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Published in:
Ecological Engineering

DOI:
[10.1016/j.ecoleng.2020.106144](https://doi.org/10.1016/j.ecoleng.2020.106144)

Publication date:
2021

Citation for published version (APA):

Evans, A. J., Lawrence, P. J., Natanzi, A. S., Moore, P. J., Davies, A. J., Crowe, T. P., McNally, C., Thompson, B., Dozier, A. E., & Brooks, P. R. (2021). Replicating natural topography on marine artificial structures: A novel approach to eco-engineering. *Ecological Engineering*, 160, [106144].
<https://doi.org/10.1016/j.ecoleng.2020.106144>

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1 **Replicating natural topography on marine artificial structures – a novel approach to**
2 **eco-engineering**

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22 **Abstract**

23 Ocean sprawl is a growing threat to marine and coastal ecosystems globally, with wide-
24 ranging consequences for natural habitats and species. Artificial structures built in the marine
25 environment often support less diverse communities than natural rocky marine habitats
26 because of low topographic complexity. Some structures can be eco-engineered to increase
27 their complexity and promote biodiversity. Tried-and-tested eco-engineering approaches
28 include building-in habitat designs to mimic features of natural reef topography that are
29 important for biodiversity. Most designs mimic discrete microhabitat features like crevices or
30 holes and are geometrically-simplified. Here we propose that directly replicating the full
31 fingerprint of natural reef topography in habitat designs makes a novel addition to the
32 growing toolkit of eco-engineering options. We developed a five-step process for designing
33 natural topography-based eco-engineering interventions for marine artificial structures. Given
34 that topography is highly spatially variable in rocky reef habitats, our targeted approach seeks
35 to identify and replicate the ‘best’ types of reef topography to satisfy specific eco-engineering
36 objectives. We demonstrate and evaluate the process by designing three natural topography-
37 based habitat units for intertidal structures, each targeting one of three hypothetical eco-
38 engineering objectives. The process described can be adapted and applied according to user-
39 specific priorities. Expanding the toolkit for eco-engineering marine structures is crucial to
40 enable ecologically-informed designs that maximise biodiversity benefits from burgeoning
41 ocean sprawl.

42

43 **Keywords:** artificial structures, eco-engineering, marine management, ocean sprawl,
44 topography, urban ecology

45

46 **1. Introduction**

47 Ocean sprawl is a growing threat to marine and coastal ecosystems globally, with wide-
48 ranging consequences for habitats and species (Firth et al., 2016a). Aside from the
49 environmental impacts of building artificial structures in the sea (Bishop et al., 2017; Heery
50 et al., 2017), structures generally provide poor quality habitats for biodiversity compared with
51 natural rocky marine habitats (Moschella et al., 2005; Wilhelmsson & Malm, 2008). In
52 nature, topographic heterogeneity generates variation in the physical environment and plays
53 an important role in sustaining biodiversity and functioning (Levin, 1974). Species exist
54 within the bounds of their differing evolutionary adaptations to physical stresses and a
55 complex interplay of biotic interactions (Huston, 1999). On rocky reefs, many habitat
56 features that offer refugia from physical stressors and predation (Aguilera et al., 2019; Hereu
57 et al., 2005; Menge & Lubchenco, 1981), such as crevices, bumps and holes, are generated as
58 a function of substrate topography. On artificial structures, topographic complexity is
59 generally much lower (Moschella et al., 2005; Wilhelmsson & Malm, 2008); for example,
60 plain concrete seawalls, uniform rock armour, and smooth jetty pilings. This is a key reason
61 for their reduced biodiversity compared with natural rocky habitats (Firth et al., 2013;
62 Moschella et al., 2005; Wilhelmsson & Malm, 2008). In some circumstances, absence of
63 surface complexity and colonisation of marine life is desirable on structures. For example, on
64 wave and tidal energy infrastructure, where local hydrodynamics are key (Langhamer et al.,
65 2009). But where marine developments contribute to the loss or fragmentation of natural
66 reefs (Hall et al., 2018), or where reef habitats and species are in decline for other reasons
67 (Jackson & McIlvenny, 2011; Perkol-Finkel et al., 2012), it would be ecologically-beneficial
68 if structures provide effective surrogate habitats for these communities, or indeed for other
69 vulnerable/valued target species.

70 There is a growing toolkit of options for eco-engineering marine structures to enhance their
71 biodiversity value by increasing their topographic complexity (O'Shaughnessy et al., 2020;
72 Strain et al., 2018b). For example, researchers have trialled creating textured surfaces
73 (Perkol-Finkel & Sella, 2016; Sella & Perkol-Finkel, 2015), microhabitats like holes and
74 crevices (Chapman & Underwood, 2011; Hall et al., 2018; Langhamer & Wilhelmsson,
75 2009), rock pools (Evans et al., 2016; Morris et al., 2017; Waltham & Sheaves, 2020), and
76 scaled-up habitat units (Firth et al., 2014; Sella & Perkol-Finkel, 2015). Others have
77 transplanted target species onto structures (Ng et al., 2015; Perkol-Finkel et al., 2012). The
78 evidence base for if and how biodiversity can be promoted through such 'greening-the-grey'
79 (Firth et al., 2020; Naylor et al., 2017) eco-engineering interventions is growing rapidly
80 (Strain et al., 2018b). The popularity of the concept is also growing amongst developers
81 tasked with demonstrating how their proposals align with increasingly-proactive conservation
82 and planning legislation (Dafforn et al., 2015; Evans et al., 2019).

83 The ecological benefits that can be delivered by greening-the-grey options from the eco-
84 engineering toolkit are variable and context-dependent (Strain et al., 2018b). In most cases,
85 novel habitat designs have been successfully colonised by reef organisms, but have not
86 always functioned in the same way as comparable natural habitats (e.g. Chapman &
87 Blockley, 2009; Evans et al., 2016; Langhamer & Wilhelmsson, 2009). This may be partly
88 because of stressful environmental conditions around artificial structures, such as poor water
89 quality in urban areas (Pinedo et al., 2007), unfavourable thermal conditions (Waltham &
90 Sheaves, 2020) or high disturbance regimes (Airoidi & Bulleri, 2011). It may also be because
91 many designs are geometrically-simplified representations of natural habitat features. For
92 example, eco-engineered pit, crevice and rock pool habitat designs are commonly drilled or
93 cast in regular forms for convenience or cost reasons (Firth et al., 2014; Hall et al., 2018;
94 Langhamer & Wilhelmsson, 2009). Some habitats have been designed theoretically using

95 computer-aided design to maximise biodiversity benefits (Loke et al., 2014). Others have
96 been designed with an emphasis on aesthetics and public engagement (Hall et al., 2019).
97 Whilst the majority of interventions are inspired by natural rocky habitat features, none have
98 been designed to directly replicate them (but see MacArthur et al., 2019). With increasing
99 affordability and accessibility of 3D habitat modelling and printing technologies (Canessa et
100 al., 2013; D'Urban Jackson et al., 2020), different ecologically-targeted outcomes may be
101 achieved by directly replicating the full fingerprint of natural reef topography in eco-
102 engineering designs.

103 Here we describe a novel approach for designing eco-engineering interventions (i.e. habitat
104 units) for marine artificial structures that directly replicate natural reef topography on
105 structure surfaces. Given that topography, and hence the distribution of habitat features,
106 physical conditions and biodiversity, is highly spatially variable on rocky reefs (Aguilera et
107 al., 2019; Meager et al., 2011), our targeted approach seeks to identify and replicate the 'best'
108 types of reef topography to satisfy specific eco-engineering objectives. This involves first
109 identifying relationships between features of substrate topography and biodiversity metrics of
110 interest, then selecting areas of topography to replicate accordingly. Acknowledging that eco-
111 engineering options and objectives are likely to be different for different structures in
112 different places, we present a five-step process that can be adapted and applied according to
113 site-specific or species-specific priorities. We then describe and evaluate our own application
114 of the process to promote three hypothetical eco-engineering objectives for intertidal artificial
115 structures.

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119 **2. Designing Natural Topography-Based Eco-engineering Habitat Units: A Five-Step**
120 **Process**

121 We propose a five-step process for designing ecologically-targeted natural topography-based
122 eco-engineering habitat units for marine artificial structures (Fig. 1). Prior to applying this
123 process, the options and objectives of the eco-engineering intervention must be known. In
124 particular, the species or communities that are the desired targets of the intervention must be
125 identified, and these must be realistic targets of topography-based intervention. Following
126 this, Step 1 is to conduct a baseline survey to sample the biology and topography of local reef
127 habitats that support those target species/communities to varying degrees. The location, scale,
128 timing and method of baseline survey must be appropriate to their biology and ecology.
129 Biological sampling must be appropriate for subsequently identifying and selecting the ‘best’
130 and ‘worst’ samples for target species/communities, according to the user’s objectives. If a
131 single species is the target (e.g. for conservation/fisheries interest), simple measures of
132 presence, abundance and/or population demographics may be sufficient. If groups of species
133 or full communities are the target (e.g. to promote natural reef communities), then
134 community-level biodiversity metrics or indices may be necessary and data should be
135 collected accordingly. Topographic sampling must allow for the construction of three-
136 dimensional digital habitat models (e.g. digital elevation models (DEMs) or point clouds) of
137 appropriate scale and resolution (e.g. using structure-from-motion (SfM) photogrammetry or
138 laser-scanning; D’Urban Jackson et al., 2020).

139 Step 2 is a biological selection step to identify subsets of the ‘best’ and ‘worst’ samples from
140 the baseline survey for target species/communities. Using appropriate biodiversity metrics,
141 samples can be scored, ranked and filtered pragmatically to select subsets of the ‘best’ and
142 ‘worst’ samples that contain enough samples for subsequently detecting associations with
143 topographic features. Step 3 is a topographic selection step to identify topographic features

144 characteristic of the ‘best’ but not the ‘worst’ samples, then to shortlist the ‘best candidates’
145 based on these. This step should include a rigorous method (e.g. statistical modelling) for
146 identifying relationships between the target species/communities and features of the
147 underlying topography. Step 4 is an engineering selection step to identify potential practical
148 issues for manufacturing eco-engineering habitat units based on the ‘best candidates’. Step 5
149 is to manufacture habitat units replicating the ultimately selected ‘best’ samples of reef
150 substrate.

151

152 **3. Application of the Five-Step Process**

153 We applied the five-step process (Fig. 1) to design natural topography-based eco-engineering
154 habitat units for artificial structures in our region (Fig. 2). We aimed to design experimental-
155 scale (25 x 25 cm) habitat units for mid-shore seaward-facing surfaces on intertidal
156 structures. We applied the approach with three hypothetical eco-engineering objectives in
157 mind: (A) to maximise the richness of colonising communities; (B) to promote local rocky
158 reef species that are normally deficient on artificial structures; and (C) to promote rocky reef
159 species that are rare in our region.

160 **3.1 Step 1 – Baseline Survey**

161 ***3.1.1 Survey Sites***

162 Natural and artificial intertidal rocky habitats were surveyed at 54 sites around the Irish Sea
163 coasts of Ireland and Wales during summer 2018 (Fig. 2; Table S1). For every natural habitat
164 sampled ($n = 27$), a nearby artificial habitat was sampled ($n = 27$) with comparable aspect and
165 wave exposure. Natural habitats were bedrock reefs formed of mixed sand/mudstones,
166 limestone or granite. Artificial habitats were walls and rock armour constructed from
167 limestone, granite or concrete. Artificial habitats were sampled because biodiversity metrics

168 calculated for two of our hypothetical eco-engineering objectives required data on the
169 biodiversity colonising artificial structures (see Section 3.2 below).

170 ***3.1.2 Biological Sampling***

171 The biological communities in natural and artificial habitats were sampled using ten 25 x 25
172 cm quadrats. Five quadrats were placed haphazardly on mid-shore seaward-facing surfaces in
173 each of two patches (approx. 20 m long, ≥ 20 m apart) in each site. We sampled steep/vertical
174 surfaces (60–90°) on walls and sloping/horizontal surfaces (0–40°) on rock armour. Surface
175 inclination was matched at the natural site loosely paired with each artificial structure.
176 Surfaces with rugosity features >10 cm were avoided. This was on account of the small size
177 (25 x 25 cm) of the experimental habitat units we wished to produce: (i) to avoid the surface
178 being dominated by a single microhabitat feature; and (ii) to avoid size/integrity issues when
179 producing and deploying the units.

180 The percent cover of canopy algae within quadrats was recorded then the canopy was
181 removed by cutting just above the holdfast. Mobile fauna were shaken from the canopy and
182 counted. The percent cover of sub-canopy algae and encrusting fauna, and counts of mobile
183 fauna remaining within the quadrat, were then recorded. Barnacles and cryptic gastropods
184 were counted from photoquadrats.

185 ***3.1.3 Topographic Sampling***

186 The topography of each 25 x 25 cm quadrat was recorded using structure-from-motion (SfM)
187 photogrammetry. All organisms were removed from within quadrats and the substrate was
188 cleaned using a wire brush. A 50 x 50 cm checkerboard frame, with six control points
189 covering three dimensions, was placed centrally around each cleared area. Photographs were
190 taken from each corner angled at 45° towards the centre. Then 16 overlapping perpendicular
191 photographs were taken in a four-by-four grid. From the total of 20 photographs per quadrat,

192 we generated accurately-scaled (0.1 mm) DEMs with Cartesian co-ordinates using Agisoft
193 Photoscan Professional v1.4 (Agisoft LLC, 2018). The central 25 x 25 cm area was clipped
194 from each model so that the final topography sample was the substrate directly beneath the
195 biological community sampled.

196 **3.2 Step 2 – Biological Selection**

197 To identify the ‘best’ and ‘worst’ natural substrate samples for our three hypothetical eco-
198 engineering objectives, three corresponding biodiversity indices were calculated: (A)
199 Richness; (B) Diversity Deficit; and (C) Rare Taxa. Each index was used to rank the 270
200 natural quadrats sampled (Fig. S1). The top and bottom 5–10% of quadrats in each ranked list
201 were selected as the ‘best’ and ‘worst’ sample subsets. This equated to 13–27 samples in each
202 ‘best’ or ‘worst’ subset. We considered this a reasonable balance between selecting only the
203 highest/lowest scores, whilst retaining large enough sample sizes to maintain power to detect
204 associations in the subsequent topographic selection step. The exact number in each subset
205 varied according to sensible cut-offs for each index – this was necessarily subjective, given
206 that there were many joint ranks.

207 **3.2.1 (A) Richness Index (R)**

208 The Richness Index (R) was calculated as the number of taxa per quadrat. Richness in natural
209 quadrats ranged from 1 to 20 (mean $8.3 \pm 4.1SD$) (Fig. S1a). Natural quadrats were ranked
210 from high to low R . The top 14 quadrats contained >16 taxa ($R = 17–20$). These were selected
211 as the ‘best’ samples. They were all sampled from sloping/horizontal surfaces. The bottom 24
212 quadrats from matching substrate inclination contained <5 taxa ($R = 1–4$). To reduce this
213 bottom selection, only quadrats from sites in which some had scored above average for R (R
214 ≥ 8.3) were included. This ensured that low richness was not due to paucity in the local

215 species pool, thus there was higher likelihood that topography had contributed to the low *R*
216 scores. The bottom 15 quadrats that met this criterion were selected as the ‘worst’.

217 **3.2.2 (B) Diversity Deficit Index (DD)**

218 The Diversity Deficit Index (*DD*) was derived by identifying key characteristic members of
219 the mid-shore community that were consistently present in natural quadrats but absent or
220 consistently less abundant in artificial quadrats. Eight diversity-deficit taxa groups were
221 identified using SIMPER analysis (Table S2). Each natural quadrat was scored and ranked
222 according to the number of these taxa groups that were present in higher than average
223 abundances (i.e. > mean across all natural quadrats; Table S2). The top 29 quadrats contained
224 higher than average abundances of more than four of the eight groups (*DD* = 5–6) and were
225 selected as the ‘best’ samples (Fig. S1b). These were all sampled from sloping/horizontal
226 surfaces. The bottom 28 quadrats from matching substrate inclination did not contain any
227 diversity-deficit groups in higher than average abundance (*DD* = 0) and were selected as the
228 ‘worst’.

229 **3.2.3 (C) Rare Taxa Index (RT)**

230 The Rare Taxa Index (*RT*) was derived by identifying taxa that occurred most infrequently in
231 our survey (i.e. recorded in ≤5% quadrats sampled). Nine rare taxa groups were identified
232 (Table S3). Each natural quadrat was scored and ranked according to the number of these
233 taxa groups that were present. The top 16 quadrats contained more than two of the nine
234 groups (*RT* = 3–4) and were selected as the ‘best’ samples (Fig. S1c). These were all sampled
235 from sloping/horizontal surfaces. The bottom 99 quadrats from matching substrate inclination
236 did not contain any rare groups (*RT* = 0). To reduce this bottom selection, only quadrats from
237 sites in which some had scored highly for *RT* (*RT* > 2) were included. This ensured that the
238 absence of rare taxa was not because they were absent at the site level, thus there was higher

239 likelihood that topography had contributed to the zero *RT* scores. The bottom 23 quadrats that
240 met this criterion were selected as the ‘worst’.

241 **3.3 Step 3 – Topographic Selection**

242 This step aimed to identify and select features of substrate topography that were characteristic
243 of the ‘best’ but not the ‘worst’ quadrat samples for each biodiversity index. We first
244 identified the most important topographic variables for discriminating between the ‘best’ and
245 ‘worst’ subsets for each index (see details below). These variables were then used to re-rank
246 the ‘best’ subsets and to select five ‘best candidate’ quadrats for each biodiversity index.
247 ‘Best candidates’ were thus the ‘best’ in terms of biodiversity scores and importantly, had
248 meaningful topographies that were able to distinguish them from the ‘worst’. Therefore,
249 features of the underlying topography are likely to have contributed, at least in part, to their
250 high biodiversity scores.

251 For each quadrat, 13 topographic variables were calculated from the DEMs of the 25 x 25 cm
252 substrate areas (Table 1). To identify the most important variables for discriminating between
253 the ‘best’ and ‘worst’ subsets, we used two statistical methods based on a random forest
254 framework. This allowed us to review variable importance and provide estimates of class
255 prediction skill (i.e. ‘best’/‘worst’ subset), whilst being robust to correlation within predictors
256 (Breiman, 2001). We first used 10-fold (5-repeat) cross-validated recursive feature selection
257 (CV-RFS) within the ‘caret’ package in R (Kuhn, 2008; R Development Core Team 2011) to
258 identify the best reduced models for predicting class membership of quadrats (Table S5) and
259 to calculate variable importance ranks (Fig. 3). We then used the ‘randomForest’ package in
260 R (Liaw & Wiener, 2002) with 500 trees to validate variable importance scores and ranks
261 within those best reduced models (Fig. 3), and provide overall model performance (i.e.
262 prediction error rates; Table S6).

263 The best performing model for predicting the ‘best’ and ‘worst’ quadrat subsets for the
264 Richness Index (*R*) included four topographic variables (Fig. 3a; Table S5a) and had a 3%
265 prediction error rate (Table S6a). The best model for predicting the Diversity Deficit Index
266 (*DD*) included seven variables (Fig. 3b; Table S5b) and had a 16% error rate (Table S6b).
267 The best model for predicting the Rare Taxa Index (*RT*) included all 13 variables (Fig. 3c;
268 Table S5c) and had a 31% error rate (Table S6c). Variable importance ranks from the CV-
269 RFS analysis, and corroborated by the additional random forest analysis, revealed the top
270 three most important variables for model performance for each biodiversity index (Fig. 3;
271 Table 1). The ‘best’ quadrats for each of the three biodiversity indices were scored according
272 to the number of these key topographic variables that had above average values (i.e. > mean
273 of all ‘best’ quadrats for each index). The ‘best’ quadrats were then re-ranked according to
274 these scores and the top five quadrats for each biodiversity index were selected as the ‘best
275 candidates’.

276 **3.4 Step 4 – Engineering Selection**

277 The DEMs of the five ‘best candidate’ quadrats selected for each biodiversity index were
278 inspected for their suitability for moulding and casting into eco-engineering habitat units. The
279 overall height (and therefore weight) of units was considered for practicality and feasibility of
280 deployment. For us, deployment would require manual handling to install experimental units
281 on artificial structures. For scaled-up eco-engineering intervention, different engineering
282 considerations may apply. The fragility and completeness of substrate features when the 25 x
283 25 cm quadrat area was clipped from the DEM was also considered. For example, if this
284 resulted in partial loss of continuous features of topography that may have influenced the
285 distribution of species on the natural shore (e.g. a ridge adjacent to an indentation that would
286 have retained water), the quadrat was considered unsuitable. Subjectivity employed at this
287 stage maximised the chances that eco-engineered habitat units could replicate the topographic

288 (and thus physico-environmental) conditions available to species on the natural shores from
289 which they were modelled. Ultimately, one ‘best’ quadrat was selected for each biodiversity
290 index and the DEMs of these were converted to stereolithography (STL) files for mould
291 creation.

292 **3.5 Step 5 – Manufacture**

293 The STL files of the three selected ‘best’ natural topography samples were 3D printed on a
294 Prusa MK3 printer using polylactic acid, with 215°C extruder temperature and 60°C bed
295 temperature. Cura software was used for slicing the STL files into machine-readable g-code.
296 Mould-making silicone rubber was poured in layers over the printed samples until 10 mm
297 thick and cured for 16 h. A rigid support shell was built around each mould using two layers
298 of Plasti-Paste© urethane resin and cured for two hours. Concrete was poured into the
299 moulds to cast habitat units replicating the original topography samples. These were cured in
300 water for 30 days.

301

302 **4. Results**

303 By following our five-step process (Fig. 1), we selected three of the ‘best’ natural topography
304 samples from our baseline survey to promote three hypothetical eco-engineering objectives.
305 We then replicated them into three experimental-scale eco-engineering habitat units (Fig. 4).
306 When plotted amongst all 270 natural quadrats sampled, the ‘best’ biological subsets (i.e. the
307 top 5–10% of biodiversity scores) were clearly dissimilar to the ‘worst’ (i.e. the bottom 5–
308 10%) in terms of their multivariate species compositions (Fig. 5 left). This was largely pre-
309 determined, given that the biological selection used elements of these full assemblages to
310 identify and select the ‘best’ and ‘worst’ subsets. The ‘best’ selected quadrats for the *R* and
311 *DD* Indices (Figs 5a,b left) were more similar to one another than the ‘best’ subsets for the

312 *RT* Index (Fig. 5c left). Numerous quadrat samples *not* selected by our process apparently had
313 very similar community structure to those that were (Fig. 5 left). This likely reflects the use
314 of univariate biodiversity indices for selection, which inevitably obscure much detail in
315 community structure.

316 The three biodiversity indices (Fig. 5 middle) and the top three topographic variables (Fig. 5
317 right) used in the selection process were correlated with the direction of separation between
318 the ‘best’ and ‘worst’ subsets for each index (Fig. 5 left). However, the ‘best candidate’
319 samples and the ultimately-selected ‘best’ quadrats were not always plotted in the quadrant of
320 maximum values for these (i.e. in the top right corner of the data cloud; Fig. 5 left). For
321 example, for *DD* (Fig. 5b left), several ‘best candidates’, including the ultimately-selected
322 ‘best’ sample, plotted relatively central. These quadrats did not have the highest *DD* scores
323 compared to others in the ‘best’ subset. Neither did they have the highest values for VRM
324 (cm), Slope (mm) and Rugosity (mm). Nevertheless, the combination of being in the top 5–
325 10% of *DD* scores and having above average topography scores led to them being shortlisted.

326 The manufactured habitat units were deployed experimentally on artificial structures around
327 Irish Sea coasts during 2019. While monitoring is ongoing, preliminary observations were
328 encouraging. Limpet recruits appeared in pools and shaded channels provided by the
329 replicated natural topography within one week (Figs 6a,c). Juvenile and adult limpets were
330 again observed in these refuge areas several months later (Figs 6b,d), in some cases creating
331 grazing halos amongst pioneer algal growth (Fig. 6d).

332

333 **5. Discussion**

334 We propose a novel five-step approach for designing natural topography-based eco-
335 engineering habitat units for marine artificial structures. We applied the approach to design

336 three experimental-scale units for intertidal artificial structures in our region. Each design
337 targeted one of three hypothetical eco-engineering objectives: (A) to maximise the richness of
338 colonising communities; (B) to promote local rocky reef species that are normally deficient
339 on artificial structures; and (C) to promote rocky reef species that are rare in our region. The
340 habitat units replicated the topography from within three of the ‘best’ natural rocky reef
341 quadrat samples from our baseline survey, and observations of early colonisation are
342 promising.

343 The habitat design to maximise richness had high mm-scale Vector Ruggedness Measure
344 (VRM), Arc-Chord Ratio and Surface Area: Planar Area Ratio. The designs to reduce the
345 diversity deficit and promote rare species also had high VRM, as well as high mm-scale
346 Rugosity and Slope. These parameters each indicate high surface ruggedness and complexity:
347 qualities known to be instrumental in supporting diversity on intertidal reefs by modulating
348 temperature, light, humidity and water flow (Aguilera et al., 2019; Guichard & Bourget,
349 1998; Meager et al., 2011), and providing refuge from predation (Menge & Lubchenco,
350 1981). Millimetre-scale ruggedness influences barnacle settlement (MacArthur et al., 2019),
351 creating habitat structure and promoting succession of colonising communities (Harley,
352 2006). These were not the only topographic variables that characterised the surfaces
353 replicated in our habitat units. Several others were similarly associated with the ‘best’
354 samples for biodiversity metrics and were unintended features of our topographic designs
355 (Fig. S4). In contrast, Topographic Position Index, the position of a point in relation to its
356 neighbours, was inversely associated (Fig. S4). Thus, surfaces with more concave than
357 convex features – more dips than bumps – were better for biodiversity. This reflects the value
358 of water-retaining features, even at the mm–cm scale, for intertidal biodiversity (Firth et al.,
359 2013).

360 A number of topographic variables combined were necessary for accurate discrimination
361 between the ‘best’ and ‘worst’ quadrat subsets for each biodiversity index. The Richness
362 Index required the fewest (i.e. 4) topographic variables to predict the ‘best’ samples and had
363 the highest accuracy. This suggests that species richness on the rocky shores we sampled was
364 closely associated with those features of the underlying topography. Promoting richness,
365 therefore, would be a realistic target of topography-based eco-engineering for intertidal
366 structures in our region. In contrast, for the Rare Taxa Index, all 13 topographic variables
367 were required in the best predictive model and this still had relatively low accuracy. This was
368 likely due to the observed greater dissimilarity amongst the ‘best’ samples for this index. It
369 may reflect a more complex relationship between rare taxa and substrate topography, e.g. if
370 different rare species have different specialist niche requirements (Verberk, 2011). A single-
371 species approach may, therefore, have been more effective for identifying topographies (at
372 the 25 x 25 cm scale) to promote rare species in our region. Alternatively, it may indicate a
373 relatively weak relationship, i.e. that topography was a poor predictor of rare species, and
374 their distributions were driven by other factors (as seen in different systems: Gunatilleke et
375 al., 2006, Wang et al., 2009). In this case, a topography-based eco-engineering approach may
376 not be suitable for the rare species we were targeting. Further work is necessary to improve
377 our understanding of which species and communities are feasible targets for natural
378 topography-based eco-engineering.

379 The fact that four or more topographic variables were required to differentiate the ‘best’ from
380 the ‘worst’ samples for all three biodiversity indices lends support to our suggestion that
381 habitat designs based on a single element of topography (e.g. regularly-shaped pits/grooves)
382 are unlikely to be effective in achieving community-level objectives, compared with an
383 approach that replicates natural topography directly. Each element of topography influences
384 and is influenced by its surroundings, within the context of the wider topographic mosaic. It

385 also suggests that shortlisting our ‘best candidates’ based on only the top three topographic
386 variables was perhaps over-simplistic. The quadrat samples on which our designs were
387 modelled are unlikely to have been the absolute best for biodiversity *or* the most aligned with
388 the key topographic drivers out of all the samples from which we could have selected. It was
389 inevitable that selecting samples based on biodiversity, topography and engineering
390 practicality would lead to compromise. However, our selection process ensured that each of
391 the ultimately-selected topography designs satisfy three criteria: 1) the samples were amongst
392 the top 5–10% of biodiversity scores, thus the units have the capacity to support the ‘best’
393 biodiversity for our eco-engineering objectives; 2) the samples scored above average for the
394 top three most important topographic variables for biodiversity, thus meaningful features of
395 the topography were likely to have contributed to their high biodiversity scores; and 3) there
396 were no practical barriers to replicating the sample topography in concrete habitat units, thus
397 the units have the capacity to replicate the topography-driven physico-environmental
398 conditions available to species on the natural shore from which they were modelled.

399 Given that eco-engineering options and objectives vary for different structures in different
400 locations, our approach can be adapted and applied to user-specific scenarios. In our
401 application, we chose three community-level objectives that could be reasonable goals of
402 eco-engineering. Objectives may alternatively focus on individual target species of
403 conservation (Perkol-Finkel et al., 2012) or commercial concern (Langhamer &
404 Wilhelmsson, 2009). Or they may focus on the functional value of organisms/assemblages
405 (Strain et al., 2018a). If objectives are multi-functional, or include a mixture of community-
406 level and species-specific targets, more than one ‘best’ topography could be replicated and
407 arranged in a mosaic. They could also be combined with other single-microhabitat
408 interventions from the eco-engineering toolkit, like rock pools or crevices. Multiple ‘best’
409 topographies, each targeting a different species/assemblage, would likely fulfil their roles

410 better than one single topography that is ‘OK’ for everything all at once. However, further
411 experimental work is necessary to understand what objectives can feasibly be targeted using
412 topography-based eco-engineering and how different patches would interact. Principally, it is
413 critical that the objectives of eco-engineering are clear before applying our five-step process.
414 This is a golden rule in restoration ecology (Ehrenfeld, 2000). The baseline survey would
415 need to be planned and executed accordingly. Biodiversity metrics and topographic
416 parameters used to identify optimal areas of topography to replicate would need to be
417 relevant. Prior to this, though, the essential first step would be to determine whether
418 replicating natural topography is likely to be effective for the eco-engineering objectives and
419 site-specific characteristics in the first place. If target species are not likely to be influenced
420 by substrate topography, or if the context of the site is such that the influence of topography
421 is likely to be overwhelmed by other factors (e.g. water chemistry, larvae/propagule/food
422 supply, disturbance/hydrodynamic regime), then this approach is probably unsuitable.

423 If the user determines that our approach *is* suitable, the next question would be one of scale,
424 both spatial and temporal. The spatial scale of sampling units in our baseline survey matched
425 the small size of the experimental units we wished to produce (25 x 25 cm). We measured
426 topographic variables at the mm- and cm-scale since we anticipated encountering taxa that
427 are influenced by habitat complexity at these scales; e.g. larval settlement and refugia for
428 mobile invertebrates (MacArthur et al., 2019). These scales are likely to be relevant for early
429 lifeforms of many rocky reef species but may be largely irrelevant for larger-bodied adult fish
430 and crustaceans that require much larger habitat niches (Caddy & Stamatopoulos, 1990).

431 Although higher trophic level organisms rely on small-bodied organisms and primary
432 producers for food and habitat, eco-engineering designs targeting them would also need to
433 target larger-scale topography. We undertook our baseline survey at the end of summer when
434 intertidal communities are likely to be well-developed in our region, i.e. with little sand-scour

435 from storms. Baseline surveys should, in practice, match the timing when target
436 species/communities/life stages are expected to be encountered. Repeat surveys (seasonal,
437 annual) would improve confidence in species distributions but may not be feasible in the
438 timeframe of planning eco-engineering enhancements for development proposals. Other key
439 considerations are the orientation, tidal level/depth and aspect of the structures subject to eco-
440 engineering intervention. Habitat units featuring topography from a horizontal orientation
441 would be unlikely to provide the same niche conditions for organisms if installed vertically,
442 and vice-versa (Connell, 1999), although this is yet to be formally tested in an eco-
443 engineering context. Similarly, features important for niche provision are likely to be
444 different for different intertidal levels, subtidal depths, and aspects to wave/current and
445 sunlight exposure (Firth et al., 2016b; Guichard & Bourget, 1998; Letourneur et al., 2003;
446 Menge & Lubchenco, 1981). We recommend matching each of these factors in baseline
447 surveys to the context of the structures to be eco-engineered.

448 Finally, we do not suggest that this novel approach to eco-engineering marine structures
449 should replace existing approaches that mimic discrete microhabitats on structure surfaces.
450 Indeed, different approaches may be complementary. Decision-makers should weigh-up the
451 options available to them according to their biodiversity objectives, engineering limitations
452 and budget, consulting the evidence base for what they can expect the cost-benefits to be. We
453 do not specify how to physically apply scaled-up areas of natural reef topography to different
454 types of artificial structures, since the mechanics of this are subject to innovation by
455 designers and civil engineers. Formliners, textured encasements and specialised moulds have
456 been used in eco-engineering previously (Firth et al., 2014; Perkol-Finkel & Sella, 2016;
457 Perkol-Finkel et al., 2018; Sella & Perkol-Finkel, 2015; see also the Living Seawalls project
458 <https://www.sims.org.au/page/130/living-seawalls-landing>) and could feasibly replicate
459 natural topography on structure surfaces during construction or retrospectively. Although

460 likely to be more expensive than manually drilling holes and crevices into structure surfaces,
461 the development and use of specialised formliners to impart textured surfaces on concrete is
462 well-established in the construction sector to add aesthetic value to products. Formliners can
463 now be re-used repeatedly, leading to by-area cost reductions and making their use
464 economically viable (Naylor et al. 2017). Using formliners or moulds for the application
465 described in this paper, however, would involve a bespoke ecologically-driven design
466 process, which may add to the cost of production. Some of the design-associated costs,
467 however, may already exist in project budgets for new developments. For example,
468 environmental assessments may already include surveys of target species/communities in
469 local natural habitats. Further work is needed to rigorously weigh up the cost-benefits of all
470 the different approaches to eco-engineering artificial structures (but see Naylor et al., 2017).
471 In particular, for our proposed natural topography-based addition to the eco-engineering
472 toolkit, understanding the effects of patch size and configuration on the potential for
473 topographies to target certain biodiversity outcomes will be key to assessing the potential
474 costs and benefits of scaled-up implementation. Nevertheless, digital habitat modelling and
475 3D printing technologies have become increasingly affordable and accessible in recent years
476 (Canessa et al., 2013; D'Urban Jackson et al., 2020), opening the door to great unrealised
477 potential for natural topography-based eco-engineering.

478

479 **Acknowledgements**

480 This work formed part of the Ecostructure project (www.ecostructureproject.eu), part-funded
481 by the European Regional Development Fund (ERDF) through the Ireland-Wales
482 Cooperation Programme 2014–2022. Data collection was also part-funded by Aberystwyth
483 University through the AberForward scheme. Thanks to Derek Holmes, John Ryan, Jennifer

484 Coughlan and Veronica Farrugia-Drakard of UCD, Harry Thatcher and Hannah Earp of
485 Aberystwyth University, and Siobhan Vye and Tim D’Urban Jackson of Bangor University,
486 plus all other research assistants for considerable help in the workshop/field. Thanks also to
487 authorities/landowners for granting site access. Finally, we are grateful to two anonymous
488 reviewers for their insightful and constructive comments that improved the manuscript.

489

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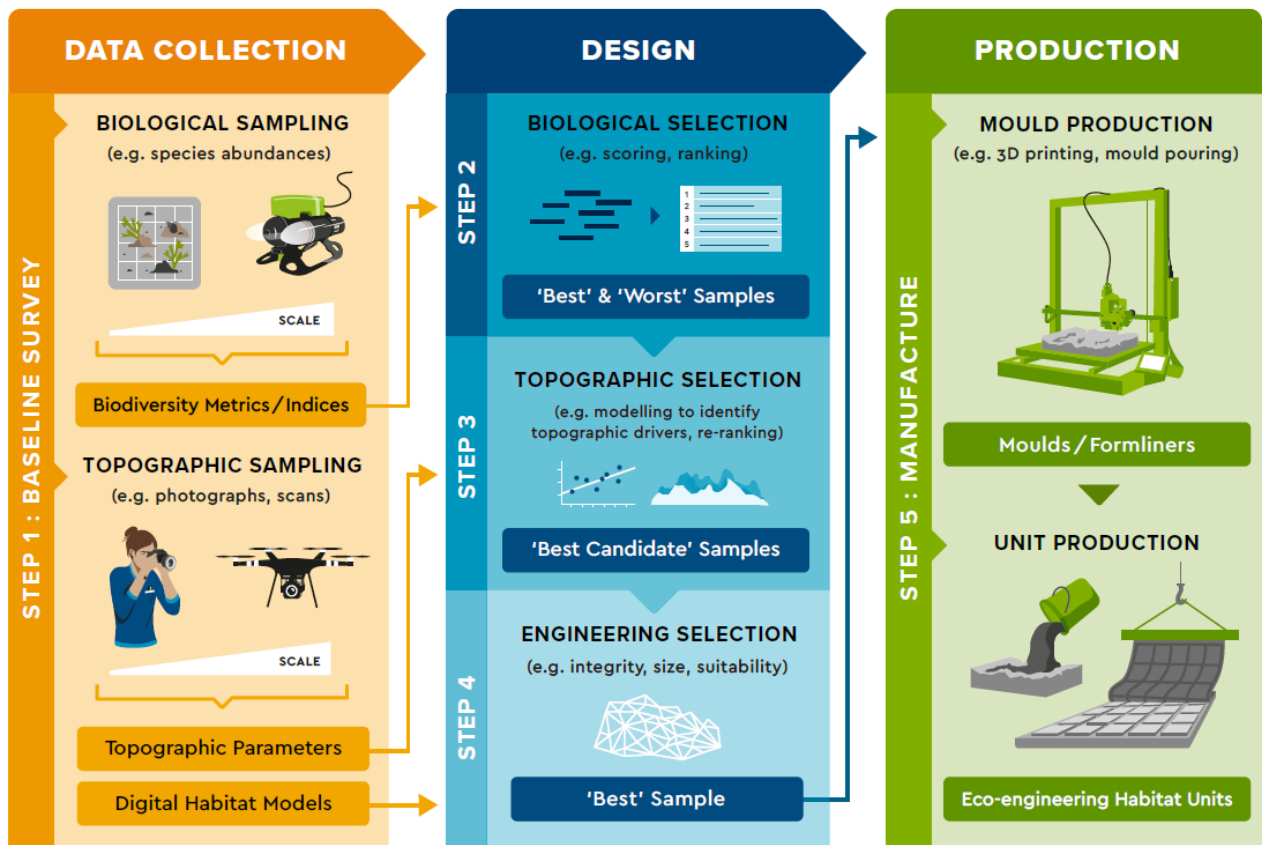
671 **Table 1** Topographic variables calculated from quadrat DEMs. Where indicated, variables
 672 were calculated at two scales (mm, cm) appropriate to the organisms present. Scale-
 673 independent variables were calculated once per quadrat. Rank Importance indicates the three
 674 most important variables for discriminating the ‘best’ from ‘worst’ quadrats for three
 675 biodiversity indices (Fig. 3). See Table S4 for references.

Variable	Scale	Definition	Rank Importance
Topographic Position Index (TPI)	mm cm	The relative elevation of a point to its neighbours.	
Slope	mm cm	The angle of a surface.	<i>DD2, RT2</i>
Rugosity (Rug.)	mm cm	The standard deviation of surface elevation.	<i>DD3, RT1</i>
Curvature (Curv.)	mm cm	The rate and direction of surface change.	
Vector Ruggedness Measure (VRM)	mm cm	The dispersal of surface aspects (surface unpredictability).	<i>R1, RT3</i> <i>DD1</i>
Surface Area: Planar Area Ratio (SA:PA)	n/a	The area of surface contained within a 2D space.	<i>R3</i>
Typical Elevation	n/a	The net protrusion/depression of a surface.	
Arc-Chord Ratio (ACR)	n/a	Rugosity index quantifying 3D structural complexity.	<i>R2</i>

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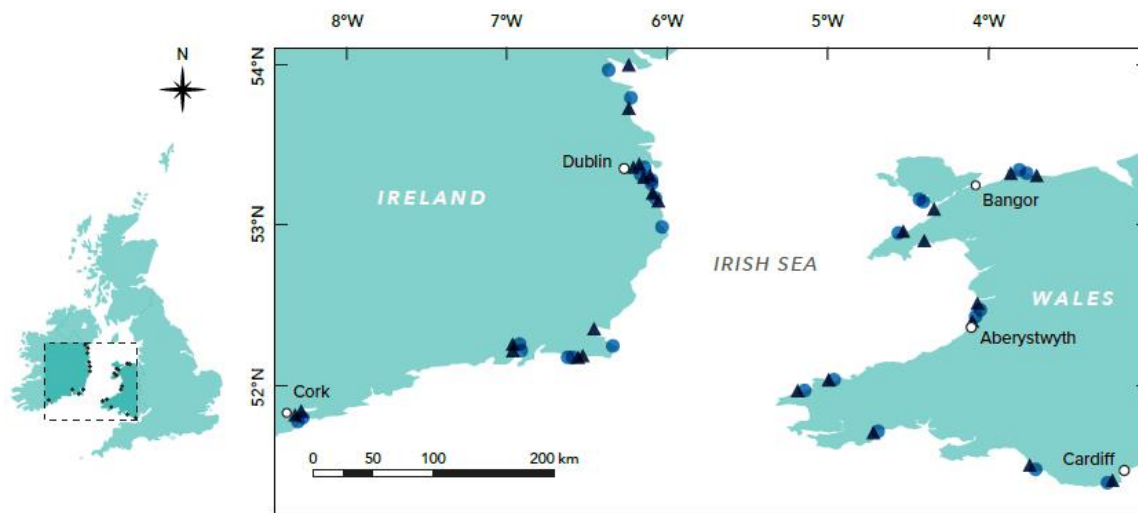


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Figure 1 Five-step process for designing natural topography-based eco-engineering habitat units for marine artificial structures. Figure by Amy Dozier.



● NATURAL HABITATS

▲ ARTIFICIAL HABITATS

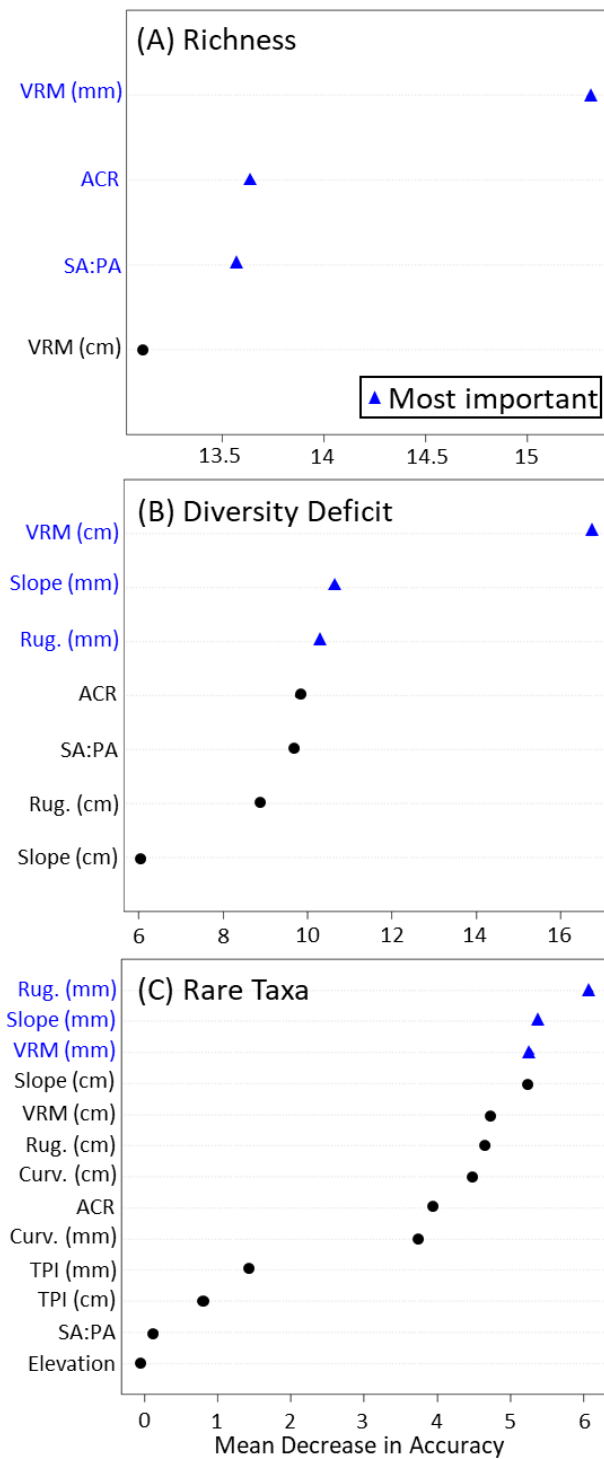


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683 **Figure 2** Fifty-four natural and artificial survey sites around Irish Sea coasts, with examples
 684 of intertidal rocky habitats surveyed (see Table S1 for site details). Figure by Amy Dozier.

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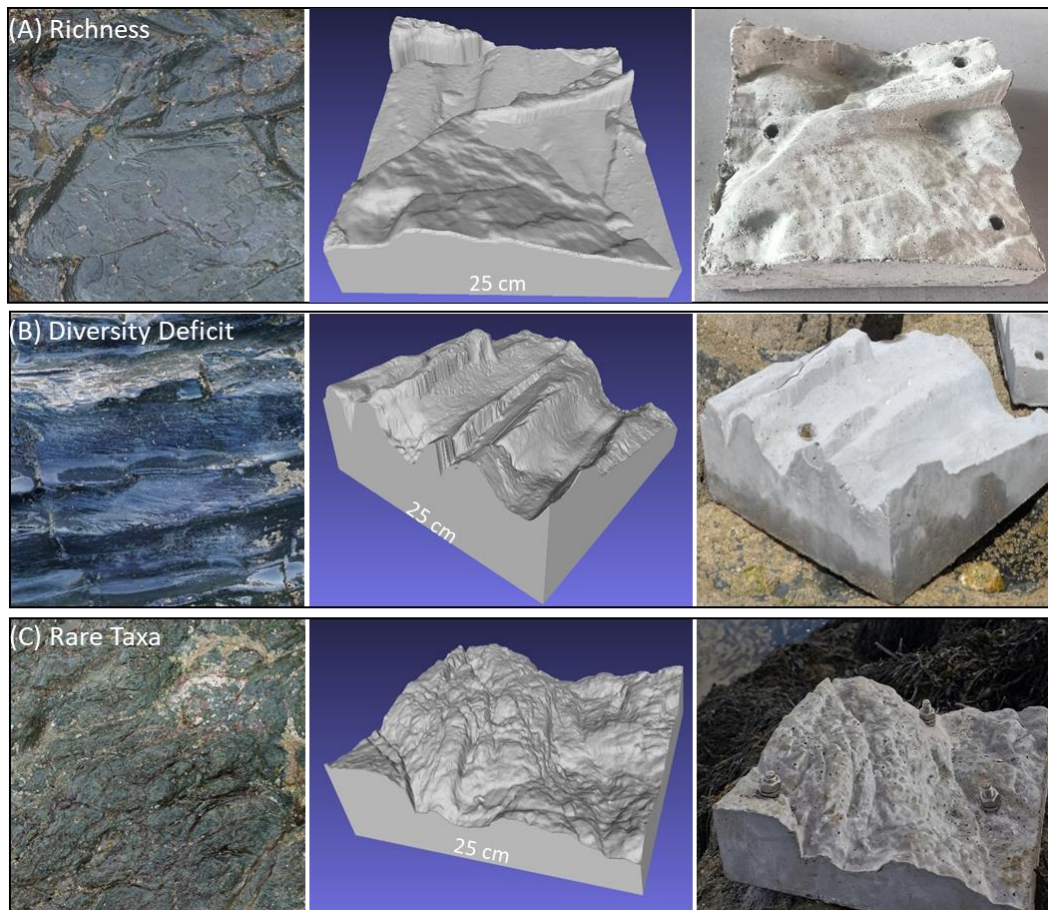
687

688 **Figure 3** Variable importance plots indicating the three most important topographic variables
 689 (Table 1) for predicting quadrat membership to the ‘best’ and ‘worst’ subsets for three
 690 biodiversity indices (A–C). Analyses based on the best predictive models for each index
 691 (Table S5).

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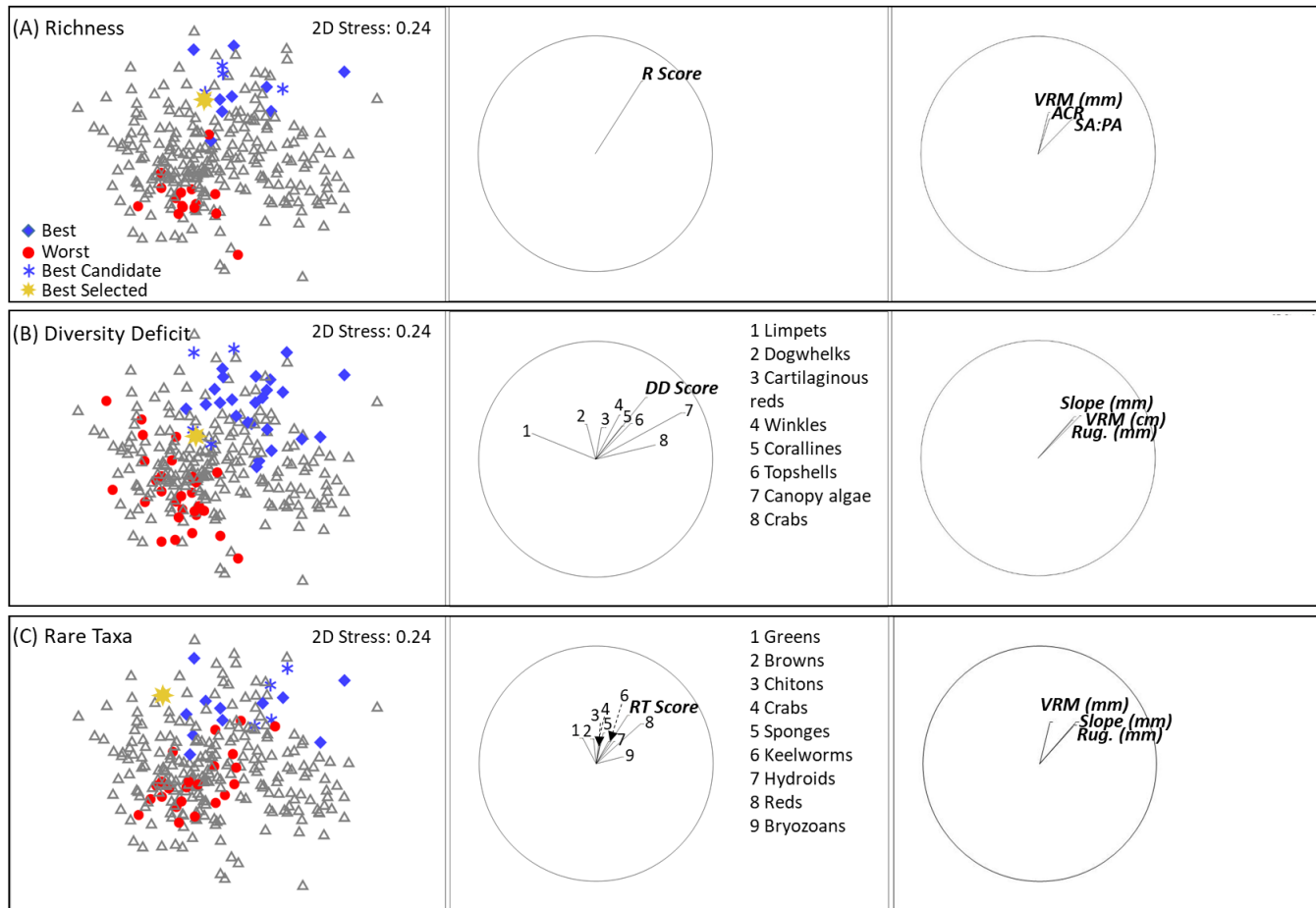
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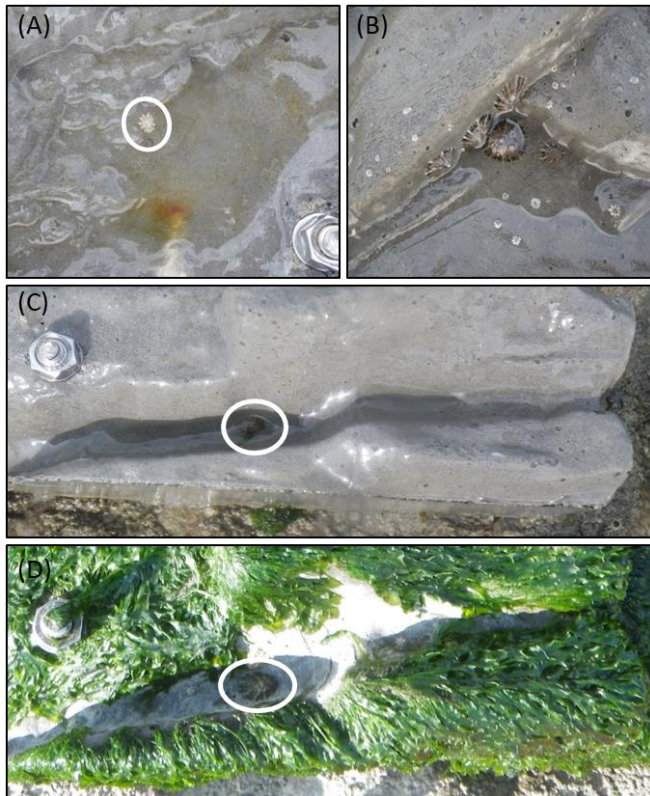
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696 **Figure 4** Left-to-right: *in situ* photographs, STLs and concrete habitat units of the ‘best’
 697 selected topography samples for three biodiversity indices (A–C). Examples of the ‘worst’
 698 samples are shown in Fig. S3.



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700 **Figure 5** Left: nMDS ordination of multivariate species composition in 270 natural rocky reef quadrats. The ‘best’ and ‘worst’ quadrat subsets,
 701 five ‘best candidates’ and the ultimately-selected ‘best’ quadrats for three biodiversity indices (A–C) are highlighted. Middle/right: vectors
 702 represent the direction and strength of multiple Pearson correlations between biodiversity indices (middle) and topographic variables (right;
 703 Table 1) used in the selection process within the multi-dimensional space. Outer circles represent correlation of 1. Ordination based on Gower-
 704 Excluding 0–0 similarities of 4th-root transformed abundances. Analyses carried out in PRIMER v7 (PRIMER-E Ltd., 2015). Vector overlays of
 705 all 13 topographic variables are shown in Fig. S4.



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Figure 6 (A–B): Water pooling in depressions, with (A) limpet recruit on Rare Taxa habitat unit after one week and (B) adult and juvenile limpets on Richness habitat unit after four months. (C–D): Shaded channels on Diversity Deficit unit, with (C) juvenile limpet after one week and (D) limpet creating a grazing halo amongst pioneer *Ulva* after two months.