currently, kelp resources are understudied, largely due to the logistics of trying to access the kelp forest habitat in the shallow, rocky sublittoral fringe. In the light of these shortcomings, there is a need for a standardised, rapid monitoring protocol to obtain baseline information of wild kelp resources, and ensure sustainable harvesting of said resources. Remote sensing technologies in the form of satellite and aerial imagery, underwater imagery, LiDAR (Light detection and ranging) and sonar (Sound navigation and ranging) have been applied to monitoring submerged aquatic flora, including kelp with varied degrees of success.

The present study used a combination of multibeam sonar information and species distribution modelling to map kelp distribution and abundance along a 35 km² stretch of the Dorset coast. Using data obtained from United Kingdom Hydrography Office (collected as part of their regular surveys), ground-truth information gained from field surveys and species distribution modelling, we pilot a novel monitoring and mapping methodology for kelp. In addition, we have identified several complications, which currently limit the expansion of the method outlined in this study, but offer remedies to these potential pitfalls.

We found the high resolution acoustic data very effective for mapping kelp distribution. A critical component of this acoustic data is a measure of the amount of acoustic energy being received by the sensor (aka backscatter). The importance of backscatter information for mapping and monitoring kelp resources has been highlighted as a crucial component of the predictive model. While choosing suitable study sites we found many areas were absent of backscatter information, despite being a typical component of multibeam sonar data. Additionally, while attempting to expand the coverage of the predictive model, difficulties were encountered as backscatter information from different vessels / echo-sounders could not be harmonised. An inability to combine backscatter data from different sources limits the transferability of the model. A standardised data collection protocol is therefore
required to ensure harmonisation of backscatter information and transferability of the predictive model. The method piloted in this study exhibits a potential low-cost solution to the data deficit of kelp resources, offering a rapid assessment technique which could be used to inform sustainable management of wild stocks.

2. Introduction

2.1 Importance of kelp

Kelps are large brown habitat-forming seaweeds, characterised by long stipes and broad fronds (Bartsch et al., 2008). They form dense kelp forests in the shallow sublittoral, supporting many species by acting as a nursery by providing a feeding ground and shelter (Nelson et al., 2015; Teagle et al., 2017).

Kelps are crucial both ecologically and socio-economically. Kelp-based habitats have been cited as some of the most ecologically rich and diverse in the world, rivalled only by tropical rainforests (Birkett et al., 1998). One of the first ecologists to recognise the importance of kelp-founded habitats to coastal ecosystems was Charles Darwin who lamented: “…I can only compare these great aquatic forests…with terrestrial ones in the intertropical regions. Yet, if in any other country a forest was destroyed, I do not believe so many species of animals would perish as would here, from the destruction of kelp.”

Many published studies have since noted the importance of kelps to coastal ecosystems (Smale et al., 2013; Brodie et al., 2014; Nelson et al., 2015; Blamey and Bolton, 2017; Teagle et al., 2017). The significance of habitat-forming kelp in coastal ecosystems was made evidently clear following its recorded decline in Alaska (Estes and Duggins 1995). The hunting of sea otters (a keystone species) started a chain reaction leading to an urchin dominated, kelp-depleted habitat of greatly reduced diversity (Estes and Duggins 1995). The productivity in these ‘barren landscapes’ has been shown to be dramatically lower in the absence of habitat-forming kelps and their associated biota (Birkett et al., 1998, Rinde et al., 2014).

Kelp forests serve as nurseries, feeding grounds and as food for a wide range of commercially important species (Tegner and Dayton 2000). A host of invertebrates, finfish, mammals, other algae, birds and epibionts rely on kelp-founded habitats for nourishment (as feeding grounds) and shelter (Mann, 1973; Teagle et al., 2017). From their holdfasts to their fronds individual structures can support thousands of invertebrate species from amphipods and decapods to polychaetes (NOAA, 2017a).

In addition, the benefits of kelp forests to coastal ecosystems exceed traditionally viewed ecosystem services and have been described as important natural barriers from hydrographic wave action (Narayan et al., 2016). Under forecasted conditions of higher sea-levels coupled with increased wave action and surges the economic
value of kelp habitats in terms of flood protection are great. It should also not be overlooked that kelp-based habitats influence tourism in many regions, recreational activities such as fishing, diving and snorkelling (Beaumont et al., 2008). The health benefits derived from interacting with nature should also not be disregarded when quantifying the socio-economic value of kelp habitats (Smale et al., 2013).

2.2 Threats to the kelp forest habitats

There are increasing reports of changes in the geographic distribution of kelp and other macroalgal species worldwide (Harley et al., 2012; Brodie et al., 2014; Yesson et al., 2015a, Krumhansl et al., 2016). As sea surface temperatures rise, cold water species are ‘moving’ toward the poles, to track more favourable conditions (Harley et al., 2012). Several possible causes have been noted as contributing to these changes in distributions, such as: climate change, invasive species and wild harvesting (Brodie et al., 2014; Yesson et al., 2015a), it has been noted that these pressures are forming a complex synergistic relationship which are compounding pressures further (Brodie et al., 2014).

2.2.1 Climate change

The northeast Atlantic has previously been described as a ‘hotspot’ for warming (Smale et al., 2013) with temperatures rising by ~0.3 – 0.8 ºC per decade (Smale et al., 2013, and references therein). Rising sea surface temperature (SST), linked with climate change, has shown association with changing distributions of large brown seaweeds in the British Isles (Yesson et al., 2015a). In the North Sea, sporogenesis (spore release and germination) has been observed to be adversely affected in Laminaria digitata at temperatures >18 ºC (Bartsch et al., 2013). Therefore, further rising temperatures will inevitably reduce reproductive potential in some populations (Bartsch et al., 2013), and result in further changes to the geographic distribution of kelps (Brodie et al., 2014).

2.2.2 Invasive species

Invasive species can enter new habitats through a number of pathways, for example as ‘stowaways’ in or on ships (Jueterbock et al., 2013, and references therein) or by attaching to manmade structures, such as renewable energy infrastructure in the ocean, and using them as a ‘bridge’ to travel from one location to another (Brodie et al., 2014). Shifting distributions present opportunities for newly arrived non-native species to colonise areas previously occupied by native species (Epstein et al., 2017). Although not every invasive species leads to ecosystem change, as demonstrated by Undaria pinnatifida in the NE Atlantic (Epstein et al., 2017), invasive macroalgal species do have the potential to disrupt and (or) alter functioning at a local and ecosystem level.
2.2.3 Wild harvesting

Wild harvesting of macroalgae has been occurring for hundreds of years (MacMonagail et al., 2017, Buschmann et al., 2017), but due to increased demand, the harvesting of seaweeds from the wild is growing at a rate of 5.7% per annum worldwide (Netalgae, 2017), with an estimated value of US$ 5.65 billion annually (MSC, 2017a). Kelps are currently harvested for a number of different uses such as alginates (Vea and Ask, 2011), biofuels (Araújo et al., 2016), food and cosmetics (Bouga and Combet, 2015). The more recent increase in demand and subsequent production of kelp has resulted in a collaborative effort from the Marine Stewardship Council (MSC) and the aquaculture stewardship council (ASC) to produce a best practice guide for the harvesting of wild kelp resources (MSC, 2017b). However, in the absence of a rapid-assessment tool, wild kelp resources are without accurate baseline information to inform harvesting standards.

Finally, threats to genetic potential should be considered relative to wild harvesting. “Genetic diversity represents the essential evolutionary potential for species to respond to changing environments” (Valero et al., 2011). Climate change and fragmentation of habitats associated with wild harvesting have the potential to negatively impact the genetic health of kelps (Barker et al., 2017). Selected populations of Laminaria digitata have demonstrated ‘healthy’ levels of genetic diversity, however further rises in SST will escalate marginality, restricting gene flow and genetic variation (Barker et al., 2017). Furthermore, wild harvesting and exploitation of resources reduces both the size and distribution of wild populations, as well as fragmenting habitats (Valero et al., 2011), leading to reduced genetic health, reduced evolutionary potential and a reduced ability for a population to respond to environmental change.

2.3 Remote sensing techniques for monitoring kelp

Remote sensing is defined as the: “observation of a target by a device separated from it by some distance” (Barrett and Curtis, 1976). Remote sensing offers an alternative monitoring technique to traditional ground survey methods which tend to be irregular and labour intensive (Yesson et al., 2015b). This is particularly true for kelp where its typically inshore location in the shallow, infralittoral fringe of rocky shores can hinder traditional monitoring efforts. Remote sensing technologies allow the detection and mapping of habitats on a much greater geographic scale with reduced labour and cost, compared to traditional monitoring methods. A number of remote sensing technologies have been applied to submerged macroalgae for monitoring purposes, for example; Satellite (Casal et al., 2011) and aerial imagery (Uhl et al., 2016), underwater imagery (Šaškov et al. 2015), LiDAR (Light detection and ranging) (Zavalas et al., 2014) and Sonar (Sound navigation and ranging) (McGonigle et al., 2011; Young et al., 2015). These listed techniques have achieved varied levels of success, but importantly, they have only been tested on an ad hoc
basis and a standardised monitoring protocol requires development and testing before large-scale monitoring efforts can begin.

2.4 Objectives

This study aims to: i) demonstrate the feasibility of using readily available multibeam sonar data to establish baseline information of kelp distribution, and ii) show how these data can be used to perform on-going monitoring. To achieve this goal we used a combination of multibeam sonar data and species distribution modelling to predict and map kelp distribution and abundance along a 20 km stretch of the southern English coastline.

3. Methodology

3.1 Choosing study sites

Study sites needed to satisfy a number of criteria to be considered for assessment. Firstly, potential sites were identified in terms of accessibility, then, using the NBN National Biodiversity Network (NBN) gateway (https://nbnatlas.org/), each potential survey site was examined for historical records of Laminariales. If these first criteria were satisfied, the United Kingdom Hyrdographic Office (UKHO) portal was used to determine whether multibeam sonar data was available for selected potential study sites.

Unprocessed multibeam sonar data, provided by UKHO (after special request), was assessed for its spatial coverage, specifically how close to the shoreline were data available. Importantly, the .gsf raw sonar data files were checked to determine if they contained backscatter information (required to aid classification of kelp). Sonar backscatter is defined as: “the amount of acoustic energy being received by the sonar after a complex interaction with the seafloor” (NOAA, 2017b). These acoustic reflectance properties are dependent on both the substratum and seabed vegetation. Two ground truthing sites were selected based on availability of appropriate sonar data, historical observations of kelp and accessibility by kayak. See Figure 1 for study area and ground-truthing sites visited during this study.
3.2 Ground-truthing

All remotely sensed data require verification via ground-truthing (Humborstad et al., 2004; Ehrhold et al., 2006). For our study, ground-truthing was carried out in order to gain training data (presence/absence of kelp) for the predictive model. In May and August 2017 field surveys were carried out at Lulworth Cove, Dorset and Kimmeridge Bay, Dorset respectively. Kayaks and a GoPro™ camera with underwater housing were used to capture footage of the seabed. The video camera was lowered from the kayak on a rope or pole until it reached the seabed. Footage was captured at regular intervals along a predetermined transect line, designed to cover areas where kelp was known to be present and absent. A GPS was used to record the survey track-line. Every instance the camera was re-deployed from the kayak, it was time-stamped by recording the time and GPS co-ordinates.

Ground-truth data were graded into two classes: 1) presence of kelp, 2) absence of kelp. Presence was based on c. >30% coverage of kelp in the video footage frame. Therefore, other macroalgal species and areas of ‘patchy kelp’ were classified as absence (Fig. 2).
3.3 Data processing

Raw sonar data files (.gsf format) were acquired from the UKHO. These required processing before they could be used to produce bathymetry and bathymetric derivative environmental layers. Processing was achieved using MB-system™ multibeam sonar processing software. Following the methods outlined in the MB-system ‘cookbook’ (Schmidt et al., 2006) data files were ‘cleaned’ by flagging and removing ‘bad beams’. MB-system was then used to correct for the angle of incidence, roll bias etc., explained in detail in the MB-System cookbook (Schmidt et al., 2006). Following processing, MB-system was used to produce raster grids of bathymetry and backscatter which could then be manipulated and interrogated in other software i.e. GIS (geographical information systems) or R.

Quantum GIS™ was used to interrogate raster layers. Firstly, bathymetric derivatives (slope and roughness) were produced. Another bathymetric derivative, fractal dimension was constructed in R using the ‘fractaldim’ package. The processing with MB-system output raster grids with a resolution of 2.25 x 2.25 m, environmental layers: slope, roughness, backscatter and fractal dimension were coarsened to 5 x 5 m grids using the aggregate function in QGIS with GRASS v7.2.0 (Table 1 and Fig. 3).
3.4 Species distribution modelling

These topographic and acoustic GIS layers were used, alongside ground-truthing data, to predict the distribution of Kelp along the Dorset coastline (Fig. 3).

The R package the 'Biomod2' (Thuiller et al., 2016) was used to create a Generalised Boosting Model (GBM) for kelp prediction. The GBM algorithm combines the strengths of regression trees and gradient boosting to increase prediction performance (Elith et al, 2008). The result is a gridded map of the study area detailing kelp habitat suitability (used as a prediction of presence/absence). Using 'Biomod2' in R the GBM model was trained using ground-truthing data and subsequently used to predict kelp distribution along a segment of the Dorset coast. Model outputs were exported as geotiff raster grids (.tiff format). Predicted kelp distribution along a ~20 km stretch of the Dorset coastline was mapped in Quantum GIS.

Table 1. Environmental layers produced from multibeam sonar data, used to predict kelp distribution and abundance.

<table>
<thead>
<tr>
<th>Environmental layer</th>
<th>Description</th>
<th>Production</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope</td>
<td>The slope can be described as the incline or steepness of the seafloor. Slope can be measured in degrees, or percent slope.</td>
<td>QGIS Digital Elevation Model (DEM) - Terrain analysis</td>
</tr>
<tr>
<td>Roughness (TRI or TPI)</td>
<td>Roughness or Topographic ruggedness index or topographic position index is a measure of elevation with reference to the overall landscape.</td>
<td>QGIS Digital Elevation Model (DEM) - Terrain analysis</td>
</tr>
<tr>
<td>Fractal Dimension</td>
<td>Fractal dimension is a measure of 'surface complexity', in this case, of the seafloor.</td>
<td>R using the 'fractaldim' package</td>
</tr>
<tr>
<td>Backscatter</td>
<td>Backscatter is defined as the amount of acoustic energy received by the sonar device after a complex interaction with the seafloor.</td>
<td>MB-System using 'mbgrid'</td>
</tr>
</tbody>
</table>
Figure 3. Bathymetry, backscatter intensity and bathymetric derivatives: slope, roughness and fractal dimension, derived from raw MBES data from the UK Hydrography office. Environmental layers (backscatter, slope, roughness and fractal dimension) were used to model kelp distribution and abundance. CRS: OSBG 1936 / British National Grid.
4. Predictive modelling of kelp in Dorset

The generalised boosting model predicted kelp distribution for an area of ~35 km\(^2\) of the Dorset coast (Fig. 5). Four class boundaries were set to visualise relative abundance of kelp (Fig. 4). The generalised boosting model produces a ‘likelihood of occurrence’ between 0-1000, the class boundaries were set at equal intervals, 0-250 was assigned absent, 250-500 was assigned the status ‘low’, 500-750 ‘medium’ and 750-1000 was assigned a classifier of ‘high’ (Fig. 5). The majority of kelp predicted fell into either medium or low class boundaries, and nearly 50% of the survey area fell into the absent class boundary (Fig. 4).

Model evaluation is presented in Table 2. The true skill statistic TSS was 0.774 and area under the curve statistic (AUC) was 0.893. These are considered ‘good’ performance values (Hodd et al. 2014).

![Figure 4](image)

**Figure 4.** Proportion (%) of kelp predicted across the entire survey area ~35 km\(^2\), absent (17.2 km\(^2\)), low (8.3 km\(^2\)), medium (6.4 km\(^2\)), high (3.4 km\(^2\)).

The model output was also evaluated against ground-truthing information obtained from site visits. Presences and absences in ground-truthing data were compared to the respective scores from the model output (Table 2). Firstly, comparing the ground-truth presence points, 31 out of 34 (91.2 %) presence points were correctly classified as presence areas by the model. The rest of the ‘presence’ points fell into the 3 abundance classifiers, low (5), medium (10) and high (16). In addition, the ‘absence’ ground-truth data produced a similar evaluation, 83.9 % of ground-truth points fell within absence class boundary areas in the model output, with 52 of 62 points correctly predicted as absent of kelp.
Figure 5. Predicted distribution of kelp across the entire study area, A: Lulworth Cove, B: Kimmeridge Bay. Colour represents the relative kelp abundance predicted using a generalised boosted model. Presence (white circle) and absence (black diamond) of kelp, confirmed by ground-truthing is also shown. CRS: OSBG 1936/British National Grid
Table 2. Evaluation of the generalised boosting model (GBM), TSS (true skill statistic) = 0.774 and AUC (area under curve) = 0.893. Ground-truthing agreement with the model is also shown, where presence and absence recordings have been compared with the model output.

<table>
<thead>
<tr>
<th>Ground-truth ↓</th>
<th>Absent</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Total % correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Present</td>
<td>3</td>
<td>5</td>
<td>10</td>
<td>16</td>
<td>91.20</td>
</tr>
<tr>
<td>Absent</td>
<td>52</td>
<td>5</td>
<td>5</td>
<td>0</td>
<td>83.90</td>
</tr>
</tbody>
</table>

4.1 Importance of backscatter information

Multibeam backscatter is a critical component of the model, and has been shown elsewhere to be vital to the correct identification of aquatic vegetation using multibeam sonar (Brown et al., 2011), as well as for seabed classification (Collier et al., 2005).

Figure 6. Using a random set of points, and ground-truth points, the model output and backscatter were sampled to show the effect backscatter is having on the model, by means of a response curve. Blue line = smoothed line of best fit, shaded area = standard error, red lines = relative abundance of kelp (<250 = absent).
To investigate the importance of backscatter for our model, a model was re-run without the backscatter layer as input. When the model is used with backscatter information there is good model performance, TSS = 0.774 (good) and AUC = 0.893 (good), in contrast, without backscatter, performance is poorer, TSS = 0.524 (fair) and AUC = 0.726 (fair). This contrast in model performance highlights its importance for monitoring and mapping. The model indicates that kelp presence is associated with backscatter in the range of 22-26dB (Fig. 6).

The values derived from the backscatter layer can vary depending on vessel, device and even settings used (Welton, 2014). This issue was encountered when attempting to expand the monitored area. Different sources of backscatter produced very different (and apparently unrelated) values (Fig. 7). It proved difficult to reconcile these different backscatter datasets, which limits the current study area to regions covered by the same survey device & vessel. Correction or harmonisation of backscatter information is required if information is going to be combined into a larger dataset, at present no standardised protocols exist for achieving this.

![Figure 7](image.png)

**Figure 7.** Relationship between two different measures of backscatter from the Dorset coast, recorded by different vessels. $R^2 = 0.4822$. Blue = regression line, shaded area = standard error.
5. Discussion

This study has shown it is possible to produce widespread predictive maps of kelp habitat using readily accessible multibeam sonar data from repeated UKHO surveys (Fig. 5). This allows the establishment of a baseline of kelp distribution and establishes an opportunity for longer term monitoring of habitats. The acoustic reflectance property 'backscatter' was shown to be an important component for producing robust predictions, which agrees with studies for other marine habitats (Brown et al. 2011, and references therein). This presents two issues for the wider applicability of these methods for monitoring UK kelp. Firstly, backscatter data is not routinely collected by UKHO, and secondly backscatter measures collected by different devices/vessels may not be comparable.

Currently backscatter information is not routinely collected or stored by UKHO. Given that backscatter is a component of multibeam surveys, it is a question of ensuring routine and consistent storage procedures. However, given the issues analysing backscatter from different sources (Welton, 2014), there must also be an effort to standardise collection if widespread consistent datasets are to be compiled. Backscatter intensity can vary in scale and range due to a number of factors, including: echo-sounder device and vessel, and has even been shown to vary somewhat between survey days (Welton, 2014). For our study, backscatter measurements from outside of the study area varied greatly in scale and range to measurements gathered inside the study area. No clear relationship was evident between the backscatter data available from different vessels, therefore the solution to this problem may simply lie in a standardised data collection protocol to ensure data are collected using the same devices and (or) settings.

Baseline information is required to accurately inform harvesting standards (Yesson et al., 2015b). Despite some issues encountered, this study presents a promising method for assessing kelp habitat distribution around the English shoreline, using data from existing surveys. As MBES surveys are routinely repeated it presents an opportunity for monitoring these habitats. Using multibeam surveys could be a cheap, rapid and most importantly: transferrable, monitoring method regardless of taxa and geographic region.
6. Conclusions and recommendations

- Kelp distribution and abundance was predicted along 35 km² of the UK coastline using MBES and species distribution modelling, and model success relied heavily on the presence and quality of backscatter information.
- Baseline information of kelp distribution and abundance is required to inform sustainable harvesting of wild kelp resources.
- An enormous amount of remote sensing data are readily available (including multibeam sonar data) for large regions of the world’s oceans, particularly in the northeast Atlantic (https://maps.ngdc.noaa.gov/viewers/bathymetry/). These data, which are regularly updated as monitoring continues and remote sensing technologies evolve, offer exciting avenues for habitat mapping and monitoring.
- Backscatter information varies between echo-sounder device and settings used. Standardised backscatter data collection is required to allow harmonization of multibeam backscatter information, delivering successful classification of kelp habitats.
- For more accurate estimates of both distribution and abundance of kelp habitats, efforts could be taken to ensure bathymetric surveys are carried out as close to the shoreline as feasibly and systematically possible, giving maximum possible coverage of MBES data and reducing the likelihood of underestimating kelp abundance.

7. Acknowledgements

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8. References


urchin distribution in previously and still grazed areas in the NE Atlantic. PloS one, 9 (6), p.e100222.


