Assessing the impact of introduced infrastructure at sea with cameras: A case study for spatial scale, time and statistical power

Anthony W.J. Bicknell, Emma V. Sheehan, Brendan J. Godley, Philip D. Doherty, Matthew J. Witt

1. Introduction

The marine coastal environment provides a major, and disproportionate, contribution to global ecosystem services (Costanza et al., 1997; Drakou et al., 2017; Liquete et al., 2013). Through human activity (e.g. commercial fishing, shipping, resource extraction, aquaculture, dredging) it has, however, become the most impacted region of our global seas (Halpern et al., 2008). A growing coastal population is expected to increase human pressure on coastal regions with further potential adverse effects on natural systems (Heery et al., 2017; Millennium Ecosystem Assessment, 2005; Neumann et al., 2015).

Coastal benthic habitat has been particularly altered by destructive fishing practices (Elgaard et al., 2015; Hiddink et al., 2017) and the introduction of artificial infrastructure (Bulleri and Chapman, 2010). The loss or disturbance of benthic habitats is concerning as they play a pivotal role in the provision and support of key ecosystem services, e.g. food provision, nutrient cycling, reproduction/nursery areas, water quality, biodiversity maintenance (Galparsoro et al., 2014). The expanding marine renewable energy sector has led offshore wind farms to become a prominent part of coastal and shelf waters of multiple countries (GWEC, 2016; WindEurope, 2017). These installations have direct impact on benthic habitats (i.e. monopile drilling and foundations), and subsequent direct or indirect effects on the associated epi-benthic faunal communities (Bailey et al., 2014; Gill, 2005; Inger et al., 2009; Pearce et al., 2014; Stenberg et al., 2015). The promise of wave and tidal energy conversion is still to be fully realised, but has the potential to further modify benthic habitats around our coastlines (Langhammer and Wilhelmsson, 2009; Witt et al., 2012). Unfortunately, the monitoring programs and environmental impact assessments (EIA) that have considered interactions between marine renewable energy installations (MREIs) and benthic habitats or species have, so far, lacked the necessary baseline characterisation or survey rigour (spatially or temporally) to robustly assess impact (positive or negative) (Boehlert and Gill, 2010; Fox et al., 2018; Wilding et al., 2017), and led authors to...
term this situation as ‘data rich, information poor (DRIP)’ (Fox et al., 2018; Ward et al., 1986; Wilding et al., 2017).

The high energy environment needed for marine energy converters to operate means they are well suited to mid to high latitude seas where these conditions regularly occur. The required strong winds, wave action and/or large tides provide physical challenges to access development sites and conduct surveys to assess impact on benthic communities, which are in addition to the inherent difficulties of underwater research. Remote camera imagery is a technique that can overcome some of these challenges, and has already proven a valuable tool for studying the impact of human activities on the marine environment (Bicknell et al., 2016; Mallet and Pelletier, 2014; Sheehan et al., 2014). Baited Remote Underwater Video systems (known as ‘BRUV’) are a method that uses either one (mono) or two (stereo) cameras to film the area surrounding a bait attractant held a short distance from a video camera and close to the seabed (also modified for mid-water; Heagney et al., 2007). The technique has been used extensively in the southern-hemisphere (tropics to temperate) to evaluate changes in demersal fish populations (e.g. Denny et al., 2004; Malcolm et al., 2007; Watson et al., 2009; Watson et al., 2007), and has demonstrated its value in sampling fishes and invertebrates in high latitude turbid coastal waters in the northern-hemisphere (Elliott et al., 2017; Unsworth et al., 2014). Recently, the method has also shown its application in assessing the mobile epi-benthic fauna at an offshore wind farm in the Irish Sea (Griffin et al., 2016), but as yet not in multi-season or multi-year impact studies. The method has bias (e.g. differentially attracting carnivores or omnivores, bait type and plume effects, restricted view, light attraction/repulsion), as do most survey methods, and these have been investigated and detailed elsewhere (Dorman et al., 2012; Harvey et al., 2007, 2012, 2018; Stobart et al., 2007). However, it has advantages on many traditional methods, such as being non-destructive, having no or limited observer bias, allowing re-analysis or review of video (data) and is unrestricted by depth (cost-dependent) (Cappo et al., 2004; Lowry et al., 2012; Whitmarsh et al., 2016; Zintzen et al., 2012). When BRUVs are used to provide an estimate of species abundance, a number of metrics have been considered (Stobart et al., 2015), but in the vast majority of cases (81% of reviewed studies, Whitmarsh et al., 2016) \( N_{\text{max}} \) (or MaxN) is used. This represents the maximum number of a particular species seen in any one video frame across the duration of the video footage. It is a useful metric to assess the relative abundance of species and considered a conservative estimate as there may be uncounted individuals around the BRUV that did not enter the field of view (Whitmarsh et al., 2016).

For monitoring programs to effectively assess environmental impact they require baseline data that characterise the natural spatial and temporal variability of the focal system or component (Judd, 2012). The challenges are then to detect the potential effect of the introduced impact from the natural ‘background noise’ (variability) (Osenberg et al., 1994), and recognize whether any detected change is biologically, ecologically or functionally meaningful (Wilding et al., 2017). In highly variable marine systems it is particularly important to determine the level of sampling effort required to gather robust baseline data and provide statistical power to detect a given degree of change (Franco et al., 2015; Osenberg et al., 1994). Ideally, prior or pilot data would be available to provide knowledge on variability within the system and enable a power analysis to be conducted, but these data are rarely available or analyses conducted (Franco et al., 2015; Maclean et al., 2014). Surveys will often be based on applying fundamental statistical principles to the design (Box 1), balanced with time, costs and logistical or methodological constraints. Many environmental impact studies focus on site characterisation during one or two years as opposed to deploying bespoke survey strategies designed to identify putative effects with anticipated levels of change in environmental receptor groups.

<table>
<thead>
<tr>
<th>Effects of design and data on statistical power</th>
</tr>
</thead>
<tbody>
<tr>
<td>The ability to detect patterns/change reduces = variance = power</td>
</tr>
<tr>
<td>Parameter estimates become more precise with = estimate precision = power</td>
</tr>
<tr>
<td>larger samples, thus differences between = estimate precision = power</td>
</tr>
<tr>
<td>estimates are easier to detect amongst the = power</td>
</tr>
<tr>
<td>‘noise’</td>
</tr>
<tr>
<td>As the effect of the impact increases the more = effect size = power</td>
</tr>
<tr>
<td>likely it is to be detected. i.e. a 40% change</td>
</tr>
<tr>
<td>in a parameter estimate is more likely</td>
</tr>
<tr>
<td>to be detected than 20% change</td>
</tr>
</tbody>
</table>


Here, we present a case study of BRUV use over five years in boreal latitude coastal waters of the northeast Atlantic to provide baseline characterisation data and impact assessment on mobile epi-benthic species at a MREI. We use these data to investigate the power to detect change in conventional ecological metrics (species richness, abundance, and assemblage composition), how well a survey design and sampling effort performs given there was little prior ecological knowledge of the site, and whether any effects on the mobile epi-benthic community could be detected. We consider the appropriateness of this technique for long-term impact monitoring at MREI, and, more generally, discuss the results in relation to future EIAs of mobile epi-benthic communities.

2. Materials and methods

2.1. Study location

Baited remote underwater video (BRUV) surveys took place off the north coast of Cornwall (UK) between 2011 and 2015. The study was located within and adjacent to a MREI development zone (Wave Hub) and the associated seabed cable (Fig. 1a). Study zones ranged between 3 and 10.5 nautical miles (5.6 and 19.5 km) offshore in water depths of 20–53 m (at Lowest Astronomical Tide). The seabed cable and marker buoys (6 in total) for the development zone were installed in autumn 2010. The cable was buried when on sand (near shore) and covered with 80,000 tonnes of rock (creating a berm of 0.3 m minimum height) and concrete matressing every 120 m when laid on hard substrate (deeper water). Access within 500 m of the electrical seabed hub (plug) was prohibited, but access was permitted elsewhere. The presence of marker buoys has prevented commercial mid-water or bottom trawling for fish. The only commercial fishing that has taken place in the development zone or close to the seabed cable since installation is crustacean potting. There were no connected deployments of operating marine energy devices during the period of the study.

2.2. Sampling equipment

Each BRUV consisted of an aluminium frame, wide-angle lens housing and white light LED lighting system (Fig. 1b). An aluminium pole was attached to each BRUV to support bait (fixed 1 m from lens); lead weights (45 kg) were fastened to the frame for deployment and stability over a wide range of tidal conditions (0.02–0.53 m). Panasonic HDC-SD60 and HDC-SD80 camcorders were used to gather video data. A temperature depth recorder (RBR, Nova Scotia, Canada) was attached to one BRUV in each sampling location during a sampling campaign. Local small commercial leisure or fishing vessels were used for BRUV deployment.

2.3. Survey design

BRUV surveys were scheduled twice per year, in spring and autumn,
commencing in autumn 2011 until 2015, and each survey campaign
took three days to complete. The sampling design consisted of: two
study zones (Wave Hub = WHSZ and Cable Route = CRSZ); three
areas (1 × Wave Hub, 2 × Cable Route); each area comprised 8 locations
(four project and four reference 1 km apart; Fig. 1a). Three replicate
BRUVs were deployed between 105 and 180 m (mean ∼130 m) apart in
each location (Fig. 2). Project locations were either inside the Wave
Hub exclusion zone or on/next to the seabed cable infrastructure
(Fig. 1a). Treatment will be used as the term to describe the comparison
between project and reference locations in the subsequent analyses
and models. BRUVs were deployed for up to 60 min during daylight
hours. Bait used was a single Atlantic mackerel Scomber scombrus
for each deployment, cut into three piece and held in a net bag (∼100 g).

In order to investigate the BRUVs greatest distance of attraction (in
metres) for teleosts, we calculated the ‘effective range of attraction’
(AR) (formulised in Cappo et al., 2004; see Appendix S3) for increasing
soak time (i.e. time cameras are in the water, or video footage analysed
from the start). The average seabed current speeds (data from POLPRED
seabed CS20 models, NOC; http://www.pol.ac.uk/) during BRUV
deployments (0.23 m s−1), and a maximum fish (endurance) swimming
speed of 0.6 m s−1 (∼200–300 mm fish length) were used as the AR
parameters \(V_c = \text{current speed, } V_f = \text{maximum fish speed}\). 

2.4. Image analysis

Gathered video datasets were analysed (using a large monitor) to
quantify species observed, the number of mobile epi-benthic species
(richness; \(S\)), the maximum number of individuals of each species ob-
served at the same time (\(N_{\text{max}}\)) and the time of each increment in \(N_{\text{max}}\)
(recorded in excel spreadsheets). The use of \(N_{\text{max}}\) as an estimator of
relative abundance has been assessed (Cappo et al., 2003; Ellis and
DeMartini, 1995; Priede et al., 1994; Willis and Babcock, 2000), and is
considered a conservative estimate of abundance especially when spe-
cies occur at high density. Each video dataset was assigned a habitat
type (1-rocky reef, 2-large sediment [small boulders], 3-medium sedi-
ment, 4-fine sediment; see Appendix S2 for habitat assignment details),
visibility (good [can see beyond end of pole] or poor [could not see
beyond end of pole]) and camera frame position (vertical or hor-
izontal).

2.5. Data analysis

Data on all mobile species were used in the following \(S\) analyses but
only teleosts were used in the \(N_{\text{max}}\) analyses. To remove the influence
of extremely high abundance values, the teleost \(N_{\text{max}}\) data were trimmed
at the 95th percentile (eliminating 3 data points). Extreme abundance
values were related to large fish shoals that were rare and not in-
formative for the purpose of determining subtle and consistent change
in species abundance.

2.5.1. Species accumulation
To examine the effect of BRUV deployment time on \(S\) and \(N_{\text{max}}\),
species and abundance accumulation curves were created for the Wave
Hub and Cable Route (project and reference location data pooled). To
investigate the potential effect of habitat, species and abundance ac-
cumulation curves were created with all data pooled for habitat types;
rocky reef and large sediment (termed RRLS), and medium (gravel) and
fine sediment (sand) (termed GS). These curves were used to determine
an optimum balance between the number of available comparative
video datasets and their recording duration (minutes) to be included in
subsequent analyses. All conducted in R version 3.4.4 (R Development
Core Team, 2011).

2.5.2. Statistical power, effect and sample size
Power analyses were conducted using the SIMR package (Green and
MacLeod, 2016) in R version 3.4.4 (R Development Core Team, 2011)
Table 1
Number of species and individuals by taxonomic phylum on BRUV footage at the Wave Hub and Cable Route study zones. The percentage of total species and individuals is shown in italics.

<table>
<thead>
<tr>
<th>Phylum</th>
<th>Wave Hub Study Zone</th>
<th>Cable Route Study Zone</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of species</td>
<td>% of total species</td>
</tr>
<tr>
<td>Arthropod</td>
<td>1</td>
<td>2.00</td>
</tr>
<tr>
<td>Crustacean</td>
<td>13</td>
<td>26.53</td>
</tr>
<tr>
<td>Echinoderm</td>
<td>6</td>
<td>12.25</td>
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<tr>
<td>Elasmobranch</td>
<td>3</td>
<td>6.12</td>
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<tr>
<td>Mollusc</td>
<td>5</td>
<td>10.20</td>
</tr>
<tr>
<td>Teleost</td>
<td>21</td>
<td>42.86</td>
</tr>
</tbody>
</table>

Total: 49 1992 42 3448

to investigate the relationships between the number of samples (sample size), the size of change (effect size) and the probability to detect change (power) in \( S \) or \( N_{\text{max}} \).

Generalised linear mixed effect models were fitted to data (pooled data with years combined) collected in spring at the WHSZ and CRSZ (separate models) using the lm4 package (Bates et al., 2015). Only spring data were used in the models to remove seasonal effects (evidenced in PERMANOVA models; Tables 3a & 3b), which may increase variability in the data and influence the power to detect change. (Step 1) The Poisson error models contained year and treatment as fixed effects and treatment within location as a nested random effect. The effect parameters from these models were used to build new simulation models with the same structure (i.e. effects and error) but replicated a complete annual survey design for each study zone (i.e. no loss of samples). (Step 2) Monte Carlo simulation was then utilised to generate values for the response variable \( S \) or \( N_{\text{max}} \) of each model (1000 runs & seed = 1234). (Step 3) Power curves were generated for a range of effect sizes to explore the trade-off between sample size and power. (Step 4). To examine inter-annual variation the steps detailed above (1–3) were repeated for separate years (WHSZ = 4 years, CRSZ = 3 years) for effect sizes where the pooled data model reached or exceeded 0.8 power. All analyses were conducted using an \( \alpha \) < 0.05 threshold.

2.5.3. Species richness, abundance and assemblage composition

Permutational multivariate and univariate mixed effect models (PERMANOVA+) were used in the software package PRIMERv6 (Anderson, 2001; Clarke and Warwick, 2001) to test potential effects of the Wave Hub exclusion zone and the cable rock armouring (Cable Route) on assemblage composition (a community structure measure incorporating both diversity and abundance), species richness \( (S) \) and abundance \( (N_{\text{max}}) \).

2.5.4. Between study zones

Models using the complete dataset were run to compare assemblage composition and \( S \) between study zones (WHSZ & CRSZ). Factor zone was fixed, with year, season, location, and treatment nested in location as random.

2.5.5. Within study zones

For each study zone (WHSZ & CRSZ), models for \( S \) and assemblage composition were performed on the complete species dataset, and all three response variables for two defined species guilds; teleost and crustacean. The factors year and treatment were fixed, and season, habitat, zone (Cable Route only; 2 zones) and treatment nested in location were random. The factor year had four and five levels for the CRSZ and the WHSZ respectively. The factor treatment had two levels (WHSZ or CRSZ project, and reference). Depth and current speed (tide indicator)
Table 3
PERMANOVA results for all species assemblage, richness (S) and teleost species relative abundance ($N_{\text{max}}$) models for the Wave hub (a) and Cable Route (b) study zones. Fixed effects are non-italicized and random effects italicized. Significant permutation p-values below the 0.05 level for fixed effects and interactions are shown in bold.

(a) Wave Hub study zone

<table>
<thead>
<tr>
<th>Source</th>
<th>d.f.</th>
<th>MS</th>
<th>Pseudo-F</th>
<th>P(perm)</th>
<th>MS</th>
<th>Pseudo-F</th>
<th>P(perm)</th>
<th>MS</th>
<th>Pseudo-F</th>
<th>P(perm)</th>
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</thead>
<tbody>
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<td>Year</td>
<td>4</td>
<td>9525.1</td>
<td>2.6593</td>
<td>0.0838</td>
<td>1.2691</td>
<td>0.1155</td>
<td>4.6522</td>
<td>16.404</td>
<td>0.1225</td>
<td></td>
</tr>
<tr>
<td>Treatment</td>
<td>1</td>
<td>3424.5</td>
<td>0.7086</td>
<td>0.6604</td>
<td>0.00532</td>
<td>0.1248</td>
<td>0.7077</td>
<td>2.2460</td>
<td>1.5607</td>
<td>0.2674</td>
</tr>
<tr>
<td>Season</td>
<td>1</td>
<td>3532.5</td>
<td>2.2758</td>
<td><strong>0.0207</strong></td>
<td>0.06245</td>
<td>0.7359</td>
<td>0.4073</td>
<td>0.2483</td>
<td>0.2947</td>
<td>0.5889</td>
</tr>
<tr>
<td>Habitat</td>
<td>3</td>
<td>5229.8</td>
<td>2.9543</td>
<td><strong>0.0001</strong></td>
<td>0.54909</td>
<td>6.9326</td>
<td><strong>0.0007</strong></td>
<td>1.8946</td>
<td>2.2991</td>
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<tr>
<td>Location(Treatment)</td>
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<td>4125.6</td>
<td>3.0025</td>
<td><strong>0.0001</strong></td>
<td>0.14502</td>
<td>2.1285</td>
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<td>1.2010</td>
<td>1.5015</td>
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<td>Year x Treatment</td>
<td>4</td>
<td>1930.3</td>
<td>1.4048</td>
<td>0.0759</td>
<td>0.23181</td>
<td>3.4023</td>
<td><strong>0.0136</strong></td>
<td>1.2459</td>
<td>1.5576</td>
<td>0.1913</td>
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<tr>
<td>Pooled terms</td>
<td>71</td>
<td>1374.1</td>
<td>0.06813</td>
<td>0.7999</td>
<td></td>
<td></td>
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Pair-wise test for Year x Treatment:

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<tr>
<th>Year</th>
<th>t</th>
<th>P(perm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011-2012</td>
<td>2.7615</td>
<td>0.0185</td>
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<tr>
<td>2011-2013</td>
<td>1.6244</td>
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<td>2011-2014</td>
<td>3.9172</td>
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<td>2011-2015</td>
<td>2.4403</td>
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<td>2012-2013</td>
<td>10.346</td>
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<td>2012-2014</td>
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<td>2013-2015</td>
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<td>2014-2015</td>
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(b) Cable Route zone

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<th>Pseudo-F</th>
<th>P(perm)</th>
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<tr>
<td>Year</td>
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<td>2.5807</td>
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<td>1.1766</td>
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<tr>
<td>Location(Treatment)</td>
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Pair-wise test for Year x Treatment:

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<th>Year</th>
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<th>P(perm)</th>
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<td>2013-2014</td>
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</tbody>
</table>

Reference

2011-2012: 1.2666 | 0.1783
2011-2013: 1.2847 | 0.1559
2011-2014: 2.1578 | 0.0007

(continued on next page)
were considered as environmental co-variates in initial models for each study zone but where removed when found not to influence models. Species $N_{\text{max}}$ models were performed for four indicator taxa, family and species: elasmobranchs, echinoderms, and Pollachius spp. (Pollack & Saithe) and Cancer pagurus (edible crab) (Jackson et al., 2009). The same model structure was used as described above.

2.5.6. Between habitats

Models were also run using the complete dataset to test whether $S$, $N_{\text{max}}$ and assemblage composition differed with habitat type. Due to the low number of sampling events on fine sediment habitats ($n = 9$), making the model unbalanced, the final model contained only 3 levels (rocky reef $[n = 84]$, large $[n = 47]$ and medium $[n = 58]$ sediment) for the fixed factor habitat, with year as random.

Prior to calculation of the Bray–Curtis (Bray and Curtis, 1957) similarity index, multivariate data (assemblage composition) were dispersion weighted and square root transformed to down weight taxa with erratic abundances and/or high abundances (Clarke et al., 2006a). As joint species absences were important to consider between treatments, data were ‘zero-adjusted by adding a dummy value of 1 (Clarke et al., 2006b). Without the dummy value, Bray-Curtis would not consider samples similarly devoid of species as similar. Euclidean distance indices were calculated for univariate data ($S$ and $N_{\text{max}}$) that were Log ($x + 1$) transformed (Anderson and Millar, 2004). Each term in the analyses used 9999 permutations of the appropriate units. Significant interactions of fixed terms were tested using PERMANOVA pairwise tests. Assemblage composition was visualised using nonmetric Multi-Dimensional Scaling (nMDS).

3. Results

3.1. Sampling and image quality

The sampling regime was designed to gather data in both spring and autumn of each year (2011–2015; full survey design = 720 deployments) to examine the potential effects of season, but due to poor weather conditions in optimal tidal survey periods, the collection of data in both seasons was only possible in 2013. Autumn sampling took place in 2011 and 2013; spring sampling took place in 2012, 2013, 2014 and 2015. Due to time and budgetary constraints, no surveys could be completed in 2015 at the CRSZ, and the original survey extent was reduced by two locations (most southerly project and reference locations in each area) in 2013–2015 at the WHSZ and 2012–2014 for the CRSZ. The reduced survey effort owing to weather, time and money resulted in a potential maximum of 312 BRUV deployments, a considerable reduction (57%) from the original sampling design.

Further adverse weather during survey activity caused 15 (5%) deployments to be cancelled. Across study areas and years, 297 BRUV deployments were successfully undertaken, of which 38 (12.8%) failed due to technical reasons (e.g. battery or camera failure). Of the remaining 259 (83% of total); 141 video datasets were 60 min or longer (45% of total), 199 video datasets were 45 min or longer (63% of total), and 247 were 30 min or longer (79% of total). Once filtered for visibility (good visibility with an unobstructed view of the seabed) the number of available videos for analysis were 116 with 60 min or more (37% of total), 161 datasets with 45 min or more (51% of total), and 198 datasets with 30 min or more (63% of total) (Fig. S2).

The BRUVs effective range of attraction (AR) for a teleost of $\sim 200–300$ mm in length was $\sim 127$ m for 30 min soak time, $\sim 287$ m for 45 min and $\sim 510$ m for 60 min for our study (Fig. S3). This would indicate the replicate BRUV deployments in our study (mean $\sim 130$ m apart) may not be independent (i.e. the same individual could attend and be recorded on more than one camera) if more than 30 min video data were used. The AR calculation does not consider current or plume direction, which could influence the range of attraction shape (e.g. not cylindrical around the location, but elongated (ellipsoid/triangular) in the direction of current). This in turn could affect the ability of animals to detect bait from a second location (reduce the AR estimate in that direction) while visiting the first, if the bait plume is directed away from the first. The BRUV replicates in our study were placed in a linear manner across the prevalent NE→SW tide, mainly N→S and NW→SE (Fig. 1). The current direction and speed data for each BRUV deployment (Fig. S4) indicates the prevalent seabed currents would advect bait plume away from other replicate locations rather than towards them, suggesting it would be more difficult for an animal to detect bait from a second location and subsequently move to it. When 30 min video data were analysed for spatial auto-correlation (Moran’s I) using teleost and elasmobranch abundance for each study zone, year and season, the only significant auto-correlation was found for teleost in 2012 (2 out of 17 tests; Table S1). When the data for 2012 were investigated further, the effect was likely caused by large aggregations of Trisopterus minutus counted on all three replicate BRUVs at locations in each study zone in this year. This is a small ($\sim 100–200$ mm) benthic species, so their ability to attend two or three BRUVs (linearly $\sim 130$ or 260 m apart) would be unlikely given the AR and current data, and the clustering (auto-correlation) would seem more likely a representation of high abundance at all these locations during that time. Given these analyses it was considered that species and abundance data gathered from 30 min video data would be independent for teleost and the (relatively) small elasmobranch species in our study.

3.2. Species accumulation

The maximum number of species identified during video datasets lasting 60 min was 12. The mean number of species occurring on RRLS habitats was 6.8, while for GS it was 5.3 (Fig. 3a and c). Mean $N_{\text{max}}$ was greater for RRLS habitats (maximum of 132 individuals) compared to GS habitats (maximum 38 individuals) (Fig. 3b and d). In both habitats, 75% or more of the total $S$ and $N_{\text{max}}$ (at 60 min) was achieved after 30 min, with the greatest increase in number of species and abundance

<table>
<thead>
<tr>
<th>Source</th>
<th>d.f.</th>
<th>MS</th>
<th>Pseudo-$F$</th>
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</table>

Table 3 (continued)
3.3. Optimal data

Data from the first 30 min of BRUV footage were considered optimal for use in further analyses as this soak period balanced sample size, coverage (study locations and years), effective range of attraction, with available species and abundance information (accumulation curves).

3.4. Species diversity and taxonomic composition

A total of 67 species from 46 families and 6 phyla were observed on the BRUV footage across the two study zones for the survey period. This equated to 5440 individual animals, the vast majority of which were fishes (∼73%). The WHSZ was more speciose (49 species) compared to the CRSZ (42 species), but total abundance was higher in the latter with > 3400 individuals (Table 1).

3.5. Statistical power, effect and sample size

Models with pooled spring data (years combined) revealed the minimum change that could be detected with 0.8 (or more) power was ∼10% in richness for both WHSZ and CRSZ, which would require ≥200 samples (∼100 within each project and reference). The samples required to detect 20% change in S reduce to ∼40–50 (∼20–25 within each project and reference) for both WHSZ and CRSZ (Fig. 4a and c sub plots). For N\text{max}, the minimum change detectable was ∼50% at the WHSZ (Fig. 4b sub plot), which required ≥100 samples (∼50 within each project and reference). The 0.8 power threshold was not reached for any level of change in N\text{max} using pooled spring data from the CRSZ, and the power to detect 50% change did not exceed 0.4, no matter the sample size (Fig. 4d sub plot).

There was considerable variation among years when data were analysed separately for 20% (S) and 50% (N\text{max}) effect size models (detailed above; Fig. 4). The sample size required to detect a 20% change in S at WHSZ with 0.8 power ranged from ∼40 to > 400 samples (Fig. 4a) and ∼40 to 60 samples for the CRSZ (Fig. 4b). Teleost N\text{max} model outputs revealed the majority of years (2 of 4 at WHSZ; 2 of 3 at CRSZ) had low power (< 0.7) to detect 50% change, independent of sample size. At the WHSZ, 2014 data were modelled to achieve > 0.8 power with ∼150 samples (∼75 within project and reference), and 2013 data would achieve this level with ∼1700 samples (∼850 within project and reference) (Fig. 4c). The only data to achieve 0.8 power to detect 50% change in N\text{max} at CRSZ was for 2012, which would require ∼200 samples (100 within project and reference) (Fig. 4d).

3.6. Assemblage, species richness and abundance analyses

3.6.1. Comparison between study zones

Assemblage composition and species richness (S) models revealed significant differences between study zones (P\text{(perm)} = < 0.001; Table 2). The species contributing most (top 4 species in SIMPER table) to the dissimilarity in composition were Poor cod Trisopterus minutus, common hermit crab Pagurus bernhardus, spiny starfish Marthasterias glacialis and cuckoo wrasse Labrus mixtus, with higher abundance of all except hermit crab in the CRSZ (Table 1).

3.6.2. Within Wave Hub study zone

No significant fixed effect or interaction term was found in the multivariate assemblage composition models for all species (all P\text{(perm)} values > 0.05; Table 3a; Fig. S5), teleosts (all P\text{(perm)} values > 0.05; Table S2a; Fig. S6) or crustaceans (all P\text{(perm)} values > 0.05; Table S3a; Fig. S6) for the WHSZ.

Species richness (S) had a significant interaction Year \times Treatment term (P\text{(perm)} = 0.0136; Table 3a), as did teleosts (P\text{(perm)} = 0.0367; Table S2a) and crustacean models (P\text{(perm)} = 0.001; Table S3a). Pairwise tests revealed that these were mainly driven by significant differences between years within the Wave Hub project and reference locations (Tables 3a, S2a & S3a), with only a significant effect of Treatment for all species in 2012 (P = < 0.05; Table 3a) and for crustaceans in 2014 (P = < 0.001; Table S3a). Relative abundance (N\text{max})...
models had no significant fixed effect or interaction term for teleosts, crustaceans, echinoderms, elasmobranchs or Pollachius spp. (all P(perm) values > 0.05; Tables 3a, S2a, S3a, S5a & S5a), but there was a significant interaction term (Year x Treatment) for Cancer pagurus (P(perm) = < 0.05; Table S5a). Pairwise tests showed significant differences between years within Wave Hub project (2011–2013 & 2012–2013) or reference locations (2011–2012), and for locations within one year (2011), however some pairwise tests could not be conducted indicating a limitation of the data.

3.6.3. Within cable route study zone

Multivariate assemblage composition analysis revealed a significant interaction term, Year x Treatment, for all species (P(perm) = 0.0421; Table 3b; Fig. S5) and teleost models (P(perm) = 0.0118; Table S2b; Fig. S6). Pairwise tests revealed both had significant differences between years within Cable Route project and reference locations, but not between Cable Route project and reference locations within years (Table 3b & Table S2b). The crustacean model had a significant Year term (P(perm) = 0.0137; Table S3b; Figs. S6) and 3 out of the 6 subsequent pairwise tests were significant (2011–13, 2011–14 & 2013–14; Table S3b). Species richness (S) models had no significant fixed terms for all species or teleosts (Table 3b & Table S2b), but the crustacean model revealed Year as significant (P = < 0.001; Table S3b). Four out of the 6 subsequent pairwise tests were significant (2011–13, 2012–13, 2012–14 & 2013–14; Table S3b). Relative abundance (Nmax) models had no significant fixed terms for teleosts, echinoderms or
elasmobranchs (all P(perm) values > 0.05; Tables S2b and S4b). Year was found to be significant in the crustacean (P(perm) = 0.0002; Table S3a) and Cancer pagurus (P(perm) = 0.0002; Table S5b) models, with 4 from 6 pairwise test significant for crustaceans (2011–14, 2012–13, 2012–14, 2013–14; Tables S3a) and 3 from 6 pairwise test significant for Cancer pagurus (2011–13, 2012–13, 2013–14; Table S5b). The only model to have a significant fixed Treatment term was for relative abundance of Pollachius spp. (P(perm) = 0.01; Table S5b), with significantly greater abundance in Cable Route project than reference locations (Cable Route: mean 1.4 ± 0.8 SD, n = 23; reference = mean 1 ± 0 SD, n = 7).

3.6.4. Habitats

Assemblage composition and species richness (S) models revealed significant differences between habitat types (Types 1–3: P(perm) = < 0.001; Table 4; Fig. S7.). No significant difference in N_{max} was found between habitats.

4. Discussion

Weather and sea state are major considerations when working in mid latitude offshore marine environments, and can be a serious limitation to survey time and sampling effort when using small vessels. In this study, poor weather conditions and logistical constraints reduced the bi-annual survey to one season a year, with the exception of 2013. Access to larger vessels may have improved this situation but would have appreciably increased costs and reduced cost effectiveness of the BRUV technique. The study period encompassed some noteworthy bad weather events across the British Isles, and the extreme 2014 storms (Masselink et al., 2016) resulted in a reduction in samples due to bad visibility rendering footage unusable (Fig. S2). With storm events predicted to increase with climate change (Coumou and Rahmstorf, 2012; Zappa et al., 2013) the potential effects on sampling success need to be considered within survey design and sampling effort plans, i.e. overestimate required sampling for planned redundancy. The coastal areas optimal for wind or wave energy generation will be, by their nature, open to weather systems that will influence access to locations (sampling opportunities) and the quality of data gathered (visibility). The sampling loss due to camera and battery failures was relatively high and likely related to the repeated demands placed on the equipment and experience of maintaining and deploying the equipment on/off small boats in challenging conditions with small research teams (2 people). These losses were minimised with experience and improved equipment, but could be further mitigated if funds and time are available for repeat sampling efforts and/or campaigns.

The loss of survey periods or samples due to weather, technical

<table>
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**Table 4**

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problems or logistical issues reduces the precision in the characterisation of spatial and temporal variability at a site, and will ultimately affect the ability to detect impact (Underwood and Chapman, 2003). Deploying BRUV systems for an optimal time can help reduce avoidable loss by limiting time in the water. Accumulation curves derived from data gathered at different locations around the world, for fish and invertebrate species, suggests BRUV deployment time (or footage time) ranging from 30 min to 2 h in order to capture a significant proportion of the number of species or individuals attracted to the bait (Bernard and Gotz, 2012; Unsworth et al., 2014). BRUVs were deployed for 60 min in our study, but only the first 30 min of the footage were used in the analyses, capturing on average 75% or more of the total richness or relative abundance observed over the whole 60 min footage (Fig. 3). Our decision is worth briefly elaborating as it considered ecological and statistical elements of BRUV sampling and, therefore, could be informative for future studies using this technique. Firstly, in our study a BRUV system was used to provide a rapid assessment of species and relative abundance for particular, small benthic areas. If longer time periods were used, the effective range of attraction (AR) would increase so mobile species (teleost and elasmobranch) could be attracted from much further afield (>500 m; not our objective), and as a consequence, the animals could potentially attend multiple cameras, leading to double counting of individuals (pseudo-replication in our design). Secondly, due to technical (camera/battery failure) and condition (visibility or field of view) related issues, the number of useable videos significantly reduced (~40%) when applying 60 min (116 videos) compared to a 30 min footage requirement (198 videos) (Fig. S1). The decrease in sample size reduces the power of these data to detect statistically significant change and, for 2011, would have translated into no data being available and removal of this year from analyses. The statistical benefit conferred by an increased sample size and inclusion of all surveyed years (inter-annual variance), combined with the ecological reasoning behind using a shorter time period, resulted in the decision to use 30 min duration video data. However, a limitation of only deploying, or using data, for a short period (30 min in our case), is the chance of missing the presence of rare and/or cautious species. Given renewable energy development sites (wave, wind or tidal) could become de facto Marine Protection Areas (MPAs) by excluding damaging seabed fishing activities, the areas could become refuges for species with small or recovering populations. Deploying a subset of BRUVs for longer could help detect such species and be incorporated into study designs, specifically for this purpose. In this study, no new species were detected when 60 min footage was compared to 30 min, but longer periods may be necessary to detect rare species. The specifics detailed here are particular to our study but highlight, more generally, the need to understand the survey technique being used and the data it is expected to capture. Moreover, how the precautionary approach to sampling effort previously recommended (over-estimation) is necessary to allow redundancy in sampling campaigns when working in highly dynamic environments.

The analyses conducted using the BRUV data provided little consistent evidence of differences in metrics (across taxa) between the locations influenced by either the trawling exclusion (Wave Hub) or cable infrastructure (Cable Route), and reference locations within study zones. The only consistent change across years was an increase in the relative abundance of pollock and saithe (Pollachius spp.) around the cable infrastructure. These are commercially important coastal species understood to associate with rocky reef and hard substrate habitat as nursery areas (Seitz et al., 2014), suggesting the addition of rock and concrete matressing on the cable may be providing suitable conditions. Greater abundance of cuckoo wrasse Labrus mixtus observed during towed camera surveys in the same area has also been attributed to the presence of the hard substrate for cable protection (Sheehan et al., 2013). Both observations are consistent with other studies of fish abundance around MREI structures (Wilhelmsson et al., 2006) and add to the evidence these introduced structures and associated infrastructure are created habitat for species to utilise (Inger et al., 2009; Miller et al., 2013; Sheehan et al., 2018; Witt et al., 2012). The lack of evidence towards an impact of trawling exclusion in the Wave Hub zone may relate to low fishing effort in the area before (Campbell et al., 2013) and during the study, creating equivalent disturbance (or lack of) in project and reference locations. Alternatively, it could be an artefact of the survey design and power to detect change. The power analyses revealed how the ability to detect change in species richness and teleost relative abundance differed considerably between zones (spatial) and among survey years (temporal), producing a range of sampling schedules to detect the same effect size and varying levels of power (Fig. 4). Low power was particularly apparent in teleost abundance indicating these data could only confidently detect large changes (>50%) with high probability ($\alpha = 0.05$), and much less for the CRSZ. This could explain the lack of significant results found for this metric in our univariate analyses (Table 2 & Table S2), with potential influence on the outcome of the multivariate assemblage composition analysis (Fig. S5). Low probability to detect directional change in abundance data due to high variability has been found for other survey techniques and species (e.g. fish, cetaceans & seabirds; Al-Chokhachy et al., 2009; Forney, 2000; Maclean et al., 2013). Our results re-iterate caution in accepting that no change is taking place when analyses fail to reveal statistically significant patterns, when a lack of statistical power may be the contributing factor (Al-Chokhachy et al., 2009; Maclean et al., 2013). Despite good statistical power (~0.8) to detect relatively small changes (20%) in species richness, the majority of statistically significant effects found in our analyses (uni- and multivariate) were associated with yearly differences (Table 2 and Tables S2–S5). Only a single year difference was found for the exclusion zone (‘Treatment’) in richness of all species combined (2012; Table 2a) and crustaceans (2014; Table S3a) at the WHS. Natural yearly variation was the main effect identified at the study zones suggesting high levels of ‘noise’ in the system, presenting potential difficulty in distinguishing impacts related to the Wave Hub exclusion zone or cable route infrastructure. Moreover, it demonstrates how multi-year data are essential to capture site variability and provide accurate baseline characterisation, from which single site or cumulative impact from renewable energy converters or manufactured infrastructure could be robustly assessed (Maclean et al., 2014).

The high natural inter-annual variation found for each metric (at both study zones; Figs. 4–6) presents evidence for the difficulty in using pilot (e.g. single survey or one year) site data to inform the design and effort (e.g. power analysis) required for robust impact assessment surveys. If the power analysis was to rely on data from only one year of our study there would be a risk of either over- or under-estimating the number of samples needed to obtain acceptable power to detect a chosen effect size (Fig. 4). The consequence could either be a lack of power in the subsequent impact analyses (under-estimate) or collecting samples that are potentially unnecessary (over-estimate). The latter has the benefits of providing redundancy in the sampling effort, as has been previously recommended, but requires additional time, effort and cost, which would need to be factored into the survey program.

The difference in assemblage composition, species richness and variance found between study zones (Table 2; Figs. 4 and 5) might be expected given the dominant habitat types found at the Wave Hub (medium to fine sediment) and Cable Route (mix of rocky reef and large boulders) study zones (e.g. Fig. S7), and the significant difference in composition and richness found among them (Table 4). The site specific nature of ecosystem components, even over a relatively small spatial area (~130 km$^2$), is effectively demonstrated using these data. The characteristics of these data offer also illustrate how useful consistent data collection methods (and survey design) can be in allowing comparison between locations. Baseline characterisation and impact studies of benthic habitats and species are required at MREIs located in coastal locations (inshore and offshore) with various physical (e.g. size, bathymetry) and ecological characteristics. While the energy converter


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Gill, A.B., 2005. Offshore renewable energy: ecological implications of generating electri-}


