1 Assessing and modeling the dynamics and persistence of mussels in rocky-

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2 shore microhabitats
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- 24 Keywords: Species distribution, intertidal height, disturbance, resilience, remote sensing,
- 25 Markov chain model.

26 Abstract

27 In intertidal rocky shores, sessile organisms are subject to local variations due to a complex 28 interplay of physical and biological drivers. Here, we examined the patterns and the dynamics of distribution of a key benthic ecosystem-engineer species, the mussel Mytilus 29 galloprovincialis. We characterized areas of loss, gain, and persistence of mussel space 30 occupancy using drone images with a resolution of one centimeter across two rocky shores 31 spanning 3121 m² and 3499 m². Then, we assessed the effect of microhabitat slope, 32 33 microhabitat orientation, and intertidal height on the dynamics of mussel distribution for the two rocky shores. Notably, substantial losses were observed, ranging from 55% to 80% 34 depending on the shore. The hierarchical impact of habitat topographic features on mussel 35 occupancy dynamics diminishes in the order of rocky shore, intertidal height, and microhabitat 36 features. To unravel the dynamics further, we calculated persistence, resilience, and the time 37 38 to recover from disturbance using a Markov Chain model. Persistence time decreased at the 39 extremes of the rocky shore —both its top and bottom edges. Contrary to expectations, mussels 40 at these edges exhibit higher resilience, preventing their disappearance despite significant losses. Our results not only provide insights into the structural dynamics but also emphasize 41 the need to consider long-term responses to environmental changes. This study underscores the 42 43 potential of integrating models with drone technology for monitoring intertidal populations, 44 offering a powerful tool to comprehend and anticipate the enduring impacts of environmental 45 shifts on spatial distribution.

46

47 Introduction

48 Understanding and predicting changes or the persistence of species distribution are 49 major goals in population ecology related to important issues (Silliman et al. 2011, Wootton & 50 Forester 2013). In marine ecosystems, the persistence and changes in the distribution of species 51 are generally addressed at high spatial scales where major drivers, such as those related to 52 climate change, modify species occurrence and geographical boundaries (Poloczanska et al. 53 2013, Thomas et al. 2020, Curd et al. 2023). However, the interaction processes between 54 organisms and their environment take place first at individual level (i.e., ecophysiological 55 processes) and thus on a small scale. This likely has repercussions on species distribution dynamics that may be contradictory to large-scale trends due to local conditions that do not 56 necessarily follow large-scale trends (Helmuth 2002). 57

In intertidal rocky shores, sessile organisms are subject to local variations due to a complex interplay of physical and biological drivers, such as microclimate temperature and small-scale topographic features and interspecific competition (Dayton 1971, Seabra et al. 2011, Meager et al. 2011, Choi et al. 2019). For instance, Meager et al. (2011) showed that topographic features and temperature influence the abundance and body-size distribution of invertebrates on a rocky shore. The relationship between environmental conditions and the spatial distribution of species seems evident, although the particular role of each factor and the 65 driving mechanisms is complex and not well understood (e.g., Barbosa et al., 2021). In these 66 habitats, mussels are sentinel species studied to understand the effect of environmental 67 conditions on species' dynamics and distribution (Helmuth et al. 2011, 2016). Mussels are one of the dominant species inhabiting the mid-intertidal zone of temperate rocky shores worldwide 68 69 (Paine 1974, Paine & Levin 1981) and are considered paramount ecosystem engineers 70 (Borthagaray & Carranza 2007, Arribas et al. 2014). The dynamics and persistence of these 71 ecosystem engineer species are of main interest because their presence increases biodiversity 72 (Arribas et al. 2014, Scrosati et al. 2021), and, thus, changes in their distribution can produce 73 cascading effects on community structure and productivity (Silliman et al. 2011).

74 Merging field observations and models allows the simplification of complex systems 75 by integrating the multiple processes involved in the dynamics of species distribution. Such 76 integration provides the tools to understand spatial and temporal changes, as well as to test 77 hypotheses (Guichard et al. 2001, Wootton 2001). The development of high-resolution spatial 78 analysis from aerial images has allowed the mapping of intertidal species distribution with high 79 accuracy and detail (Guichard et al. 2000, Gomes et al. 2018, Garza 2019, Barbosa et al. 2022), 80 and could help to understand its long-term dynamics. The majority of studies on mussel 81 distribution dynamics focus on observations of recovery after experimental disturbance, such as in-situ removal of mussels in a specific square area (e.g., Carrington et al., 2009; Guichard 82 83 et al., 2003). Hunt and Scheibling (2001) studied natural disturbance in two rocky shores, but 84 their conclusions were based on the entire area rather than on the microhabitat scale. Studying 85 the distribution dynamics using drone images would not only allow to map entire rocky shores 86 but also to determine the spatial patterns among microhabitats. Combining observations and 87 models has been successfully applied to assess the colonization process or successions between 88 species (Wootton 2001, Guichard et al. 2003). Markov chain approach is based on probabilities 89 of transitions between different states, e.g., the probability of transition from an occupied to an 90 empty state and vice versa. Among other advantages, Markov chains allow the assessment of 91 the equilibrium state and estimate the time needed to reach this equilibrium after a disturbance, 92 and offer the prospect of a change in scale (Hill et al. 2002). Experimentally tractable local 93 scales can be scaled up to recreate larger-scale patterns (Wootton 2001, Guichard et al. 2003). 94 In a previous study, drone images were used to map mussel distribution (Barbosa et al. 95 2022). Results showed that distribution of mussels was primarily related to the intertidal height

gradient and, to a lesser extent, to habitat morphology in slope and orientation (Barbosa et al.
2022, see also Gilek et al. 2001). Based on that pattern, we hypothesized that the persistence
of mussel aggregations determines higher occupancy at intermediate intertidal heights.

According to this hypothesis, the proportion of occupied area (relative to the available area) would increase if mussels persist over time. In contrast, the top and bottom intertidal boundaries should present a higher probability of loss with a consequent decrease in occupancy. Similarly, we hypothesized that the topographic microhabitat conditions, slope, and orientation, are related, but to a lesser extent, to mussel dynamics.

104 Here, we used both mapping (drone surveys) and modeling (Markov chain modeling) 105 to assess the effect of microhabitat features on the dynamics of the distribution of a benthic 106 intertidal mussel, Mytilus galloprovincialis, and to estimate key properties of the temporal 107 dynamics of mussel distribution. We studied two rocky shores of the same bay as a natural 108 laboratory where the general oceanographic conditions affect microhabitats similarly within 109 both shores but differ depending on the shore orientations (mesoscale). Specifically, we 110 evaluated the effect of shore and microhabitat intertidal height, slope, and orientation angle on 111 the mid-term (annual changes) dynamics of *M. galloprovincialis* distribution. We also assessed the long-term effect of intertidal height on the persistence and resilience of the population, as 112 113 well as the potential role of disturbance on the species' occupancy pattern along the intertidal height gradient. To do that, we 1) evaluated the temporal dynamics of the distribution (loss, 114 115 persistence, and gain) of mussel aggregations during a period of a year from drone images, 2) 116 related the observed dynamics with the microhabitat intertidal height, slope, and orientation angle, and 3) modeled the long-term dynamics of lost and gained areas to estimate their long-117 118 term persistence, resilience capacity, and time to return to equilibrium after a disturbance.

119 Methods

120 Study site

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The study was conducted at "Le Petit Minou" site, located on the western coast of French Brittany, France (Fig. 1A). This site is characterized by a macrotidal regime at the entrance of the Bay of Brest. The site comprises two rocky shores on both sides of a sandy beach, here referred to as the West and East shores based on their positions. The West shore is oriented to the south-southeast, whereas the East shore is oriented to the west (Fig. 1B). The West and East rocky shores encompass a total available intertidal area within the mussel distribution range (3.32–5.80 m) of 3121 m² and 3499 m², respectively (Barbosa et al. 2022).

129 "Le Petit Minou" site has been characterized by a dominance of *Mytilus* 130 galloprovincialis (Simon et al. 2020), although hybrid individuals are common in the Brittany 131 region (Bierne et al. 2003). The mussel structure is mainly compound by monolayer 132 aggregations in both rocky shores (Barbosa et al. 2021).

133 Drone image acquisition and processing

Drone surveys were performed on two dates, June 5, 2019, and June 23, 2020, on each 134 135 of the two rocky shores. Images were processed to construct the digital surface model (DSM) 136 and orthomosaics of both rocky shores and dates using PhotoScan v.1.4.0 software (Agisoft 137 LLC, St. Petersburg, Russia, currently known as Metashape). We employed the Time-SIFT 138 approach (Feurer & Vinatier 2018), which involves aligning all images from different periods 139 (specifically, June 2019 and June 2020) and then separating the previously aligned images for 140 each date to create 3D dense point clouds and generate the SDM and orthomosaic. This process 141 ensured perfect alignment between the orthomosaics of both dates, facilitating a more precise 142 evaluation of temporal changes (Feurer & Vinatier 2018). Due to the high number of cells in 143 the resultant layer (cell resolution 0.5×0.5 cm) and the difficulty of processing the total ~16M 144 cells/rows, we resampled the layer at a cell resolution of 1 x 1 cm in QGis v.3.14.16 (QGis 145 Development Team, 2020) for further analyses. Subsequently, we identified changes at each cell of the orthomosaic, i.e., at a centimeter resolution. 146

147 Identification of mussels' distribution on two dates

148The identification of mussels was carried out by calculating the Mussel Visualization149Index (MVI) from the orthomosaics (Barbosa et al. 2022).

150 MVI =
$$\left(B - \frac{(R+G)}{2}\right)100$$

151 where *B* represents blue, *R* represents red and *G* represents green, the three bands 152 (RGB) of each cell (pixel) in the orthomosaics. Then, we applied a date- and site-specific 153 threshold to differentiate mussels from other species and substrates based on manually sampled 154 pixels of mussels and non-mussel areas from the constructed orthomosaic (details in Barbosa 155 et al. 2022).

156 Areas with the presence of algae and lichens in the bottom and upper intertidal height 157 (outside the mussel range) as well as some shadow areas exhibited similar MVI values to 158 mussel areas. To enhance mussel identification, we performed the following workflow: 1) 159 mask by hill-shade distribution, 2) identify mussel intertidal height range, 3) select site's cells 160 within mussels' MVI range, and 4) select mussels' cells by intertidal height range (after 161 Barbosa et al. 2022). This workflow was applied for each date, with the dataset and analyses 162 from June 2019 identical to those presented in Barbosa et al. (2022). The intertidal height range 163 of mussel distribution in the study site was recorded as between 3.2 to 5.80 m above the Lowest 164 Astronomical Tide (LAT) in 2019 (Barbosa et al. 2022). Cells outside this range were 165 considered false positives (false mussel coverage cells) and discarded from both orthomosaics 166 (2019 and 2020).

The accuracy of the resultant distribution dynamics was assessed by sampling 130 cells 167 168 from each orthomosaic (total of 520 cells; 130 cells x 2 rocky shores x 2 dates). For each 169 orthomosaic, 30 cells corresponded to mussels and 100 to non-mussel cells. Non-mussel cells 170 were manually selected from the orthomosaic, where high resolution allowed unequivocal visual differentiation of mussels from the substrate or other species' cells. Mussels' cells were 171 172 also manually selected to represent the wide spatial distribution of mussels. Mussels and non-173 mussels' reference cells were compared with the result of the mussel identification process in 174 a confusion matrix. The confusion matrix presents the proportion of cells corresponding to 175 mussels and non-mussels' cells that were correctly identified, as well as the proportion that 176 was erroneously classified. Then, the overall accuracy (Congalton 1991) and the Kappa index 177 (Kruskal & Wallis 1952, Cohen 1960), were used to determine the accuracy of the supervised 178 classification. Overall accuracy represented the percentage of cells correctly classified, 179 whereas the Kappa index represented the concordance between the supervised classification 180 and the real distribution of mussels. The Kappa index can take values from -1 to 1, with -1 181 equivalent to zero, whereas 1 indicates perfect concordance (true positives and true negatives).

182 Characterization of the dynamics of mussel's occupied area

The temporal dynamics of mussel distribution were derived by comparing both orthomosaics, from June 2019 and June 2020, to create a layer with three categories: 'persistence', gain' and 'loss'. Areas initially covered in 2019 that continued to be occupied in 2020 were classified as 'persistence areas'. Areas initially covered in 2019 that showed an absence of mussels in 2020 were classified as 'lost areas', and areas with an initial absence of mussels that were occupied in 2020 were classified as 'gained areas'.

189 To characterize the distribution dynamics, we initially measured the net area of 190 persistence, gain and loss on each rocky shore, calculating their proportions relative to the 191 entire shore. Additionally, we computed the probability of loss, gain and persistence along the 192 intertidal height range on both rocky shores. Loss probability was defined as the ratio of 193 occupied cells in 2019 that became empty in 2020; Persistence probability as the ratio of 194 occupied cells in 2019 that remained occupied in 2020; and, Gain probability as the ratio of empty cells in 2019 that became occupied in 2020. Probabilities were averaged at 20 cm 195 196 intervals along the intertidal zone occupied by mussels, ranging from 3.2 to 5.8 m above the 197 LAT (Barbosa et al. 2022).

198 Furthermore, we determined the probability of loss, persistence, and gain for each 199 topographic microhabitat (intertidal height-slope-orientation). To achieve this, we aggregated 200 cells (from the distribution dynamics layer) with similar microhabitat features, i.e., intertidal 201 height, slope and orientation, and calculated loss, persistence, and gain probabilities as 202 indicated above. The slope was classified into five ranges, each spanning 10 degrees from 0 to 203 60 each. Similarly, the orientation was divided from 0 to 360 every 30 degrees 204 (counterclockwise, with 0 representing North). We created a merged dataset containing mussel 205 distribution dynamics and topographic features corresponding to each cell in the orthomosaic. 206 To achieve this, the distribution dynamics layer was converted from raster to points, and this 207 point layer was used to extract information from layers of topography (DSM), slope, and 208 orientation (at a resolution of 20 x 20 cm). Topographic feature layers were downscaled from 209 1 to 20 cm resolution to facilitate processing across the entire study area and avoid very 210 localized roughness effects.

To identify the main features related to observed mussel distribution dynamics, we evaluated the amount of variance explained by each feature and their potential interactions using the linear models function in R. We calculated the variance explained using the 214 proportion of the total variation explained by a variable, denoted as η^2 (Lane, Online Statistics 215 Education).

216 $\eta^2 = SSQ_{effect} / SSQ_{total}$

217 where SSQ_{effect} is the sum of squares due to an effect or factor, and SSQ_{total} is the total sum of 218 squares. It is important to note that we used the model fit to extract the calculated sum of 219 squares, not to test for the statistical significance of the factors. The proportion of the total 220 variation explained by each variable (η^2) was represented as a percentage in a Venn diagram 221 for loss, persistence, and gain from each shore. Intertidal height was treated as a continuous 222 variable represented by ranges of 20 cm along the intertidal zone occupied by mussels. The 223 slope and orientation topographic features (independent variables) were treated as categorical 224 variables with several levels determined by a range of values. Cells with a slope higher than 60 225 were excluded from the analyses due to their low representation (few cells and lack of 226 representation of all orientation angles) in the study area. The entire process of extracting layer 227 information and creating the complete dataset was performed in R (R Core Team, 2020) using 228 raster package functions (Hijmans 2020).

229 Model of the dynamics of mussel's occupied area

230 The model represents the dynamics of a theoretical cell defined as a square area of 1 231 cm², which is the same scale of observations made at a given intertidal height position on a 232 single shore. Cells occupied by mussels may become empty due to disturbances, such as 233 dislodgement or mortality, related to the effect of external factors. Each cell can be in two 234 ecological states, depending on the presence (Occupied) or absence (Empty) of mussels (Fig. 235 2A). An Occupied cell has a probability to stay occupied for one more year (persistence 236 probability, denoted as p). Each Occupied cell may also become Empty with a loss probability 237 1-p. The probability of change from *Empty* to *Occupied* between two consecutive years is 238 defined as the gain probability q (Fig. 2A).

Markov chain theory predicts that the proportions of cells in *Occupied* vs *Empty* states reach equilibrium, remaining constant over time (Wootton, 2004; Fig. 2B). Consequently, mussel distribution is expected to fluctuate annually due to disturbances, while the proportions of *Occupied* vs *Empty* cells remain stable unless additional disturbances occur. The main calculations are as follows (refer to Supplementary 2 for mathematical proof):

244 - the proportion of *Empty* cells is
$$\mu = \frac{1-p}{1-p+q}$$

- 245 the proportion of *Occupied* cells is $\lambda = \frac{q}{1-p+q}$
- 246 the *Gained* cells result from the changes from *Empty* to *Occupied* states and are 247 equal to $q.\frac{1-p}{1-p+q}$. At equilibrium, the proportion of *Gained* cells equals the 248 proportion of *Lost* cells, thus, there is no absolute lost or gained area since they 249 cancel each other.

The model properties allowed us to derive important features characterizing the population's long-term dynamics, such as (refer to Supplementary 2 for explanations and mathematical proofs):

- 253 the persistence time, defined as the maximum time during which 90 % of *Occupied* 254 cells remain occupied (90th percentile) in the absence of disturbance, is equal to: 255 $a = \frac{log(0.1)}{log(p)}$
- 256 the resilience index, a metric of the capacity to return to equilibrium after a 257 disturbance (loss event), is equal to r = 1 - |q - p|. This indicator ranges 258 between 0 and 1 facilitating comparison across systems. Values close to 1 259 correspond to more resilient systems, following the definition given by Viejo 260 (2009) and Grimm & Wissel (1997) as the speed at which an ecological system 261 returns to a reference condition after a temporary disturbance.
- the return time to equilibrium (Fig. 2B) after a disturbance is $e = \frac{log(0.01)}{log(|p-q|)}$. This metric is related to the resilience index but gives the measure of time, as cells with a high resilience index will present a shorter return time. The return time can be site/system-specific, whereas the resilience index is a standardized metric allowing comparison with other systems.
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Probabilities p, 1-p and q likely depend on the intertidal height range and shore and were derived from the drone image analyses by aggregating all cells from the overlapped orthomosaics at each specific intertidal height range from the West or East shore. We used the equations and the observed proportions of *Occupied*, *Lost*, and *Gained* cells to estimate the two parameters p and q for each shore and intertidal height range. One approach to achieve this is by utilizing an algorithm that minimizes the difference f between predicted and observed proportions of *Occupied* and *Gained* cells. We defined f as:

275
$$f = \frac{1}{3} \sqrt{\left(\frac{q}{1-p+q} - 0ccupied\right)^2 + \left(q\frac{1-p}{1-p+q} - Lost\right)^2 + \left(q\frac{1-p}{1-p+q} - Gained\right)^2}$$

where *Occupied* represents the observed proportion of occupied cells averaged over 2019 and 2020, *Gained* represents the observed proportion of gained cells relative to the empty cells in 2019, i.e. gain probability, and *Lost* represents the observed proportions of lost cells. We used the *optimal* function of the R package to find (p,q) that minimizes *f*.

280 For each shore and intertidal height range, we used the metrics defined above to analyze 281 and compare the properties of mussel cells in these microhabitats. The predicted proportion of 282 Occupied cells relative to the *Empty* cells would not change over time if the system is in 283 equilibrium. Since observed values in 2019 and in 2020 were different, we assumed that some 284 additional disturbance occurred between the two years and we estimated the time needed to 285 reach equilibrium, denoted as the return time. Since the proportions of *Occupied* and *Empty* 286 cells at equilibrium are asymptotic values, we defined the time to get as close as 1% of the 287 equilibrium values with an initial proportion of Occupied cells equal to 0 (see Supplementary 288 2).

289 **Results**

290 Accuracy of the identified mussels' distribution dynamics

The accuracy of the image classification process was very good, with more than 79% of agreement between cells identified as mussel cells and the true mussel cells, as indicated by the Kappa index, across the two shores and dates studied (Table 1). The overall accuracy of the image classification was high, with 93% to 98% of evaluated cells correctly classified among the processed image datasets (Table 1).

296 Observed mussel's distribution dynamics

From the initially covered area in June 2019 (58.3 m²), 80% (46.6 m²) was lost, and 48% (27.9 m²) was gained on the West shore, whereas in the East (280 m² in 2019), 55% (154.0 m²) of the covered area was lost, and 14% (38.2 m²) was gained (Table 2, Fig.3). The gained area was, thus, smaller than the lost area, resulting in a net decrease of the covered area of 32% and 41% on the West and East shores, respectively (Table 2, Fig. 3). 302 The probabilities of loss, persistence and gain varied principally between the West and 303 East shores and among intertidal height positions, slope and orientation (Fig. 4). Between 304 shores, the West presented higher loss probabilities and lower persistence probabilities than 305 the East shore, mainly in the mid-intertidal area, whereas the gain probabilities were low on 306 both shores and along the entire intertidal height gradient (Fig. 4). The loss probability and 307 persistence probability varied from 0 to 1 in the West and East shore (Fig. 4). The gain 308 probability varied between 0 and 0.22 and between 0 and 0.39 in the microhabitats of the West 309 and East shore, respectively (Fig. 4). Along the intertidal height gradient, the loss and 310 persistence probabilities presented a pattern with lower loss and higher persistence probability 311 in the mid-intertidal height, mainly on the East shore, but no evident pattern was observed in 312 the gain probability on both shores (Fig. 4). Regarding the microhabitat slope and orientation, 313 there was no evident pattern either at specific intertidal positions or shore (Fig. 4).

314 Analyzing the proportion of variance explained by each of these factors also evidenced the higher importance of intertidal height over the slope and orientation of microhabitats on 315 316 the probabilities of loss, persistence, and gain (Fig. 5, Table S1 in Supplementary 1). This highlighted that topographic features impact the two shores differently, with higher effects 317 318 observed in the East compared to the West shore. The total variance not explained by either 319 intertidal height, slope, and orientation (white area; Fig. 5) was higher in the West shore (76.9% 320 to 80.1%) than in the East (36.1% to 66.6%), indicating an effect of the shore on the observed 321 patterns of loss, persistence, and gain. A large part of the variance observed in the West shore 322 would therefore be associated with another factor not related to the topographic features studied 323 here. In the East shore, intertidal height dominates and explained 53.6% and 58.3% of the loss 324 and persistence variation, respectively, while it explained only 9.1% and 13.6% on the West 325 shore. Contrarily, the variance explained by slope and orientation was small and relatively 326 similar between West and East shores, ranging from 0.5 to 1.2% and from 0.3 to 4.1% for slope 327 and orientation, respectively.

328 Considering the dominating effect of intertidal height on mussel distribution dynamics, 329 we explored how mussels' loss, persistence, and gain probabilities were distributed along both 330 East and West intertidal heights. The distribution of their probabilities showed different 331 patterns along the intertidal height (Fig. 6). On both shores, the persistence showed an 332 unimodal distribution along the intertidal height, distributed on a wider range of values on the 333 East shore and centered on 4.5 m above the LAT, relative to the West where values were 334 observed over a lower range, between 4.3 m and 5.3 m, and centered on 4.7 m above the LAT. 335 Gain probabilities showed a more similar unimodal pattern between shores, centered on 4.5 m

above the LAT (Fig. 6; note the different scales). The loss probability presented an inverse
pattern relative to the persistence, with a bimodal distribution on both shores, with maxima
observed at both margins, through the top and bottom intertidal heights (Fig. 6).

339 Properties of the mussel dynamics predicted by Markov model

340 Based on the major effect of the rocky shore and intertidal height on the probabilities of loss, persistence, and gain, we estimated model parameters along the intertidal height on 341 342 each rocky shore. The comparison between observation and model predictions indicated that 343 the model underestimates the occupancy of mussels in 2019 and overestimates the occupancy 344 in 2020 (Fig. 7). This is due to the estimation procedure of model parameters, which assumes 345 that the predicted occupancy ratios lie in between the values observed in 2019 and 2020. 346 Predicted loss probabilities were very close to observations as opposed to the predicted gains 347 probabilities, which were overestimated by the model (Fig. 7). This is again explained by the 348 criterion used in the estimation procedure, which gives a larger weight to large values (e.g., 349 Loss - see Methods).

350 The time to return to stable Occupied and Empty proportions after a disturbance varied 351 between 2 and 8 years (Fig. 8A). The resilience index was above 0.5 for all combinations of shore and intertidal height, indicating a high capacity to return to equilibrium (Fig. 8B). 352 353 Resilience is inversely (but not linearly) correlated to Return time (see Methods). Resilience 354 was higher on the West than on the East shore, which corresponded with a slightly shorter 355 return time shown by the simulations (Fig. 8B). For both shores, resilience was lower in the mid intertidal zone, around 4.6 m above the LAT. The persistence time and resilience index 356 distribution along the intertidal height were opposite. Persistence time was higher on the East 357 358 shore and varied along the intertidal height with maximum values of 3.7 years at intermediate 359 intertidal height (Fig. 8C).

360 **Discussion**

Using drone images and a Markov chain model, we showed that the covered area by 361 mussels (Mytilus galloprovincialis) on rocky shore habitats over a year was highly dynamic 362 363 and spatially heterogeneous. The proportion of area with loss, gain, and persistence of mussels 364 differed between the two rocky shores studied and among intertidal height ranges but they were quite similar among microhabitats of different slopes and orientations. Our results then support 365 366 our first hypothesis about the persistence of covered areas determining the higher occupied 367 proportion of the area at intermediate intertidal height and its decrease at the top and bottom 368 edges. On the contrary, our second hypothesis about the effect of microhabitat slope and 369 orientation on the dynamics of occupancy was not supported, since the variation related to 370 these features represented less than 4% of the overall variation. The modeling approach showed 371 a higher capacity of the population to recover from a disturbance at the top and bottom intertidal 372 edges (maximum resilience index greater than 0.5 and return time lower than 3 years), as well as the potential of intermediate intertidal height areas to persist over 3.5 years in the absence 373 374 of disturbance. In the following, we discuss the spatial heterogeneity of mussel dynamics and 375 associated predicted long-term population properties (resilience and persistence time) and how 376 they may relate to environmental factors or population traits. Finally, we discuss the value of 377 combining observations and modeling in the study of population ecology.

378

379 Mussels occupancy and temporal dynamics

380 The mussel-covered areas in "Le Petit Minou" decreased substantially, between 50% 381 and 80%, from June 2019 to June 2020 on both rocky shores and were only partially recovered. 382 This highly dynamic character is not specific to the studied population and has also been 383 described for mussels in different ecosystems. For example, monitoring of a wild population 384 of *M. californianus* in the Northwest Pacific showed that natural disturbance in a rocky shore 385 led to annual losses from 30% to 40% during the 1970-1978 period (Paine & Levin 1981). 386 Other studies, based on experimental disturbance approaches and monitoring of small areas on 387 rocky shores in Rhode Island, Northwest Atlantic, highlighted highly dynamic seasonal cover 388 loss and recovery of mussels in the middle intertidal zone (0.5 to 1.0 m above mean lower low 389 water). By monitoring fixed quadrats over a 3-yr period (2001-2003), Carrington et al. (2009) 390 showed a cover loss of about 50% in the first year followed by stability and recovery or gain 391 in the third year, a similar recovery time as our prediction for the East shore from "Le Petit 392 Minou". Another quadrat showed about 20% of loss area in the first years, followed by a similar

recovery and a subsequent loss of ca. 40% which was not recovered in the second year, but increased in the third year reaching ca. 100% of loss, which was recovered to 70% coverage in only ca. 4 months. These results showed the high spatial variability and temporal dynamic in loss and recovery at a single intertidal range.

397 Our methodological approach, using remote-sensing imagery, provides extensive 398 coverage of the mussel habitat and has enabled us to show that mussels' distribution dynamics 399 varied principally along the intertidal height gradient on both shores, with between 8 to 58% 400 of the variation related to it. This supports our first hypothesis that the persistence of mussel 401 aggregations determines the higher occupancy at intermediate intertidal height. In other words, 402 our results showed that the spatial distribution of disturbance, observed as lost areas, could 403 determine the unimodal distribution of mussels along the intertidal gradient. This suggests that 404 there is an optimum habitat for *M. galloprovincialis* when intertidal height is between 3.8 and 405 5 m above the LAT. Based on mussels' dynamics observation, Markov chain modeling showed 406 that the pattern of persistence time was consistent with the observed persistence probabilities 407 and, thus, higher at this optimum intertidal height. Mussels were predicted to reach a maximum 408 persistence time of 3.7 years at intermediate intertidal height and about 1 year at the distribution 409 edges. That estimation appears much lower than the maximum age of mussels individuals 410 recorded in "Le Petit Minou", which was about 12 years old based on sclerochronology 411 analyses (Barbosa et al. 2021). Such a mismatch could reflect the randomness of a few 412 individuals reaching such an age of 12 years. The model simplifies the dynamics of mussels in 413 a square area and assumes a complete change of state in such an area, whereas in reality, even 414 in a disturbed area, some individuals can persist and create mussel aggregations of 415 heterogeneous age as observed in-situ (e.g., Barbosa et al. 2021). In addition to the pattern of 416 persistence time, our modeling approach showed an intertidal pattern of the resilience index 417 and return time, which suggested that the population distribution is highly resilient mainly in 418 the top and bottom edges of the intertidal range. It could sound contradictory since the areas 419 with a lower resilience are the most occupied. However, mid-intertidal areas had a lower loss 420 probability, which suggests that the ecological strategy is likely to increase their resilience in 421 areas with higher disturbance. Higher resilience was also recorded at higher intertidal position, 422 with higher environmental stress in macroalgal communities (Viejo 2009). The predicted return 423 time at mid-intertidal height was in concordance with slow recovery in mussel coverage in 424 wave-exposed areas in Patagonia, from 5 to 15% recovery after 3 years of experimental 425 disturbance (Bertness et al. 2006). The trade-off between disturbance probability and resilience

426 could explain how the species can inhabit the upper and lower intertidal areas, where, without427 a high recovery capacity, mussels would disappear over time.

428 Contrary to expected, the spatial distribution of loss and gain probability (i.e., the 429 dynamics of mussels' distribution) recorded between 2019 and 2020 was only marginally 430 related to microhabitat slope and orientation. This result may seem contradictory to 431 observations made by Harley et al. (2008) who found higher mortality in microhabitats oriented 432 to the south during high temperature periods. However, our one-year period dynamics balance 433 must limit our ability to identify the effect of microhabitat features at specific seasons, since 434 disturbance patterns must vary among seasons. Furthermore, our results also contradict 435 observations made by Barbosa et al. (2022), who showed a link between the distribution of 436 mussels on the East shore of "Le Petit Minou" in 2019 and microhabitats' features. The 437 occupancy pattern recorded on the East shore should thus result from a different process than 438 disturbance either between 2019 and 2020 or even before 2019. Another potential explanation 439 could be that a cumulative effect of longer-term processes would produce the observed occupancy pattern linked to orientation and slope, and short-term disturbances would be mainly 440 441 linked to the intertidal height profile and the effect of shore (i.e., mesoscale).

442

443 Potential factors driving the distribution dynamics

444 Our observations of a net decrease in the total occupied area indicated that the gained 445 area was not enough to compensate for the loss of individuals in a period of a year. The system was, therefore, not at equilibrium, i.e., it does not have a constant proportion of Occupied vs. 446 447 *Empty* area over time, which calls for an explanation based on one or more sources of 448 disturbance. The low gain area observed in the present study indicated slow recolonization 449 during the 2019-2020 period. Recolonization of lost areas occurs generally by the growth of 450 individuals still in place and movement of individuals from the perimeter of the lost areas, also 451 called clearings or gaps, while recruitment in such bare areas is almost insignificant (Paine & 452 Levin 1981, Littorin & Gilek 1999). The growth rate of mussels on both shores is generally low, with estimates of less than 1 cm growth over a year (Barbosa et al. 2021). This could 453 454 explain the observed low gain area in only one year. Differently, in subtidal habitats, mussels' 455 growth rate seems to determine the differences in coverage and biomass among depths (Gilek 456 et al. 2001). This must be related to the lower effect of waves and the independence from tides 457 effect on the feeding time on subtidal areas, whereas we showed that in intertidal rocky shores, 458 the intertidal height position, which determines the immersion time, was the main factor related 459 to the dynamic of mussels.

460 Mussel bed disturbances are mainly known to be related to wave action and temperature (Harger & Landenberger 1971, Paine & Levin 1981, Denny 1987, Harley & Helmuth 2003, 461 462 Guichard et al. 2003, Harley 2008, Carrington et al. 2009, Seuront et al. 2019). Combined 463 conditions of high-temperature stress and wave action cause extreme mortality by 464 dislodgement in summer, when mussels' attachment is generally weaker (Carrington 2002, Carrington et al. 2008, 2009). The high loss observed in our study area could result from this 465 466 type of extreme event. Indeed, an event combining high spring and summer temperatures 467 compared to long-term records and a period of high waves occurred in early August (Figure 468 S1 in Supplementary 1). The occurrence and intensity of marine heatwaves have been 469 increasing over the last decade as a result of global warming in the Bay of Biscay, English Channel and Bay of Brest (Simon et al. 2023). Consequently, disturbances of mussel 470 471 distribution related to marine heatwaves are likely occurring at a larger spatial scale and a 472 higher frequency.

473 Sand dynamics can also affect mussel distribution, mainly at the lower intertidal level 474 (Zardi et al. 2008, Bagur et al. 2022). Sand dynamics increases mussels' mortality and 475 determines mussels' lower limit of distribution in other areas (Zardi et al. 2008, Bagur et al. 476 2022). Sand intertidal level in the studied site was observed to change by about 1 m in height 477 during the winter of 2019 (Fourer et al. 2023). These movements of the sand and changes to 478 the overall topography of the site may have caused additional disturbance, helping to explain 479 the low rate of gain observed. Sea star predators, which determine lower limits in the Northwest 480 Pacific, are almost absent in our study area (Tsuchiya and Retiere, 1988). This would not play 481 a main role in the limit of mussel range, as also observed in Patagonia (Bertness et al. 2006), 482 which supports the possibility of sand dynamics limiting mussels' lower distribution.

483 Spatial variability in disturbance sources, combined with differences in biological 484 features of mussel aggregations between shores, could explain differences in mussel cover 485 dynamics between the East and West shores. Mussel aggregations in the West appear to be less 486 stable, presenting a higher probability of loss and consequently lower persistence than those in 487 the East. Differences in wave exposure and sun exposure are expected between the East and 488 West shores, given their distinct orientations. These differences in exposure to sun and waves 489 could result in differences in the average temperatures experienced by individual mussels 490 (Helmuth & Denny 2003, Gilman et al. 2006, Seabra et al. 2011). Potentially higher sun 491 exposure and temperature could intensify the combined effect of waves and thermal stress. 492 Furthermore, patterns of mussel occupancy were related to mesoscale orientation differences 493 between shores (Barbosa et al. 2022). Population features, such as density and crowding 494 structure, could also influence the effect of disturbance. Disturbance would spread through 495 direct neighbors, and the formation of hummocks tends to decrease the attached surface when 496 density increases (Tanaka & Magalhães 2002, Guichard et al. 2003, Gutiérrez et al. 2015). 497 Similarly, the density of aggregations and substrate type can influence the recolonization, i.e., 498 gain, of mussels (Bertolini et al. 2018). The density of mussels is higher in the West than in the 499 East shore, with a higher recruitment and lower growth rate (Barbosa et al. 2021). All these 500 features could explain the higher resilience estimated for the West compared to the East shore.

501 The major heterogeneity in mussel dynamics along the intertidal height, compared to 502 the microhabitat slope and orientation, could reflect the marked tidal dynamics throughout the 503 year compared to horizontal spatial change conditions. A tidal cycle would be relatively similar 504 throughout the entire year (e.g., the lower intertidal remains always submerged for a longer 505 period), whereas no particular pattern favoring specific orientation and slope emerges due to 506 the high seasonality of temperature and waves exposure at a small scale (Littorin & Gilek 1999, 507 Gilek et al. 2001). For instance, Helmuth & Denny (2003) highlighted the difficulty of 508 classifying microhabitats based on the hydrodynamic forces experienced by individuals living 509 there, due to the high temporal and spatial heterogeneity in wave microscale forces (see also 510 Burel et al. 2019, Focht & Shima 2020, Gaylord 1999).

511 Other processes such as the spreading of disturbance and density-linked stochasticity, 512 as well as some limitations of our methods could create noise that impacts the identification of 513 a microhabitat effect on the probability of loss. In reality, the spreading of the disturbance 514 among neighbors could cause a larger loss than the one produced by the actual disturbance 515 (Denny 1987, Guichard et al. 2003). Furthermore, density-linked stochasticity has been 516 predicted to play an important role in the long-term dynamic of mussels (Wootton & Forester 517 2013). Between the limitations of our methods, the resolution of microhabitat features (slope 518 and orientation; 20 x 20 cm resolution), could affect the analysis. Then, we do not discard the 519 potential relationship between the slope and orientation on the probability of an initial loss of 520 individuals, which could then expand to all microhabitat areas where the aggregation of 521 mussels is connected.

522 Interest and limits of the modeling approach

523 Markov chain theory proved to be useful in describing temporal dynamics in population 524 ecology, e.g., long term persistence (Pandolfo et al. 2017), succession between species or 525 functional groups (Wootton 2001, Wootton 2004, Hill et al. 2004, Tsujino et al. 2010) or 526 species extinction (Hill et al. 2002). The matrix of transition probabilities between states help 527 comparing sites, assessing patterns of local biodiversity and evaluating changes over time. Going a step further, Wootton (2004) computed system resilience and assessed the contribution of each functional group using a Markov model with a dozen of states based on successions between functional groups. Pandolfo et al. (2017) derived transition probabilities over 26 years and computed persistence of mussel assemblages. In our study, we derived resilience, return time and persistence time of mussel covered areas from the transition matrix between 2 states. Though we only gave the equations for this simple system, these properties could be easily computed for systems with more than 2 states.

535 Estimation of model parameters is usually based on monitoring quadrats (Tsujino et al., 536 2010) or experiments (Guichard et al. 2003, Wootton 2004). One important difference with our 537 study is that we had a full coverage of the studied area, which reinforces the accuracy of the 538 estimation of transition probabilities. On the other hand, we made observations at only two 539 different dates and results showed an important change in the areas covered by mussels. This 540 change reflects the stochasticity of the occupation process and yields uncertainty in the 541 estimation of model parameters. We therefore made the assumption that the predicted 542 occupancy lies between the values derived from the observations made at 2 different dates. 543 Additional observations would likely yield the same patterns linked to the effects of intertidal 544 height and shore orientations, even though the values of predicted persistence time, resilience 545 and return time would differ from our actual results. Monitoring mussel distribution over a 546 longer period of time would therefore help estimating model parameters more precisely.

547 We explained that the gradient of environmental drivers would result in different 548 transitions between states. One perspective is to move towards more explicit formulations of 549 mechanisms which account for the variability of species distributions over space and time. 550 Such a mathematical formulation would allow assessing local interactions and pattern 551 formations. For instance, Guichard et al. (2003) used a spatially explicit Markov Chain model 552 to predict patterns emerging from local interactions. In their approach, the recovery probability 553 of an empty cell mimics the lateral movement of adult mussels into bare space and depends on 554 the proportion of occupied nearest neighbors in a regular spatial grid. They explored the response of spatial patterns (e.g. edges between occupied and empty cells) to environmental 555 556 conditions through the sensitivity of model properties to parameter setting. As a consequence, 557 they suggest that Markov models help inform on environmental drivers of mussel bed spatial 558 patterns at local and large scales. High-resolution imaging could therefore be combined to a 559 mechanistic model of spatial interactions at a small scale to quantify more precisely how local 560 disturbances, movement and settlement of new individuals explain the differences in temporal 561 dynamics among intertidal heights that we predicted.

562 **Conclusions and perspectives**

563 Our analyses allowed for an evaluation of mussel distribution dynamics over one-year, with changes observed at a spatial resolution of one centimeter along two entire rocky shores. 564 565 Our results outline the role of intertidal height on the temporal and spatial dynamics of mussel distribution, the occurrence of major disturbance, and the probability of long-term persistence. 566 This work highlights the power of image analyses in the study of spatial ecological processes 567 568 related to disturbances, which has predominantly been explored through experiments 569 conducted in limited, specific areas (generally small square areas). A monitoring strategy 570 incorporating more frequent surveys, alongside ongoing temperature monitoring projects (e.g., 571 Seabra et al. 2015, Seuront et al. 2019) would enable the assessment of seasonality in 572 population dynamics, including responses to events such as storms, and the identification of the main drivers involved. The use of drone images in conjunction with modeling approaches 573 574 would be particularly apt for long-term monitoring, shedding light on the long-term persistence of populations facing changes in the frequency and intensity of marine heatwaves (Simon et 575 576 al. 2023).

577

578 Funding

579 This study and RVB benefited from the financial support of the Region Bretagne and 580 Université de Bretagne Occidentale (UBO). Scientific committee of IUEM funded student's 581 training related to the project.

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Table 1 Overall accuracy and Kappa index indicating the performance of the supervised
 classification results performed for each shore and date.

Rocky shore	Dataset	Overall accuracy (%)	Kappa index			
 West	June 2019	0.98	0.93			
	June 2020	0.93	0.79			
East	June 2019	0.93	0.80			
	June 2020	0.94	0.82			

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Table 2 Summary of the dynamics of distribution in the West and East shores in "Le Petit
 Minou". Percentages are calculated with respect to the total initial area of the corresponding
 shore (2019; 100%).

Shore	Occupied Initial area, 2019 (m²)	Occupied Final area, 2020 (m ²)	Net area difference m ² (%)	Loss surface m ² (%)	Persistence surface m ² (%)	Gain surface m ² (%)
West	58.3	39.5	-18.7 (32.2%)	46.6 (80%)	11.7 (20%)	27.9 (48%)
East	280.0	164.0	-116.0 (41.3%)	154.0 (55%)	126.0 (45%)	38.2 (14%)





Figure 1. A) Study site location, "Le Petit Minou", France, and B) the West and East rocky
shore areas surveyed by the drone in "Le Petit Minou".

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Figure 3 Mussel coverage distribution dynamics between June 2019 and June 2020 in the West and East rocky shore in "Le Petit Minou", France. Inset images from the West (top panels) and East shore (bottom panels) show mussel occupancy in 2019 and 2020, along with the resultant dynamics. Areas where individuals were present in 2019 but absent in 2020 (loss), areas without mussels in 2019 but with mussel presence in 2020 (gain), and areas where mussels were present in both 2019 and 2020 (persistence) are indicated. Yellow stars indicate the location of inserted images; scale bars are in meters.



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Figure 4. The probability of loss, persistence, and gain area for all microhabitats with different slopes (increasing from the center to the border), orientation (cardinal orientations indicated with letters; N: North, E: East, S: South, and W: West), and intertidal height (increasing from bottom to the top panels). Loss probability is the ratio of occupied cells in 2019 that become empty in 2020; Persistence probability is the ratio of occupied cells in 2019 that continue to be occupied in 2020; and Gain probability is the ratio of empty cells in 2019 that become occupied in 2020. Probabilities were averaged at each microhabitat type.





Figure 5. Venn diagrams with the percentage of variance (based on the sum of squares, Table S1 in Supplementary 1), that was related to each of the three topographic features evaluated (circles) and the interactions among them (overlapped areas). The percentage of variance not explained by the topographic features is indicated with the white background area.



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Figure 6. Relative distribution dynamics are represented as the probability of loss, persistence, and gain at specific intertidal height range on the West and East shore. Loss probability is the ratio of occupied cells in 2019 that become empty in 2020; Persistence probability is the ratio of occupied cells in 2019 that continue to be occupied in 2020; and, Gain probability is the ratio of empty cells in 2019 that become occupied in 2020. Probabilities were averaged at each intertidal height range. The left axis represents Loss and Persistence probabilities, whereas the right axis represents Gain probability.



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Figure 7. Comparison between observations and model predictions of gain probability, loss

- 811 probability, and the proportion occupied in 2019 and 2020. Dots correspond to the intertidal
- 812 heights in the two shores. The line represents the bisector and corresponds to perfect agreement
- 813 between observations and predictions.



815 816

Intertidal height (m above the LAT)

Figure 8. Predicted values along the intertidal height of the West and East shores, A) Return 817 time (years) to equilibrium; B) resilience index (no unit; values between 0 and 1); C) 818 persistence time (years) defined as the time during which 90% of the occupied cells remain 819 occupied (quantile 90).

Supplementary 1 820

Table S1. Results of variance partitioning analyses of loss, persistence, and gain in the 821

West and East rocky shores from "Le Petit Minou", France. The proportion explained 822 represented in Figure 5 corresponds to the percentage representation of η^2 . 823

shore	Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)	eta2	dynamics
West	intertidal height	2	8.6972	4.3486	143.03	1.4E-59	9.1	loss
West	orientation	11	0.4772	0.0434	1.43	1.5E-01	0.5	loss
West	slope	5	0.3299	0.0660	2.17	5.5E-02	0.3	loss
West	intertidal height:orientation	22	1.8250	0.0830	2.73	2.6E-05	1.9	loss
West	intertidal height:slope	10	1.0834	0.1083	3.56	1.0E-04	1.1	loss
West	orientation:slope	55	1.5521	0.0282	0.93	6.3E-01	1.6	loss
West	intertidal height:orientation:slope	110	5.1042	0.0464	1.53	4.5E-04	5.3	loss
West	residuals	2529	76.8895	0.0304	NA	NA	80.1	loss
shore	Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)	eta2	dynamics
West	intertidal height	2	9.3979	4.6990	224.04	2.6E-90	13.6	persistence
West	orientation	11	0.5011	0.0456	2.17	1.4E-02	0.7	persistence
West	slope	5	0.6452	0.1290	6.15	1.1E-05	0.9	persistence
West	intertidal height:orientation	22	1.3901	0.0632	3.01	3.1E-06	2.0	persistence
West	intertidal height:slope	10	0.8481	0.0848	4.04	1.6E-05	1.2	persistence
West	orientation:slope	55	0.9714	0.0177	0.84	7.9E-01	1.4	persistence
West	intertidal height:orientation:slope	110	2.2169	0.0202	0.96	6.0E-01	3.2	persistence
West	residuals	2529	53.0415	0.0210	NA	NA	76.9	persistence
shore	Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)	eta2	dynamics
West	intertidal height	2	0.0268	0.0134	124.20	3.5E-52	7.8	gain
West	orientation	11	0.0038	0.0003	3.18	2.7E-04	1.1	gain
West	slope	5	0.0108	0.0022	20.08	1.1E-19	3.2	gain
West	intertidal height:orientation	22	0.0060	0.0003	2.54	1.0E-04	1.8	gain
West	intertidal height:slope	10	0.0073	0.0007	6.75	1.9E-10	2.1	gain
West	orientation:slope	55	0.0048	0.0001	0.80	8.5E-01	1.4	gain
West	intertidal height:orientation:slope	110	0.0099	0.0001	0.83	9.0E-01	2.9	gain
West	residuals	2529	0.2731	0.0001	NA	NA	79.7	gain

shore	Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)	eta2	dynami
East	intertidal height	2	57.0249	28.5125	1721.98	0.0E+00	53.6	loss
East	orientation	11	0.8421	0.0766	4.62	5.2E-07	0.8	loss
East	slope	5	0.3563	0.0713	4.30	6.7E-04	0.3	loss
East	intertidal height:orientation	22	0.5610	0.0255	1.54	5.2E-02	0.5	loss
East	intertidal height:slope	10	0.7792	0.0779	4.71	1.1E-06	0.7	loss
East	orientation:slope	55	1.8212	0.0331	2.00	2.1E-05	1.7	loss
East	intertidal height:orientation:slope	110	2.7239	0.0248	1.50	8.1E-04	2.6	loss
East	residuals	2559	42.3717	0.0166	NA	NA	39.8	loss
shore	Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)	eta2	dynam
East	intertidal height	2	59.8353	29.9176	2067.45	0.0E+00	58.3	persist
East	orientation	11	1.1222	0.1020	7.05	6.9E-12	1.1	persist
East	slope	5	0.6046	0.1209	8.36	7.5E-08	0.6	persist
East	intertidal height:orientation	22	0.4904	0.0223	1.54	5.2E-02	0.5	persist
East	intertidal height:slope	10	0.5713	0.0571	3.95	2.3E-05	0.6	persist
East	orientation:slope	55	1.4124	0.0257	1.77	4.3E-04	1.4	persist
East	intertidal height:orientation:slope	110	1.6307	0.0148	1.02	4.1E-01	1.6	persist
East	residuals	2559	37.0308	0.0145	NA	NA	36.1	persist
1	Variable	Df	Sum Sq	Mean Sq	F value	Pr(>F)	eta2	dynam
shore	Variable							I .
shore East	intertidal height	2	0.0449	0.0224	390.36	1.1E-148	20.3	gain
shore East East	intertidal height orientation	2 11	0.0449	0.0224	390.36 4.28	1.1E-148 2.4E-06	20.3 1.2	gain gain
East East East East	intertidal height orientation slope	2 11 5	0.0449 0.0027 0.0092	0.0224 0.0002 0.0018	390.36 4.28 31.86	1.1E-148 2.4E-06 1.4E-31	20.3 1.2 4.1	gain gain gain
East East East East East	variable intertidal height orientation slope intertidal height:orientation	2 11 5 22	0.0449 0.0027 0.0092 0.0024	0.0224 0.0002 0.0018 0.0001	390.36 4.28 31.86 1.93	1.1E-148 2.4E-06 1.4E-31 5.6E-03	20.3 1.2 4.1 1.1	gain gain gain gain
East East East East East East	variable intertidal height orientation slope intertidal height:orientation intertidal height:slope	2 11 5 22 10	0.0449 0.0027 0.0092 0.0024 0.0032	0.0224 0.0002 0.0018 0.0001 0.0003	390.36 4.28 31.86 1.93 5.55	1.1E-148 2.4E-06 1.4E-31 5.6E-03 3.2E-08	20.3 1.2 4.1 1.1 1.4	gain gain gain gain gain
East East East East East East East	variable intertidal height orientation slope intertidal height:orientation intertidal height:slope orientation:slope	2 11 5 22 10 55	0.0449 0.0027 0.0092 0.0024 0.0032 0.0055	0.0224 0.0002 0.0018 0.0001 0.0003 0.0001	390.36 4.28 31.86 1.93 5.55 1.74	1.1E-148 2.4E-06 1.4E-31 5.6E-03 3.2E-08 6.4E-04	20.3 1.2 4.1 1.1 1.4 2.5	gain gain gain gain gain gain
East East East East East East East East	variable intertidal height orientation slope intertidal height:orientation intertidal height:slope orientation:slope intertidal height:orientation:slope	2 11 5 22 10 55 110	0.0449 0.0027 0.0092 0.0024 0.0032 0.0055 0.0058	0.0224 0.0002 0.0018 0.0001 0.0003 0.0001 0.0001	390.36 4.28 31.86 1.93 5.55 1.74 0.92	1.1E-148 2.4E-06 1.4E-31 5.6E-03 3.2E-08 6.4E-04 7.1E-01	20.3 1.2 4.1 1.1 1.4 2.5 2.6	gain gain gain gain gain gain



Figure S1. Daily dynamics of water temperature (black y-axis and continuous line) and maximum wave height (grey y-axis and grey dots). The central black line represents the mean water temperature from the historical period 2009-2018; red and blue fill indicate the positive and negative difference of daily temperature against the historical mean, respectively. Blue triangles indicate the date of drone surveys. The period of high temperature and wave height occurred from late July to mid-August 2019.