

Three-dimensional mapping reveals scale-dependent dynamics in biogenic reef habitat structure

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Remote Sensing in Ecology and Conservation

DOI:
[10.1002/rse2.213](https://doi.org/10.1002/rse2.213)

E-pub ahead of print: 15/05/2021

Peer reviewed version

[Cyswllt i'r cyhoeddiad / Link to publication](#)

Dyfyniad o'r fersiwn a gyhoeddwyd / Citation for published version (APA):
Jackson-Bué, T., Williams, G., Walker-Springett, G., Rowlands, S., & Davies, A. (2021). Three-dimensional mapping reveals scale-dependent dynamics in biogenic reef habitat structure. *Remote Sensing in Ecology and Conservation*. <https://doi.org/10.1002/rse2.213>

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1 **Three-dimensional mapping reveals scale-dependent**
2 **dynamics in biogenic reef habitat structure**

3

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| | |
|----|--|
| 20 | <u>Running Title</u> |
| 21 | Scale-dependent biogenic reef dynamics |
| 22 | |
| 23 | <u>Word count</u> |
| 24 | Abstract: 290 |
| 25 | Main text: 5139 |
| 26 | Acknowledgements: 111 |
| 27 | References: 2179 |
| 28 | Table and figure legends: 953 |
| 29 | |
| 30 | Tables: 0 |
| 31 | Figures: 7 |
| 32 | |
| 33 | |

34 **Abstract**

35

36 Habitat structure influences a broad range of ecological interactions and ecosystem functions across
37 biomes. To understand and effectively manage dynamic ecosystems, we need detailed information
38 about habitat properties and how they vary across spatial and temporal scales. Measuring and
39 monitoring variation in three-dimensional (3D) habitat structure has traditionally been challenging,
40 despite recognition of its importance to ecological processes. Modern 3D mapping technologies
41 present opportunities to characterise spatial and temporal variation in habitat structure at a range of
42 ecologically relevant scales. Biogenic reefs are structurally complex and dynamic habitats, in which
43 structure has a pivotal influence on ecosystem biodiversity, function and resilience. For the first time,
44 we characterised spatial and temporal dynamics in the 3D structure of intertidal *Sabellaria alveolata*
45 biogenic reef across scales. We used drone-derived structure-from-motion photogrammetry and
46 terrestrial laser scanning to characterise reef structural variation at mm to cm resolutions at a habitat
47 scale (~35,000 m²) over one year, and at a plot scale (2,500 m²) over five years (2014-2019, 6-month
48 intervals). We found that most of the variation in reef emergence above the substrate, accretion rate
49 and erosion rate was explained by a combination of systematic trends with shore height and positive
50 spatial autocorrelation up to the scale of colonies (1.5 m) or small patches (up to 4 m). We identified
51 previously undocumented temporal patterns in intertidal *S. alveolata* reef accretion and erosion,
52 specifically groups of rapidly accreting, short-lived colonies and slow accreting, long-lived colonies.
53 We showed that these highly dynamic colony-scale structural changes compensate for each other,
54 resulting in seemingly stable reef habitat structure over larger spatial and temporal scales. These
55 patterns could only be detected with the use of modern 3D mapping technologies, demonstrating their
56 potential to enhance our understanding of ecosystem dynamics across scales.

57

58 **Keywords**

59 autocorrelation, ecosystem dynamics, reef accretion, reef erosion, reef mapping, spatial ecology

60

61 **Introduction**

62

63 Ecosystems are dynamic (Odum, 1969). Gradients in biophysical and human socioeconomic drivers
64 create complex mosaics in ecosystem properties (Legendre and Fortin, 1989; Perry, 2002; Williams et
65 al., 2019), with the patterns we observe determined by the scale of our observations (Levin, 1992;
66 Wiens, 1989). Because ecosystem patterns and processes are intrinsically linked, we can gain a deeper
67 understanding about ecological processes and their drivers by quantifying these underlying patterns
68 across scales (Horne and Schneider, 1995; Underwood et al., 2000). Quantifying patterns in
69 ecosystem properties not only advances ecological insight, but also facilitates evidence-based
70 management by enabling us to detect change in ecosystem characteristics like habitat structure in
71 response to disturbance (Landres et al., 1999).

72 Physical habitat structure can be abiotic like rocks on a shoreline, or biogenic like the trees of a forest.
73 These features determine habitat structural complexity and influence the biodiversity and community
74 composition of associated ecological communities through myriad processes. These include buffering
75 organisms from extreme environmental conditions (Scheffers et al., 2014), mediating resource
76 availability (Safriel and Ben-Eliahu, 1991), and providing shelter for prey species from predation
77 (Stevenson et al., 2015; Warfe et al., 2008). Biogenic reefs are complex habitats in which substrate
78 and structure is generated and amplified by engineering organisms (Jones et al., 1994). Biogenic reefs
79 represent global biodiversity hotspots and provide a range of ecosystem services to humanity
80 (Bruschetti, 2019; Connell, 1978; Dubois et al., 2002; Woodhead et al., 2019). Spatially and
81 temporally dynamic three-dimensional (3D) structure is critical to the biodiversity, ecological
82 functioning and conservation value of biogenic reefs (Graham and Nash, 2013; Holt et al., 1998).
83 Metrics of reef structure can also be an indicator of the health of the engineering species (Curd et al.,
84 2019) and reef recovery potential following acute disturbance (Graham et al., 2015). To understand
85 organism-habitat interactions within biogenic reef systems, we must first identify the patterns and
86 scales of variation inherent within their structures (Holt et al., 1998; Jenkins et al., 2018).

87 Much of our understanding about scale-dependent processes in ecosystems derives from terrestrial
88 landscape ecology. The study of spatial patterns in terrestrial systems has greatly benefitted from
89 remote sensing, providing high-resolution, spatially continuous data for a variety of ecosystem
90 properties including 3D habitat structure (Chambers et al., 2007; Vierling et al., 2008). Remote
91 sensing of 3D structure in the marine environment from satellite or crewed aircraft improves
92 ecological insight in clear, shallow waters (Wedding et al., 2019), but similar information is
93 challenging and expensive to capture in deep or turbid waters (Lecours et al., 2015). Recent
94 developments in high-resolution 3D mapping technologies including structure-from-motion
95 photogrammetry and laser scanning offer the potential to study patterns in 3D structure from organism

96 to habitat scales, and are practical for investigation of scale-dependent properties in marine and
97 coastal habitats (Calders et al., 2020; Urbina-Barreto et al., 2021). This creates opportunities to apply
98 conceptual and analytical frameworks from landscape ecology, such as identification of dominant
99 spatial scales of variation (Legendre and Fortin, 1989), at new scales and in new systems. The ability
100 to record spatially continuous 3D habitat structure across km-extents at mm resolution, with rapid
101 repeats and low operating costs is sparking a revolution in the scope and scale of ecological
102 investigations (D'Urban Jackson et al., 2020).

103 Here we use intertidal habitat structure built by *Sabellaria alveolata*, a reef-building annelid, as a
104 model system to characterise scale-dependent structural dynamics in complex biogenic reef habitats
105 using high-resolution 3D mapping. *S. alveolata* reef comprises colonies of sediment tubes
106 biocemented together, creating extensive reefs on northeast Atlantic and Mediterranean coasts
107 (Bruschetti, 2019; Godet et al., 2011; La Porta and Nicoletti, 2009). Similar reefs built by other
108 species in the Sabellariidae family are found globally (Capa et al., 2012). Our current understanding
109 of the scale-dependent structural dynamics in biogenic reefs is hampered by a lack of spatio-temporal
110 information about habitat structure across scales. To explore this, we quantify spatial and temporal
111 patterns in reef structure at mm to cm resolution, at plot- (2,500 m²) to habitat-scale (~35,000 m²)
112 extents and over temporal scales of 1-5 years. Our findings reveal previously undescribed patterns of
113 structural variation in intertidal biogenic reefs and demonstrate the enhanced ecological insight gained
114 from the application of modern remote sensing technologies for 3D ecosystem mapping in structurally
115 complex habitats.

116 **Methods**

117

118 **Data collection**

119 *Study site*

120 To characterise variation in biogenic reef habitat structure across scales we conducted high-resolution
121 3D mapping at a *Sabellaria alveolata* reef habitat at Llanddulas, Wales, UK (53.294 N, 3.632 W)
122 using two techniques between 2014 and 2019 (Fig. 1). The reef at Llanddulas occupies the low shore
123 for at least one kilometre along a moderately exposed, unconsolidated cobble beach with a gentle
124 slope gradient of 3%.

125

126 *Plot-scale (2,500 m²) 3D mapping*

127 We collected data to investigate multi-annual temporal patterns in *S. alveolata* reef structure using
128 terrestrial laser scanning (HDS ScanStation C10, Leica Geosystems, Switzerland) of a permanent
129 2,500 m² reef plot at approximately 6-month intervals (autumn and spring) over 5 years from
130 September 2014 to October 2019. Terrestrial laser scanning generates high-resolution (thousands of
131 points per m²) data with mm precision and was the most advanced 3D mapping technology available
132 for field sampling at the start of the study in 2014. We conducted medium resolution (0.1 m point
133 spacing at 100 m range) scans of the plot from several stationary positions per time point, ensuring
134 similar data coverage among time points. We used retroreflective sphere reference targets to align
135 scan datasets within a time point. Aligning datasets from different time points typically uses global
136 navigation satellite system (GNSS) georeferencing or permanent reference targets. Our plot was
137 intertidal with an unconsolidated substrate, so permanent targets could not be left and expected not to
138 move, and alignment by GNSS georeferencing would have introduced error on the same scale (cm) as
139 the changes we expected to detect, limiting their reliable detection and interpretation. Therefore, to
140 enable accurate alignment of repeat surveys we increased the laser scanning data coverage to include
141 permanent nearby features (rock groynes, cycle path and buildings), enabling us to align the datasets
142 using the geometry of these stable features, without constraining the data across the dynamic
143 foreshore.

144 We quality checked, aligned, georeferenced and manually cleaned the laser scanning point cloud data
145 in Cyclone v9 software (Leica Geosystems, Switzerland). Within a time point, we aligned datasets
146 from different scanner positions to 6 mm accuracy using target positions. We then aligned complete
147 datasets from different time points to 6 mm accuracy using the geometry of permanent features. We
148 made a final adjustment to the vertical alignment within the plot based on stable regions of non-reef

149 substrate. We standardised datasets from different time points by cropping to the plot extent,
150 subsampling point clouds to a minimum point spacing of 5 mm, and removing isolated points using
151 the *statistical outlier removal* tool in the open source software CloudCompare v2.11 (CloudCompare,
152 2019).

153

154 *Habitat-scale (~35,000 m²) 3D mapping*

155 Terrestrial laser scanning was impractical for the larger extent of habitat-scale sampling within short
156 low-tide windows. Therefore, to investigate spatial and temporal patterns in *S. alveolata* reef structure
157 at a habitat scale (~35,000 m²) we used structure-from-motion photogrammetry derived from drone
158 aerial imagery, in April 2018 and April 2019. Drone-derived structure-from-motion photogrammetry
159 generates continuous 3D information across large extents, with comparable accuracy to terrestrial
160 laser scanning in complex habitats like *S. alveolata* reef (D'Urban Jackson et al., 2020). We used a
161 Phantom 4 Pro (DJI) with a 20 MP camera flying at 46 m altitude to capture images with 14 mm XY
162 ground resolution, covering approximately 150,000 m² of the coastline. The flight pattern was pre-
163 determined and flying was automated using software (Maps Made Easy) to ensure the same survey
164 pattern was flown in both years. To optimise the 3D modelling process, we used a high image
165 overlap, so that every XY position in the area of interest was captured in at least 5 images. We
166 generated 3D models for each survey using the industry standard software Pix4Dmapper Pro v4.
167 Unlike terrestrial laser scanning, for structure-from-motion photogrammetry we required
168 georeferenced ground control points to scale, constrain and align the 3D models. We used 11 (2018)
169 and 19 (2019) control points surveyed with commercial GNSS equipment (system 1200, Leica
170 Geosystems, Switzerland), giving root mean square errors of 9 mm and 32 mm respectively. Because
171 there were no permanent features within the study area, we verified vertical alignment accuracy by
172 calculating elevation difference at 100 random points along a cycle path adjacent to the study area,
173 giving a median difference of 23 mm and root mean square error of 26 mm. This represents a worst-
174 case estimate because the cycle path was outside the area constrained by control points. From the 3D
175 models and aerial images, we generated digital surface models (DSMs, 0.1 m XY resolution) and
176 orthomosaics (0.02 m XY resolution) for 2018 and 2019.

177

178 **Data analysis**

179 *Habitat-scale (~35,000 m²) spatial patterns in S. alveolata reef emergence, accretion rate*
180 *and erosion rate*

181 To study habitat-scale spatial patterns of variation in *S. alveolata* reef structure we conducted
182 variography (Fig. 2, Supporting information) using the drone-derived digital surface models (DSMs)
183 from 2018 and 2019. To investigate reef structure independently from trends in the underlying non-
184 reef substrate, we calculated reef *emergence*, defined as the height of the DSM surfaces above a
185 standardised digital elevation model (DEM) representing the lowest levels in the non-reef substrate
186 (Fig. 3). We used a threshold of emergence to classify DSM cells as reef (≥ 0.15 m) or non-reef
187 substrate (< 0.15 m) within a *reef area* polygon (36,363 m²) digitised from the 2018 orthomosaic. We
188 validated the classification by manually classifying 500 random points on the orthomosaic and
189 interpreting a confusion matrix of predicted against observed classes. Overall accuracy (correct
190 predictions out of total predictions) was 81.2%, precisions (true positives out of total positive
191 predictions) were 91.7% and 80.1% for reef and non-reef substrate, respectively. To study spatial
192 patterns in accretion (positive change) and erosion (negative change) of *S. alveolata* reef we
193 calculated the vertical difference between the DSMs from April 2018 and April 2019, to provide
194 accretion and erosion rates as positive and negative vertical change per year.

195 To characterise spatial variation in habitat-scale *S. alveolata* reef structure, we modelled trends and
196 conducted variography using emergence, accretion rate and erosion rate values of the 9140 reef cells
197 in a random sample of 100,000 cells in the reef area. Our data exploration indicated that emergence,
198 accretion rate and erosion rate had trends with shore height and along-shore distance and were
199 anisotropic with a major axis along the shore and minor axis down the shore. To meet the gaussian
200 distribution requirements of linear modelling and variography, we transformed the data using ordered
201 quantile transformation (Peterson and Cavanaugh, 2020), then modelled trends using ordinary least
202 squares linear regression. We conducted variography on the linear model residuals along two axes:
203 along the shore (120° from north) and down the shore (30° from north), with maximum lags of 250 m
204 and 50 m respectively, approximately two thirds of the maximum reef area dimensions, using the
205 *gstat* package in R (Graler et al., 2016; Pebesma, 2004; R Core Team, 2020). We fitted an initial
206 variogram model to each experimental variogram automatically, then improved the fit by adjusting
207 the model parameters and adding a secondary variogram model where appropriate, until a visual good
208 fit was found to the experimental variogram (Gringarten and Deutsch, 2001). To investigate whether
209 patterns in reef structure were related directly to patterns in the underlying non-reef substrate

210 topography we conducted variography using emergence data from 10,000 random non-reef substrate
211 DSM cells.

212 The trend in mean emergence with shore height explained only a small amount of the variation ($R^2 =$
213 0.043, Supporting information table S1). Our data exploration showed that the reef comprised
214 colonies at all stages of emergence, from the classification threshold of 0.15 m up to an emergence
215 limit that was related to shore height. Therefore, shore height appeared to represent a limiting factor
216 and so maximum emergence was a better metric for characterising habitat structure than a measure of
217 central tendency (Kaiser et al., 1994). To examine the relationship between maximum reef emergence
218 and shore height we used a sample of 2,000 reef cells with a minimum point spacing of 1.5 m derived
219 from the variography results, 1.5 m being the dominant range of spatial autocorrelation. We modelled
220 the relationship between maximum (99th percentile) reef emergence and DEM elevation with linear
221 quantile regression, using the *quantreg* package in R (Koenker, 2020).

222

223 *Plot-scale (2,500 m²) temporal patterns in reef structure*

224 To characterise multi-annual structural changes in *S. alveolata* reef structure, we used terrestrial laser
225 scanning to survey a 2,500 m² plot in autumn and spring from September 2014 to October 2019. To
226 track vertical changes in reef emergence through time we digitally sampled locations within the plot
227 ($n = 454$) that had reef presence in at least one time point, avoided reef colony edges where lateral
228 accretion and erosion would confuse interpretation, and were spatially independent (Fig. 4,
229 Supporting information). At each sample location and for each time point, we extracted mean
230 emergence above a common DEM. To examine common characteristics in temporal changes in reef
231 emergence, we derived accretion and emergence metrics from each sample timeseries. We calculated
232 mean and maximum annual accretion rate, maximum emergence, and time spent within 80% of
233 maximum emergence, which we termed *persistence*. We then used partitioning around medoids
234 (PAM) clustering, a common data clustering method that is robust to outliers (Kaufman and
235 Rousseeuw, 1990), to classify sample timeseries' into two groups with similar metrics using the
236 *cluster* package in R (Maechler et al., 2019).

237 Following evidence of multiannual cycles of habitat-scale accretion and erosion (Gruet, 1986), we
238 hypothesised that mean plot-scale reef emergence would vary over the 5 year study period. We also
239 hypothesised that due to higher productivity in summer and lower growth rates coupled with more
240 destructive wave action in winter, plot-scale emergence would be higher in autumn than in spring. We
241 tested these hypotheses using a two fixed-factor (year and season) permutational analysis of variance
242 (Anderson, 2001) with reef emergence as a univariate response. The permutational nature of the test
243 removes the need to satisfy normality in the response variable as the routine permutes the raw data to

244 generate the null distribution (Anderson, 2001). To ensure a balanced design with no missing data and
245 no repeat sampling, we first divided reef sample locations ($n = 454$) randomly and equally among
246 season (2 levels: autumn and spring) and year (5 levels: 2015-2019) combinations (10 combinations, n
247 = 45). Some reef sample locations contained missing data for certain season and year combinations,
248 so we iteratively exchanged these reef sample locations among groups until no missing data remained.
249 Homogeneity of variance between factor levels was confirmed with Levene's test ($P > 0.05$). Our
250 permutational analysis of variance was based on a Euclidean distance similarity matrix of the raw reef
251 emergence data, with 9999 random permutations under a reduced model and Type III (partial) sums
252 of squares. Where there was global model significance, permutational pairwise tests were used to
253 determine where the differences occurred between factor levels.
254

255 **Results**

256

257 *Habitat-scale (~35,000 m²) spatial patterns in S. alveolata reef emergence, accretion rate*
258 *and erosion rate*

259 We estimated the percentage cover of *S. alveolata* reef within the 36,363 m² reef area as 26.8% or a
260 total coverage of 9,745 m² based on our binary classification of the 0.1 m XY resolution emergence
261 raster into reef or non-reef substrate (Fig. 5A). Maximum reef emergence (99th percentile) increased
262 down the shore from approximately 0.2 m at 0 m ordnance datum Newlyn (ODN) to a maximum of
263 0.5 m above the substrate at 2.8 m below ODN (Fig. 5B). The relationship was described by:

264

$$265 \quad \log(emergence_{max}) = -0.308(shore\ height) - 1.551 \quad (1)$$

266

267 Reef emergence was positively spatially autocorrelated up to 1.5 m in both along shore and down
268 shore directions, represented by a spatial structure that described 65-70% of the variance (Fig. 5C,
269 Supporting information table S1.). There was a smaller amount of residual positive autocorrelation in
270 reef emergence over larger distances along the shore (up to 110 m) and down the shore (up to 20 m)
271 (Fig. 5C, Supporting information table S1). At larger distances still, the variogram indicated
272 additional patterns in spatial dependence of reef emergence including cyclicity, but these were not
273 quantified because variogram model fitting becomes less reliable at larger distances relative to the
274 study extent. The variogram of non-reef substrate emergence showed that the dominant
275 autocorrelation pattern mostly occurred over a larger distance of 4.5 m and explained a higher
276 proportion (90%) of the variation compared to reef emergence (Supporting information table S1). A
277 small amount of spatial autocorrelation in non-reef substrate emergence was also evident over larger
278 distances (up to 50 – 90 m).

279

280 At the habitat scale (~35,000 m²), the elevation of *S. alveolata* reef colonies changed by 19 ± 82 mm
281 (mean \pm 1 sd) between April 2018 and April 2019 (Fig. 6A). The small magnitude of mean elevation
282 change across the total reef area was the result of a balance between variable positive and negative
283 changes of individual samples (0.1 m XY resolution cells). A high proportion of reef samples (80%)
284 showed a small positive elevation change (accretion, 49 ± 30 mm), with the remaining samples (20%)
285 showing larger and more variable negative changes (erosion, -99 ± 113 mm). Both accretion and
286 erosion maxima increased towards the lower shore (Fig. 6A) and showed different spatial
287 autocorrelation patterns. Positive spatial autocorrelation in accretion mostly occurred within short
288 distances (up to 0.75 – 1.05 m), with a small proportion of positive autocorrelation extending over
289 larger distances up to 40-130 m (Fig. 6B, Supporting information table S2). In contrast, erosion of

290 reef material was only positively spatially autocorrelated up to distances of 2.9 – 3.8 m, beyond which
291 the variogram indicated spatial randomness (Fig. 6C, Supporting information table S2).

292

293 *Plot-scale (2,500 m²) temporal patterns in reef structure*

294 Within the 2,500 m² plot, overall reef emergence across all 11 time points over 5 years was $0.22 \pm$
295 0.13 m (mean \pm 1 sd). We found scale dependent variation, with high variation in emergence at each
296 sample location (colony-scale, $n = 454$) through time and high variation among samples at each time
297 point, but low variation in plot-scale emergence through time. The coefficient of variation (mean \pm 1
298 sd) in sample location emergence through time was 52 ± 32.3 , and per time point was 56.5 ± 3.7 ,
299 whereas the coefficient of variation in plot-scale mean emergence through time was 8.8.

300 Timeseries' of emergence at reef sample locations revealed diverse temporal patterns in emergence,
301 accretion, and erosion metrics of colonies, that we classified into two groups called *fast* and *slow*
302 colonies (Fig. 7). These two groups clustered moderately well, indicated by an average silhouette
303 width of 0.35 on a scale from 0 (poorly clustered) to 1 (perfectly clustered) (Kaufman and
304 Rousseeuw, 1990). Fast colonies were characterised by higher maximum and mean annual accretion,
305 higher maximum emergence and shorter persistence (time spent within 80% of their maximum
306 emergence) than slow colonies (Fig. 7, Supporting information table S3). Visual assessment showed
307 that slow colonies were evenly distributed throughout the plot, whereas fast colonies were
308 concentrated in the northern, lower-shore half of the plot (Supporting information figure S1). We
309 found that erosion of reef colonies often occurred rapidly in both groups; it was common for
310 emergence to drop to the level of the non-reef substrate within 6 months to a year (Fig. 7).

311 There was a significant interaction between 'year' and 'season' on plot-scale reef emergence ($F_{4,440} =$
312 3.48 , $P = 0.009$, Supporting information table S4) driven entirely by emergence being higher in
313 autumn than spring in 2015 ($P = 0.001$). Across season, there were no differences among years in
314 spring emergence, but there were significant differences in autumn, with 2015, 2016 and 2019 having
315 higher emergence than 2017 and 2018 ($P < 0.05$, Supporting information figure S2, Supporting
316 information table S4).

317

318 **Discussion**

319 Habitat structure strongly dictates ecological function in complex 3D ecosystems. Quantifying how
320 3D habitat structure varies across space and time is therefore a crucial step in understanding
321 ecosystem dynamics and guiding their effective management. Here, for the first time, we quantified
322 patterns of spatial and temporal variation in 3D habitat structure across scales in an ecologically
323 important but understudied *Sabellaria alveolata* biogenic reef habitat. Our results reveal that patterns
324 in reef emergence, accretion rate and erosion rate are spatially autocorrelated and highly scale-
325 dependent. In this system, reef colonies formed groups of rapidly accreting short-lived colonies and
326 slow accreting long-lived colonies, creating dynamic structure at fine spatial (m) and temporal (6
327 month) scales. However, these colony-scale dynamics cancel each other out at larger spatial (50m – 1
328 km) and temporal (5 year) scales, resulting in seemingly stable reef habitat (Fig. 7). This habitat
329 steady-state despite the mosaic of small-scale dynamics is akin to other biogenic systems like forests,
330 where scale-dependent patterns in ecosystem properties have been better studied using remote sensing
331 (Chambers et al., 2013). Using modern 3D mapping we have quantified spatially continuous, cross-
332 scale habitat structure in a biogenic reef, revealing scale-dependent patterns that indicate parallels in
333 structural dynamics between terrestrial and marine biogenic habitats.

334

335 *Spatial patterns in reef habitat structure*

336 We identified predictable trends in maximum reef emergence, accretion rate and erosion rate, that all
337 increased towards the lower shore. Shore height trends are ubiquitous in intertidal ecosystems like
338 rocky shores and saltmarshes because numerous biological, chemical and physical structuring
339 processes correlate with vertical position (Chappuis et al., 2014; Connell, 1972; Pennings and
340 Callaway, 1992). The trends in our data can be explained by spatially varying hydrodynamic forces,
341 proposed as the most important abiotic structuring factor of *S. alveolata* reef habitat (Collin et al.,
342 2018; Gruet, 1986; Wilson, 1971). Wave forces are predicted to be greatest at the lower shore, with
343 energy attenuated as waves travel across the rough reef surface (Bouma et al., 2014; Lowe et al.,
344 2005). We suggest that higher wave energy at the lower shore results in more coarse sediment being
345 resuspended higher in the water column, enabling faster reef colony accretion and higher maximum
346 emergence. Wave energy can also be destructive, increasing reef erosion rate towards the lower shore.
347 In addition, longer periods of immersion experienced lower on the shore give more time for both reef
348 accretion and erosion.

349 Interactions between individuals can produce spatially coherent self-organised patterns that influence
350 ecosystem-scale processes in many natural systems, including mussel reefs (Van De Koppel et al.,
351 2008) and arid vegetation (Klausmeier, 1999). We found evidence for self-organisation in *S. alveolata*

352 reef emergence and accretion rate, that were spatially clustered (positively autocorrelated) up to
353 colony scales (1.5 m). Prograding *S. alveolata* reef colonies have characteristic smooth surfaces
354 comprising the openings of dense, parallel tubes (Fig. 1) (Curd et al., 2019; Ventura et al., 2020). To
355 maintain this morphology as the colony grows, within-colony accretion rate and emergence must be
356 similar among worms. Self-organisation enhances habitat resilience (Guichard et al., 2003; Liu et al.,
357 2014), and in this system the colony morphology may contribute to the remarkable wave-resistance in
358 the friable intertidal structures (Le Cam et al., 2011), analogous to massive stony coral morphologies
359 that can dominate wave-exposed subtidal tropical reefs (Chappell, 1980).

360 Spatial patterns in biogenic reef properties provide insight into the biotic and abiotic drivers of
361 ecosystem structuring processes (Aston et al., 2019; Edwards et al., 2017; Ford et al., 2020). In our
362 system, reef emergence and accretion rates showed secondary spatial clustering at habitat scales (20-
363 40 m down the shore, 110-130 m along the shore), whereas erosion rates showed spatial randomness
364 beyond 4 m. Habitat-scale spatial clustering in reef emergence and accretion rate may be due to
365 spatial variation in resources (e.g., sediment or food quality), environmental conditions (e.g., salinity),
366 biotic factors (e.g., recruitment density) or anthropogenic influence (e.g., trampling). Interactions
367 between myriad drivers are likely to influence reef structure at various scales (Collin et al., 2018).
368 Identification of the relative importance of these factors and how they vary in time and space warrants
369 further investigation, and may help explain why *S. alveolata* reef structure is highly variable among
370 sites (Stone et al., 2019). Spatial clustering of erosion rates up to 4 m indicates that erosion mostly
371 occurs as the catastrophic collapse of entire *S. alveolata* colonies and platform sections. The lack of
372 larger scale spatial autocorrelation in erosion rates shows that colony collapse is random after
373 accounting for shore height trends, suggesting that destructive processes are similar horizontally along
374 the shore.

375 Modern remote sensing technologies are advancing our ability to describe and interrogate spatial
376 patterns in marine reef systems. In intertidal habitats like *S. alveolata* reef, aerial methods can capture
377 a range of ecologically relevant information at high resolution across large extents of several km²
378 (Bajjouk et al., 2020; Collin et al., 2019, 2018). The importance of 3D ecosystem structure in
379 ecological investigations is recognised, and tools to capture and analyse 3D structure in diverse
380 systems including subtidal reefs are becoming increasingly powerful and accessible (D'Urban Jackson
381 et al., 2020; Lepczyk et al., 2021).

382

383 *Temporal patterns in biogenic reef structure*

384 Identifying key scales of variation and their forcing processes has been a persistent challenge in
385 ecology (Chave, 2013; Denny et al., 2004; Levin, 1992), especially in marine systems beyond the
386 observation capabilities of traditional remote sensing (Lecours et al., 2015; Wedding et al., 2011). Our

387 study reveals previously undescribed patterns of scale-dependent spatio-temporal variation in *S.*
388 *alveolata* reef structure. We found that individual *S. alveolata* colonies on the scale of metres undergo
389 independent and compensatory accretion and erosion cycles, resulting in stability at larger spatial
390 (2,500 m²) and temporal (5 year) scales. Previous characterisation of *S. alveolata* reef structural
391 dynamics have described multiannual accretion and erosion cycles operating over large areas of reef
392 (10s – 100s m) at some sites, and multiannual stability at others (Gruet, 1986; Lecornu et al., 2016).
393 While we recorded stability in reef structure over a period of 5 years, at decadal time scales the habitat
394 can be transient (Firth et al., 2015). Scale-dependent structural dynamism is a feature of other systems
395 like terrestrial forests (Chambers et al., 2013), and our results indicate that conceptual frameworks
396 from terrestrial landscape ecology can be applied to biogenic reef systems. For instance, the stability
397 of a forest ecosystem can be modelled as a product of the spatial and temporal scales of disturbance
398 events that it experiences (Turner et al., 1993). Applying this concept to our study system, disturbance
399 events (colony collapse) were small in size (up to 4 m) relative to the habitat size (~35,000 m²) and
400 disturbance (collapse) intervals were generally longer than recovery (accretion to maximum
401 emergence) intervals. As predicted by the conceptual model (Turner et al., 1993), we observed
402 stability in the system at the habitat scale.

403 We identified two distinct types of reef colonies: “fast” colonies with rapid accretion, high maximum
404 emergence, and short lifespan, and “slow” colonies with slower accretion, lower maximum emergence
405 and longer lifespan. Accretion rates of “fast” *S. alveolata* colonies in our study (mean 0.109 m yr⁻¹,
406 max 0.215 m yr⁻¹) were comparable to upper estimates of 0.105 m yr⁻¹ in Cornwall, UK, and >0.5 m
407 yr⁻¹ in Normandy, France (Gruet, 1986; Wilson, 1971). These studies documented faster accretion
408 rates in new, small colonies and a similar general pattern could be seen in our timeseries’, although
409 variation was high and many colonies had incomplete structural cycles within our study period. We
410 found new, low emergent colonies accreted rapidly and then accretion slowed as they approached a
411 maximum emergence, followed by a period of persistence at the maximum emergence and eventual
412 rapid collapse. A similar accretion pattern has been documented in oyster (*Crassostrea virginica*)
413 reefs, with rapid accretion in deeper edges of a reef (8 m diameter) while no change was recorded in
414 the shallowest central portions, just 2 m away (Rodriguez et al., 2014). This fine-scale spatial
415 variation in structural characteristics would be lost at larger observational scales, highlighting the
416 need for a multiscale approach when assessing the resilience of biogenic reefs to pressures like sea
417 level rise.

418 Seasonal patterns of accretion and erosion in *S. alveolata* reef and their driving processes are not well
419 understood. We did not find evidence for a consistent seasonal pattern in reef emergence, and while
420 reef emergence measured in autumn showed some variation, spring observations were stable over 5
421 years (Supporting information figure S2, Supporting information table S4). However, we did find a
422 seasonal difference in one survey year (2015). Temperature and wave energy are two dominant

423 seasonally varying factors in intertidal habitats. The habitat is vulnerable to severe winter
424 temperatures and damage from winter storms (Crisp, 1964; Firth et al., 2015). In summer, higher
425 temperatures and increased food availability in summer may promote worm productivity that
426 translates to increased accretion rate, but the availability of resuspended sediment with low summer
427 wave action may limit accretion rate. Hydrodynamic energy promotes both *S. alveolata* reef accretion
428 and erosion, so the effects of seasonal variation in wave energy are difficult to predict. Higher
429 emergence in the autumn of 2015 compared to the spring appeared to be a result of heavy recruitment
430 during the summer of that year (TDJ, *pers. obs.*), resulting in many new, rapidly accreting colonies.
431 Recruitment of pelagic larvae to *S. alveolata* reefs is through a combination of continuous low-level
432 settlement and stochastic heavy settlement events when hydrodynamic conditions are favourable
433 (Ayata et al., 2009; Bush et al., 2015; Dubois et al., 2007). Sabellariid worms respond to storm
434 damage with increased reproductive output in a similar way that some plants respond to fire (Barry,
435 1989) and *S. alveolata* larvae show high levels of retention within local geographic areas (Bush et al.,
436 2015; Dubois et al., 2007). These factors likely result in compensatory self-recruitment to a damaged
437 reef, contributing to long term reef persistence.

438

439 *Conclusion*

440 Our findings represent the most comprehensive characterisation of *S. alveolata* biogenic reef habitat
441 structure across spatial and temporal scales to date, expanding our understanding of scale-dependent
442 structural dynamics in this complex 3D habitat. We found that *S. alveolata* reef structure is
443 characterised by a mosaic of different colony successional states leading to a dynamic landscape at
444 smaller scales (m), while displaying relative stability (a steady state) at larger spatial and temporal
445 scales. This phenomenon is characteristic of other structurally complex ecosystems like forests and
446 we hypothesise could be true for other colonial reef systems, such as subtidal tropical coral reefs. We
447 also identified previously undocumented temporal patterns in reef structure, specifically distinct
448 groups of “fast and “slow” colonies. The patterns we documented could only be detected with high-
449 resolution 3D mapping, demonstrating the enhanced ecological insight gained from the adoption of
450 contemporary technologies in modern ecology. Scale-dependent ecosystem patterns have historically
451 been challenging to study due to necessary trade-offs in observation scale, especially in marine
452 systems. By embracing modern mapping technology in ecology, these long-standing constraints can
453 be overcome, leading to an improved understanding of ecosystem dynamics in complex 3D habitats.

454

455 **Acknowledgements**

456 This work formed part of the SEACAMS and SEACAMS2 projects, part-funded by the European
457 Regional Development Fund (ERDF) through the West Wales and the Valleys Programmes 2007-
458 2013 and 2014-2020, with collaboration from Tidal Lagoon Power, Gloucester, GL2 5RG, UK. AJD
459 was supported by the USDA National Institute of Food and Agriculture, Hatch Formula project
460 accession number 1017848. Aerial imagery was provided under contract by OcuAir, Westbury, BA13
461 4JT, UK. We would like to thank Michael Roberts and Jonathan King for facilitating the study, and
462 Laura Bush and Alex Vierød for their valuable insights. We thank two anonymous reviewers and
463 Associate Editor Vincent Lecours for their valuable comments that improved the paper.

464

465 **Author Declaration**

466 All authors have seen and approved the submitted version of the manuscript. All authors have
467 substantially contributed to the work, and all persons entitled to co-authorship have been included.
468 TJB, AJD and GJW conceived and developed the study, TJB, GWS and SR collected the data, TJB
469 processed and analysed the data, TJB, AJD and GJW wrote the manuscript. The manuscript has been
470 submitted solely to *Remote Sensing in Ecology and Conservation* and it has not been published
471 elsewhere, either in part or whole, nor is it in press or under consideration for publication in another
472 journal.

473

474 **Data accessibility**

475 Data and R code supporting this manuscript are available in Figshare repositories, DOI:
476 10.6084/m9.figshare.14480709 and DOI: 10.6084/m9.figshare.14480703

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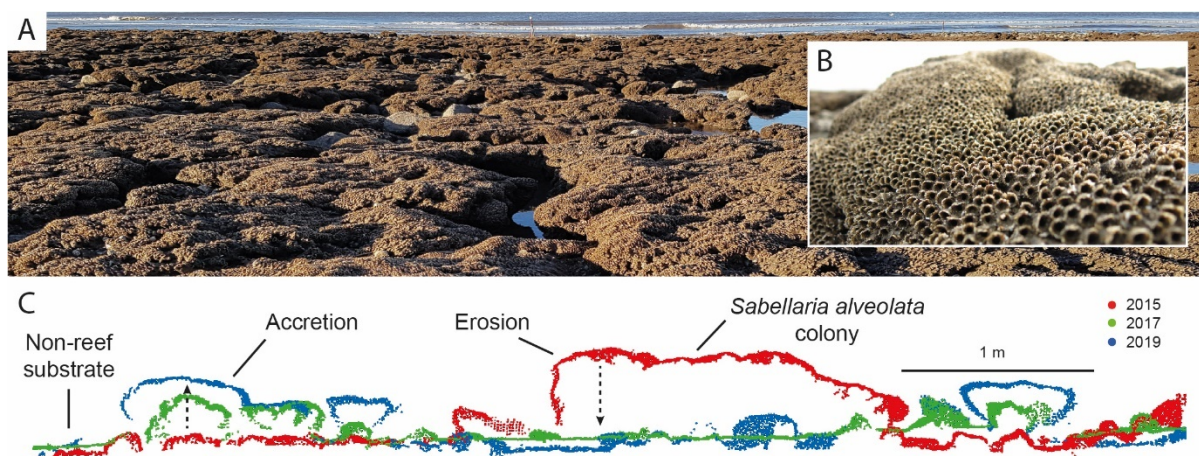
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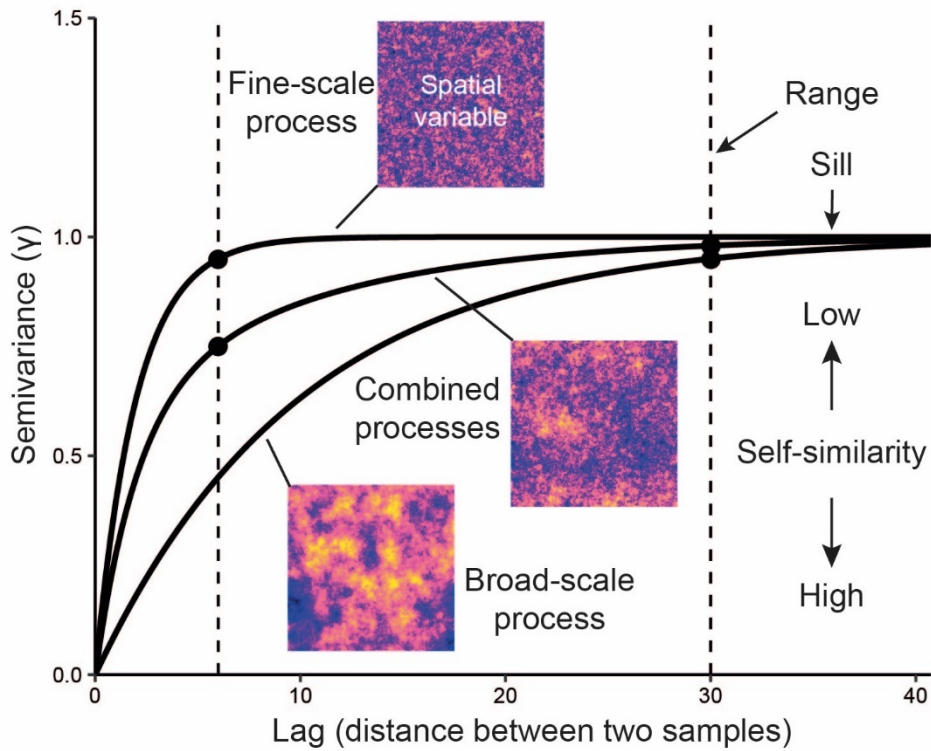
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702 **Figures**
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706 **Figure 1.** A) *Sabellaria alveolata* biogenic reef habitat comprises aggregations of sediment tubes in
707 colonies that emerge above a hard, non-reef substrate. B) Close-up image of a prograding colony
708 surface showing dense tube openings of ~5 mm diameter. C) Cross section of 3D terrestrial laser scan
709 point cloud data from 3 years, demonstrating the detailed information about spatial and temporal
710 dynamics in habitat structure that can be captured using modern 3D mapping technology. Reef
711 colonies accrete upwards and outwards from the non-reef substrate in characteristic mushroom-like
712 hummocks that coalesce into platforms. Erosion of reef colonies is often rapid and catastrophic.

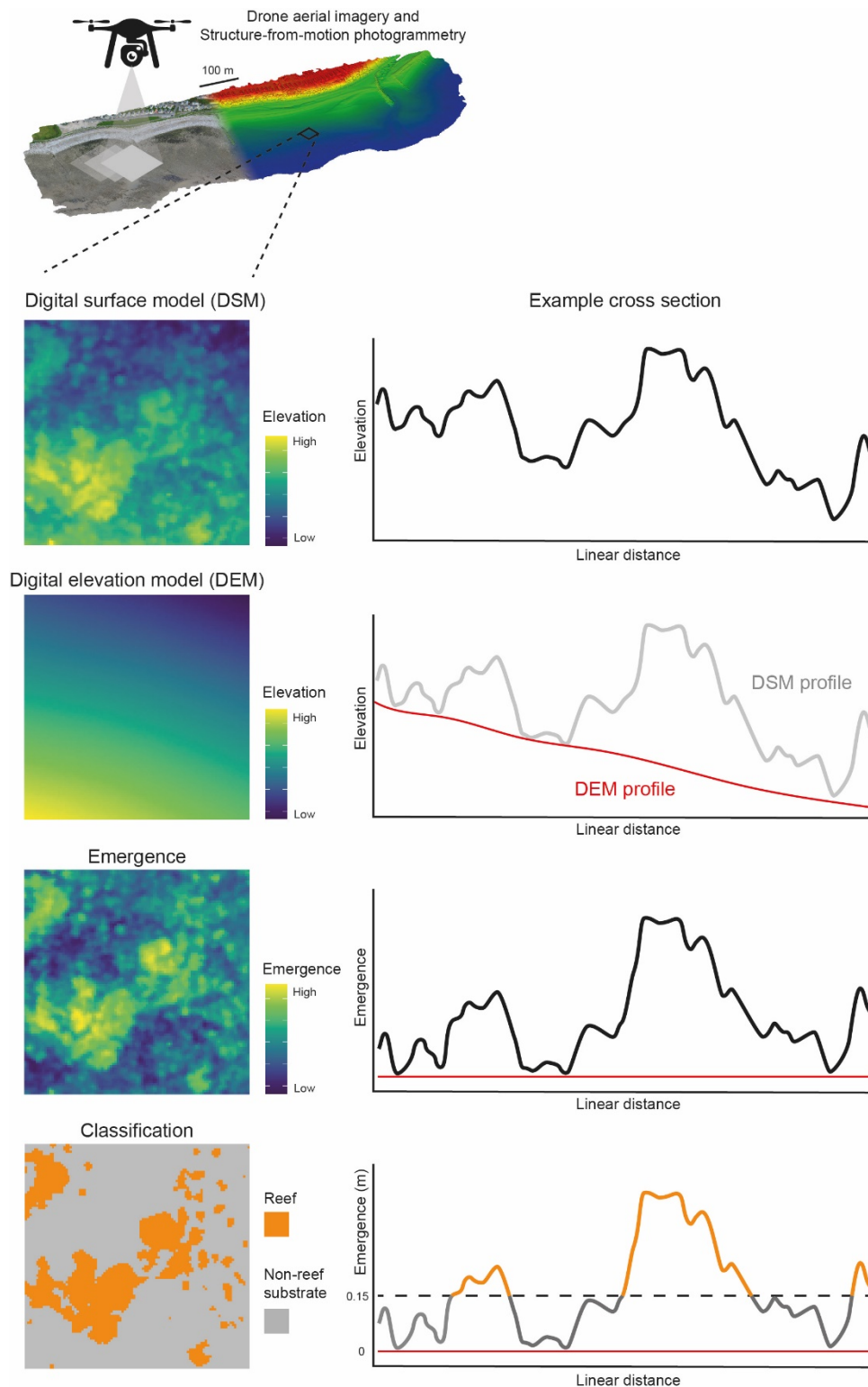


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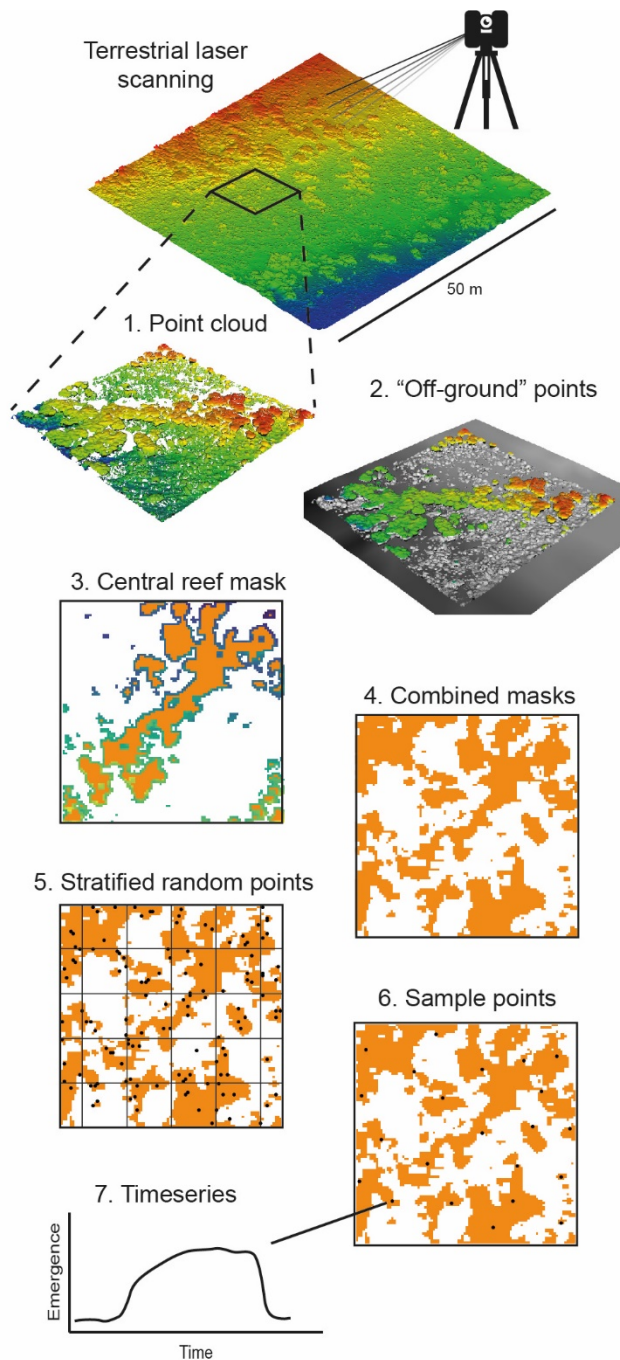
715 **Figure 2.** Interpreting spatial patterns in processes that generate spatial variables using variography.
 716 Variograms visualise spatial self-similarity, or autocorrelation, in a variable by plotting semivariance
 717 (γ) against lag, the distance between two samples. As lag increases samples become less similar
 718 (higher γ) until a plateau (sill) is reached at a distance (range), beyond which sample values are not
 719 autocorrelated. Here we show three simulated examples of a variable generated with different
 720 processes, and their respective variograms. Top: a fine-scale process generates a variable that is
 721 autocorrelated only over short distances, so the range (point and dashed line) is small. Bottom: a
 722 broad-scale process generates a variable that is autocorrelated over longer distances, producing a
 723 variogram with a larger range. Middle: the fine- and broad- scale processes have been added together,
 724 producing a variable with both short- and long-distance autocorrelation, generating a nested
 725 variogram with two ranges.

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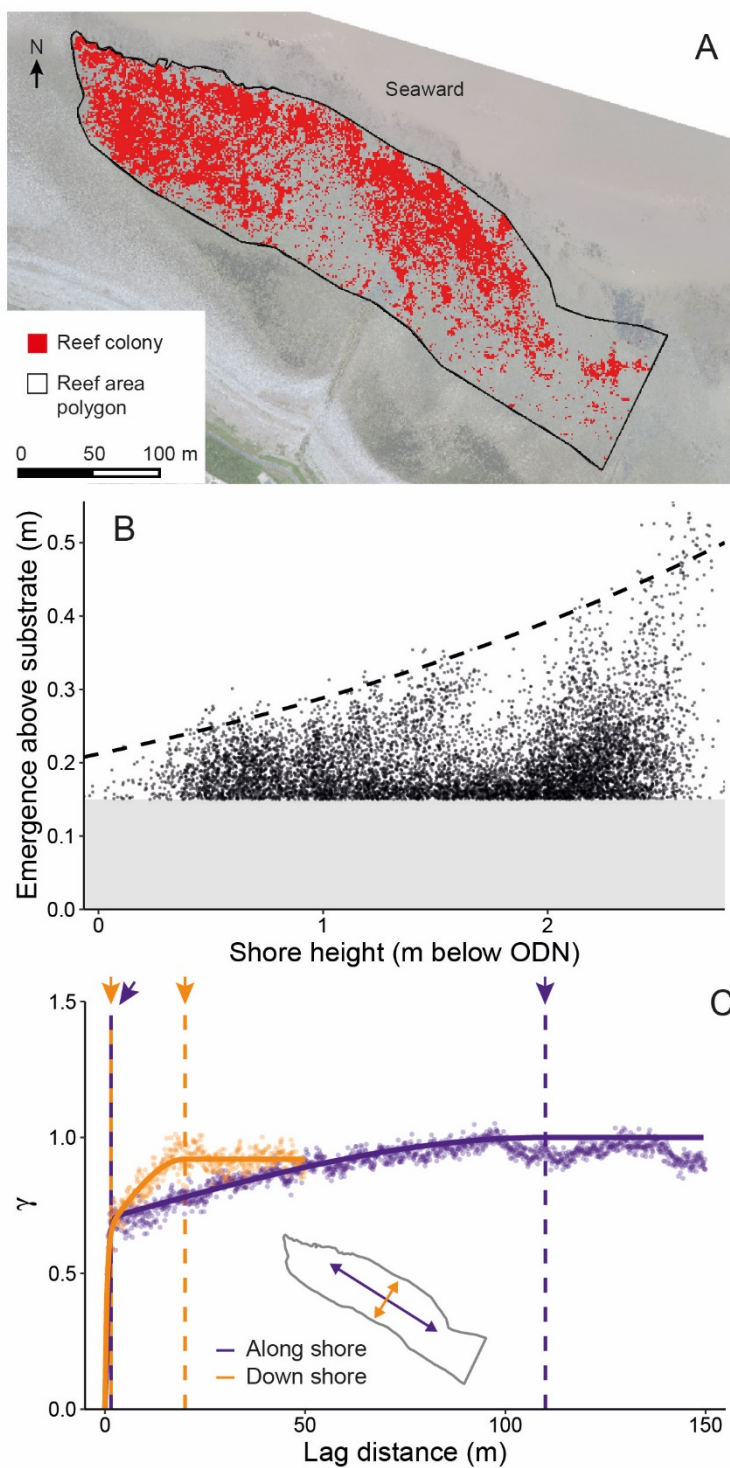
727

728 **Figure 3:** Data processing method used to classify habitat-scale digital surface models (DSMs) as reef
 729 or non-reef substrate. We generated 0.1 m XY resolution DSMs using drone aerial imagery and
 730 structure-from-motion photogrammetry. From the DSM we generated a digital elevation model
 731 (DEM) representing the ground level at the same resolution by interpolating between the lowest point
 732 elevation. Finally, within the known reef area (Fig. 5A) we used a binary classification of reef (≥ 0.15
 733 m emergence) and non-reef substrate (< 0.15 m emergence).
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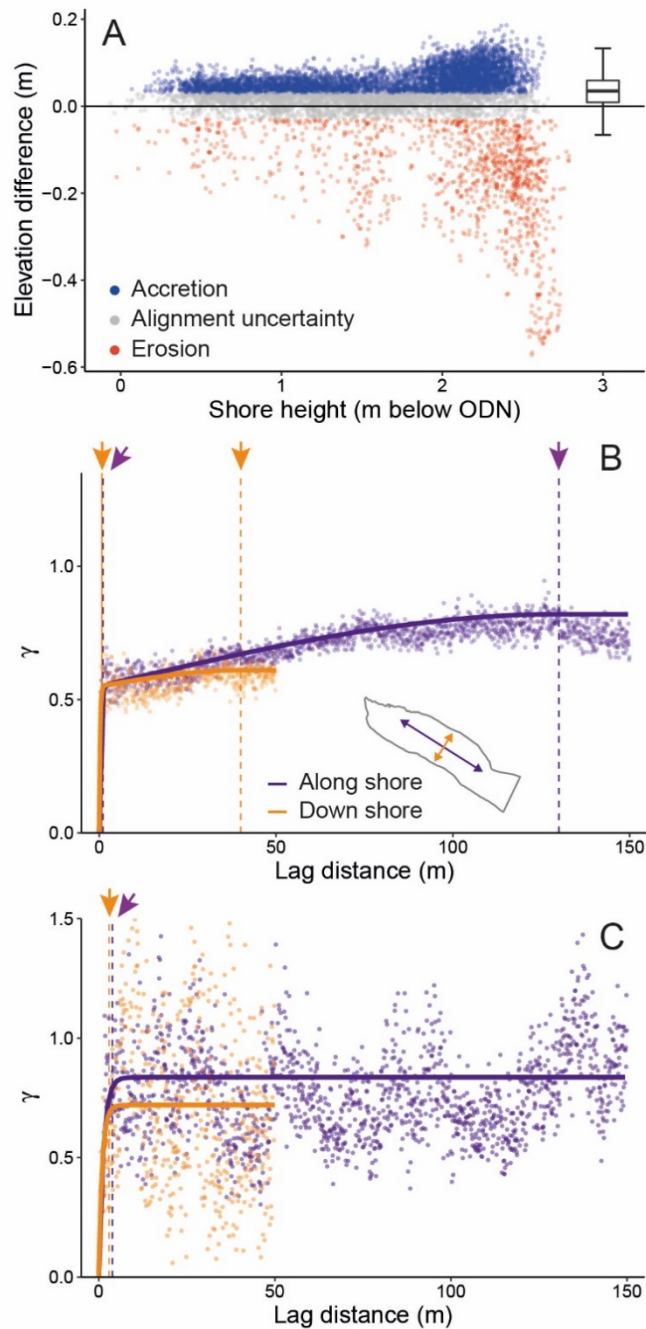


736

737 **Figure 4.** Data processing method used to sample reef emergence through time at independent reef
 738 locations within a 50 x 50 m plot mapped using terrestrial laser scanning at 6-month intervals over 5
 739 years (Supporting information). 1) Example section of 3D point cloud data. 2) We used a cloth
 740 simulation filter to generate a digital elevation model (DEM) for each time point and retained only
 741 points ≥ 0.2 m above the DEM. 3) We generated a digital surface model (DSM, 0.1 m XY resolution)
 742 of mean point elevation, then used the DSM to generate a mask that removed low point density cells,
 743 isolated cells, and colony edges. 4) We combined the masks from all time points. 5) We used a 2 m
 744 grid to generate spatially stratified random points (5 points per strata). 6) We randomly selected one
 745 point per strata with a minimum spacing of 1.5 m to generate our sample point locations. 7) At each
 746 sample location we calculated a timeseries of emergence by subtracting the elevation of a common
 747 digital elevation model representing the ground level from the DSM for each time point (Fig. 7).

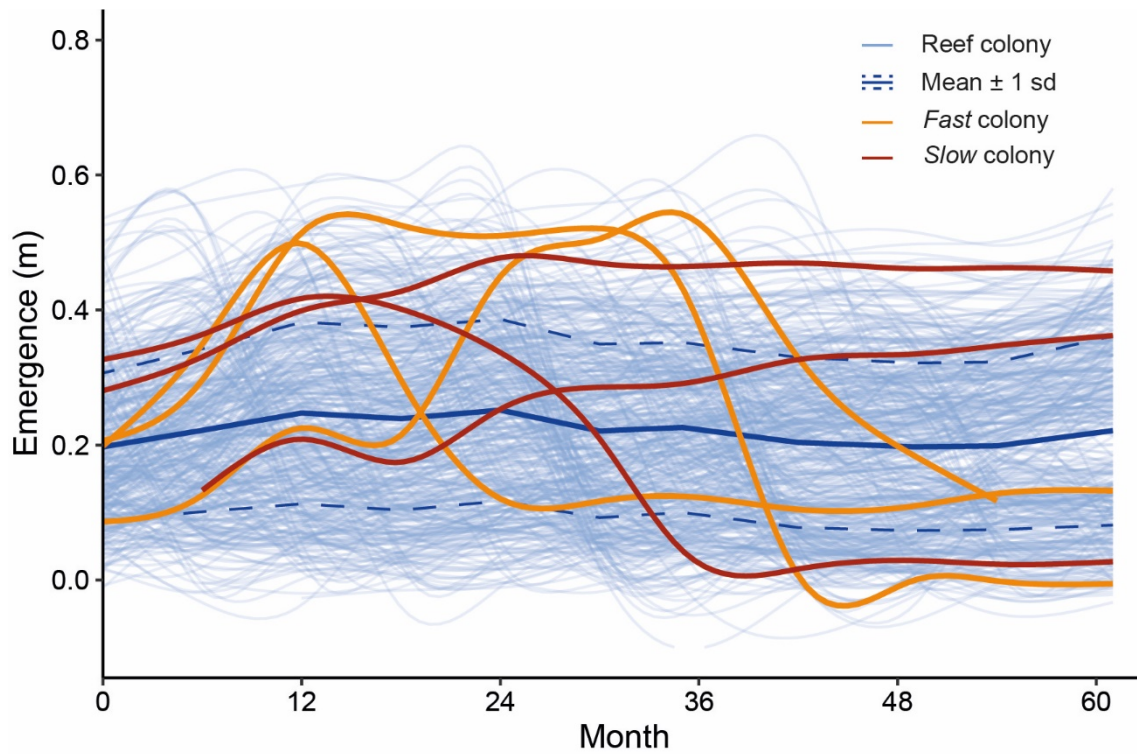


750 **Figure 5.** A) The foreshore at Llanddulas, Wales, UK. Habitat-scale 3D structure data were analysed
 751 within a 36,363 m² reef area polygon digitised from an aerial imagery orthomosaic. Presence of
 752 emergent reef is shown at 1 m XY resolution. B) Maximum reef colony emergence increases lower
 753 down the shore. The reef colonies that we analysed had a minimum emergence of 0.15 m. C) Reef
 754 colony emergence was spatially autocorrelated over short distances (1.5 m) both along the shore
 755 (purple) and down the shore (orange), ranges indicated by left-most vertical lines and arrows. There
 756 was a secondary autocorrelation structure that had a longer range (110 m) in the along shore direction
 757 compared to down the shore (20 m), ranges shown by right-most vertical lines and arrows.



758

759 **Figure 6.** Spatial variation in *S. alveolata* reef elevation changes from April 2018 to April 2019
 760 within the reef area (Fig. 5A). A) Both positive and negative elevation changes increased towards the
 761 lower shore. Samples showing positive changes (blue) were greater in number than those with
 762 negative change (red), but the larger average magnitude of negative changes resulted in little change
 763 in overall elevation, shown by the boxplot of all samples crossing 0. Grey points represent samples
 764 with changes within the alignment uncertainty estimate of ± 0.03 m. B) Variogram showing spatial
 765 autocorrelation scales of positive elevation changes (accretion) after accounting for trend (Supporting
 766 information table S2). The majority of spatial autocorrelation is explained by a short range (0.75 –
 767 1.05 m) structure (left-most vertical lines and arrows), with a secondary structure showing a longer
 768 range (130 m) in the alongshore orientation compared to down the shore (30 m). C) Variogram
 769 showing spatial scales of negative elevation changes (erosion) after accounting for trend (Supporting
 770 information table S2). Spatial autocorrelation only occurs up to a short range (2.9 – 3.84 m, vertical
 771 lines and arrows).



772

773 **Figure 7.** Colony-scale variation balances out to produce plot-scale stability in *S. alveolata* reef
 774 habitat structure over several years. Emergence was measured at 454 stratified random, spatially
 775 independent sample locations in a 2,500 m² plot in autumn and spring each year from September 2014
 776 (month 0) to October 2019 (month 61). Thin blue lines show individual sample timeseries. Bold blue
 777 line and dashed lines show the mean \pm 1 sd emergence of all samples. Six example sample timeseries'
 778 are highlighted to show the diversity of fine-scale dynamics in reef accretion and loss over time,
 779 clustered into two groups: *fast* colonies with rapid accretion and short persistence (orange) and *slow*
 780 colonies with slower accretion and longer persistence (red).