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Classification of underwater photogrammetry data for temperate benthic rocky reef mapping

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Authors agreement to the submission

All authors declare being agree to the submission

Other specifications

Colour should be used for Fig. 1, 2, 4 and 6, and is recommended for Fig. 3, 5 and 8 and table 2 and 3.

30 Abstract

31 The fine characterization of the substrate is a baseline to thoroughly investigate the
32 relations between organisms and their biotopes. Cutting edge spatial technologies now
33 provide access to accurate information on biotopes and biocenoses both in terrestrial
34 and in marine environments. Photogrammetry is one of them and has recently been
35 applied in submarine environments especially in shallow clear water. In this study, we
36 investigated the potential of photogrammetry to characterize benthic habitats in turbid
37 environments. Although more challenging, turbid environments are more frequent in
38 temperate marine coastal areas. We selected two rocky sites in the bay of Saint-Malo
39 (Brittany, France), differentiated by their level of turbidity, one being a marine site
40 exposed to natural tides (Buharats), while the other (Bizeux) is subjected to both
41 natural tides and artificial currents created by the functioning of a hydroelectric dam.
42 The different substrates observed were classified into eight classes at a centimetre
43 resolution using photogrammetry-based spatial and multispectral predictors. The
44 spatial benthic terrain predictors were derived from a digital surface model (DSM) at
45 various spatial scales, and the multispectral predictors were retrieved from the red-
46 green-blue (RGB, natural colours) orthomosaic imagery. An overall classification was
47 computed for Buharats and Bizeux, with accuracies of 84.76 % and 79.54 %
48 respectively, revealing a good quality of the substrate classification. The combination
49 of RGB, DSM, and several spatial benthic terrain variables, with a pixel resolution of 5
50 and 10 mm, and a kernel size of 30, 60 and 90 pixels leads to the best benthic substrate
51 classification (highest overall accuracy). At the class scale, producer's (PA) and user's
52 (UA) accuracy showed that big boulders and field material were correctly distinguished.
53 Small boulders and cobbles, having similar sizes, showed the lowest classification
54 performances. This classification methodology provides new perspectives for

55 mesoscale (100 m² to 1 km²) semi-automatic mapping of the fine resolution (1 cm)
56 relationship between benthic organisms and their substrate.

57 **Key words**

58 Photogrammetry; Temperate rocky reefs; Turbid water; Classification; Terrain
59 variables; Substrate mapping

60

61 **Author contributions**

62 Quentin Ternon, Éric Feunteun, Frédéric Ysnel, Pierre Thiriet and Antoine Collin
63 developed the study approach.

64 Quentin Ternon and Valentin Danet collected the data.

65 Quentin Ternon and Antoine Collin conducted the data analysis.

66 Quentin Ternon wrote the paper.

67 All authors participated to the manuscript revision.

68 Antoine Collin supervised the research.

69

1. Introduction

70
71
72 Substrate characteristics are known to control marine benthic communities specific
73 composition and abundance. Reviews have recently highlighted a range of
74 geomorphometric variables that could influence at various scales the descriptive
75 parameters of sub-tidal rocky habitat communities (algae, invertebrates and fishes)
76 both in tropical and temperate sub-tidal environments (Pygas et al., 2020 ; Borland et
77 al., 2021). More particularly, the terrain complexity (e.g. rugosity, bathymetric variance
78 and slope of the slope), its morphology (curvature and aspect), the substrate type
79 (nature, features and engineer species) and other information (bathymetry and slope)
80 have an influence on the presence, abundance, cover and diversity of algae and
81 sessile invertebrates both in tropical (Duckworth, 2016), subtropical (Holmes et al.,
82 2008; Zavalas et al., 2014, Bravo et al., 2020) and temperate environments (Castric-
83 Fey et al., 1973, Castric-Fey and Chasse, 1991; Guinan et al., 2009; Elvenes et al.,
84 2014). Studies have demonstrated that the terrain complexity is one of the key-factor
85 strongly structuring the fish communities on tropical (Kuffner et al., 2007; Pittman
86 et al., 2007; Pittman et al., 2009; Knudby et al., 2010; Pittman and Brown, 2011;
87 Sekund and Pittman, 2017), subtropical (Moore et al., 2009; Monk et al., 2010; Moore
88 et al., 2010; Monk et al., 2011; Coleman et al., 2016; Rees et al., 2018; Williams et al.,
89 2019), and temperate reefs (Cameron et al., 2014). Therefore, the accurate
90 characterisation of the substrate has the potential to provide a precise understanding
91 of the relationship between sessile organisms and their substrate. For instance, this
92 substrate-based information can be used to predict benthic community compositions
93 (Rattray et al., 2009; Collin et al., 2011).

94 The development of novel mapping technologies such as satellite, LiDAR and
95 acoustic tools now allow to fine-tune at various scales the characterisation of benthic

96 and demersal habitats in relation with community composition (Fig. 1). Although, these
 97 technologies are currently able to define the substrate at macroscale ($>1 \text{ km}^2$), with
 98 high spatial resolution ($\sim 10 \text{ cm}$ through acoustic, $\sim 1 \text{ m}$ through LiDAR and Satellite),
 99 LIDAR and satellite technologies are limited to the first 50 m of depth in clear water

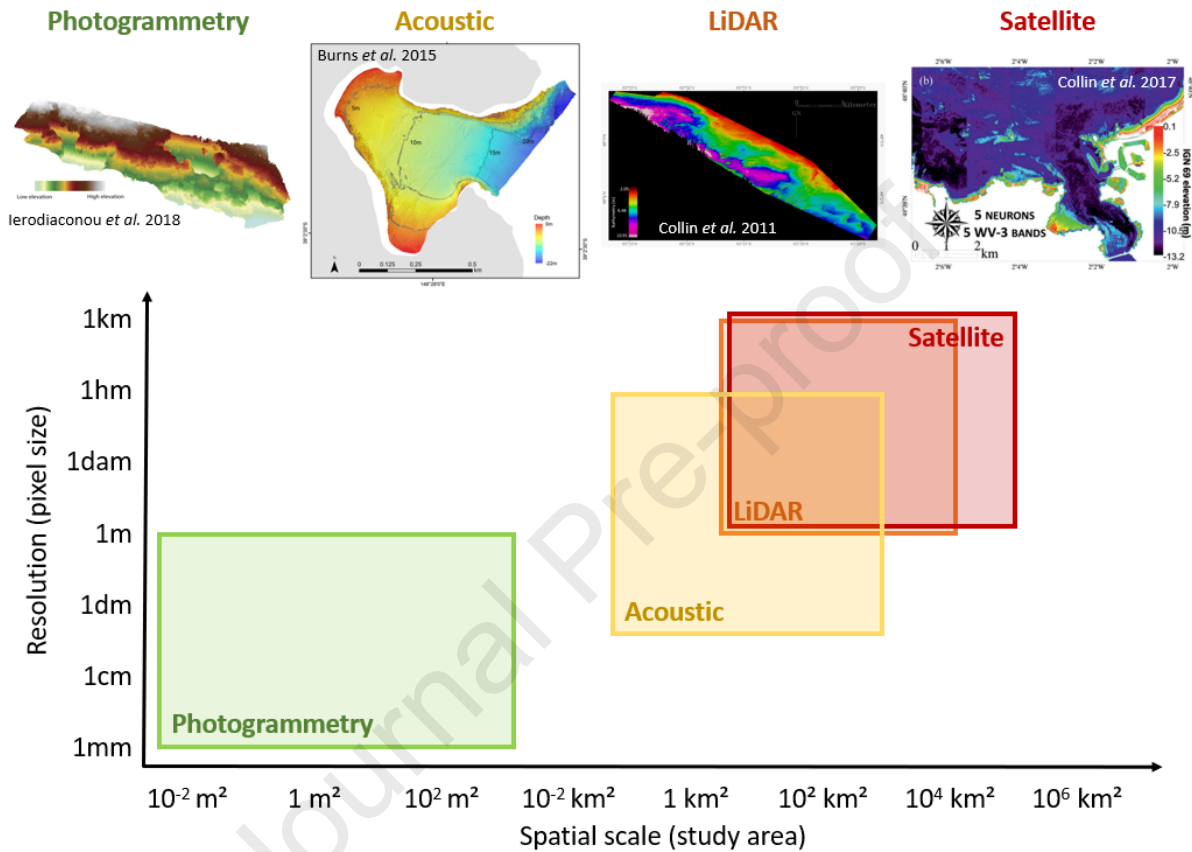


Fig. 1. The different techniques for benthic substrate imagery, their scope and performances. For each methodology, the limits of the rectangle indicate the range of spatial scale (horizontal) and resolution (vertical), and illustrations of benthic substrate imageries are given at the top of the diagram (data Irish and Lillycrop, 1999; Diaz et al., 2004; Bock et al., 2005; Collin et al., 2011; Knudby et al., 2011; Galparsoro, 2012; Collin et al., 2013; Dierssen and Theberge, 2014; Zavalas et al., 2014; Burns et al., 2015; Calvert et al., 2015; Smith et al., 2015; Wahidin et al., 2015; Ierodiaconou et al., 2018; Madricardo et al., 2019; Marre et al., 2019; Jackson et al., 2020; Marre et al., 2020a; Marre et al., 2020b).

100 because of water absorption (Irish and Lillycrop, 1999; Diaz et al., 2004; Bock et al.,
101 2005; Collin et al., 2011; Knudby et al., 2011; Galparsoro, 2012; Collin et al. 2013;
102 Dierssen and Theberge, 2014; Zavalas et al., 2014; Calvert et al., 2015; Smith et al.,
103 2015; Wahidin et al., 2015; Ierodiaconou et al., 2018; Madricardo et al., 2019). LiDAR
104 and sonar surveys can provide relevant information on the terrain characteristics,
105 essential to describe and map benthic habitats (biotopes and biocenoses) (Pickrill and
106 Todd, 2003; Collin et al., 2008; Pittman et al., 2009; Brown et al., 2011; Collin et al.,
107 2011; Walbridge et al., 2018). Hence, this mapping constitutes an effective baseline to
108 both target habitats of interest and evaluate the sampling effort required. More recently
109 the photogrammetry technique has been developed and is now widely deployed in sub-
110 tidal environments. This technique allows a 3D reconstruction with a more detailed
111 characterisation of benthic rocky substrates and at larger scale of their associated
112 landscapes (Hatcher et al., 2020). Based on multi-view optical information (either
113 photographic or videographic), the photogrammetry has been mainly used in clear
114 water environments to describe coral reefs structure at various biological levels from
115 individuals to reefs (Burns et al., 2015; Figueira et al., 2015; Leon et al., 2015; Burns
116 et al., 2016; Ferrari et al., 2016; Anelli et al., 2017; Carlot et al., 2020; Fukunaga et al.,
117 2020). To date, this approach has been used to describe, up to a scale of 120 m²
118 (mesoscale), the morphology of the substrate below a centimetre resolution (Fig. 1;
119 Burns et al., 2015; Jackson et al., 2020; Marre et al., 2019; Marre, et al., 2020b).
120 However, the substrate typology (i.e. bed rock, boulders, pebbles, gravel, sand),
121 determinant for the structure and organisation of biological communities, has not been
122 derived from photogrammetry in these studies. There is currently a clear need to produce
123 fine resolution (< 1 m) characterisations (geomorphology and typology) and maps of
124 temperate rocky reefs, to better understand and monitor processes involved in habitat

125 dynamics as a response to environmental changes (Keith et al., 2020; see also
126 European Commission and European Environment Agency). Additionally, testing the
127 potential of photogrammetry applications in turbid water systems is lacking.

128 In this study, we propose an innovative method to produce a mesoscale (120
129 m²) fine resolution (1 cm) classification of benthic substrates in turbid waters combining
130 photogrammetry and supervised classification models. We selected two rocky
131 temperate reefs, located in the bay of Saint Malo, France, with similar topographic
132 features but characterised by different turbidity and hydrodynamic conditions. We
133 analysed the ability of the supervised classification to detect and quantify the relative
134 surface of eight substrate classes commonly used in the literature. A visual description
135 of the transect landscape (distribution patterns of the substrate types) has been
136 conducted to rapidly evaluate if differentiation of landscape patterns could be made.
137 The contribution of the spatial (terrain) and multispectral (red-green-blue, RGB)
138 predictors was investigated, and the best combination of predictors was statistically
139 examined. This research aims to develop a classification method to spatially quantify
140 the main biotope components of benthic rocky reef habitats.

141 2. Material and Methods

142

143 2.1. Study area

144

145 The sampling area is located in the English Channel in the St Malo Bay (Brittany,
146 France). Two distinct rocky reef sites have been sampled by scuba-diving. The islet of
147 Bizeux (48°37'40.95" N, 2°01'34.96" W; WGS84) is under the influence of natural tides,
148 but also of functioning of the hydroelectric dam of the Rance, which create strong
149 bidirectional currents and turbid episodes (Gallon et al., 2013). The second site, the

150 reef of Buharats ($48^{\circ}40'24.08''$ N, $2^{\circ}07'12.88''$ W; WGS84) located 3 km offshore, is
 151 more subject to marine influence but less turbid than Bizeux (Fig. 2).

152

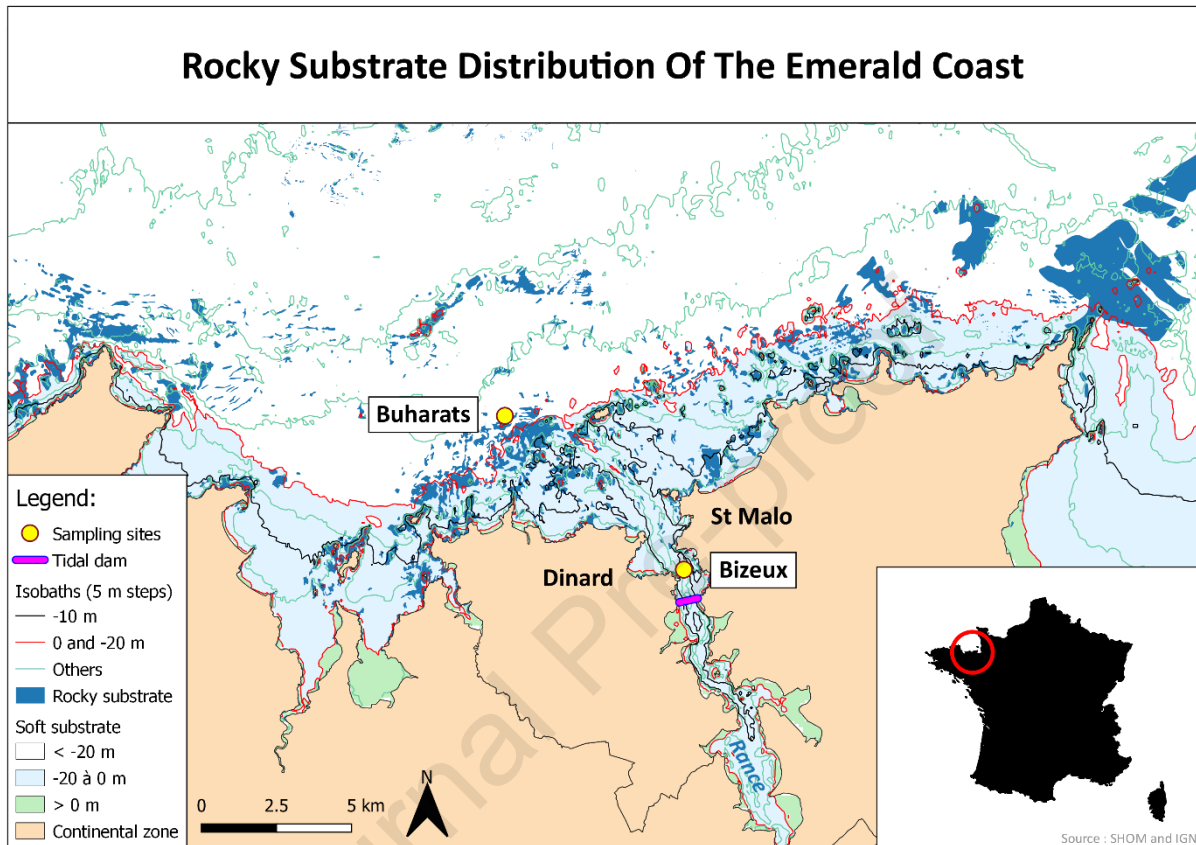


Fig. 2. Locations of the two sampling sites (Buharats and Bizeux) inside the rocky substrate distribution of the Emerald Coast. The different isobaths are displayed with a 5 m step.

153 For each reef, a 120 m² transect (30 m long and 4 m wide ; Fig. 3) was
 154 investigated in circa-littoral habitats, under the kelp belts, at depths of 13 +/- 1 m (0 m
 155 corresponding to the lowest astronomical tide level).

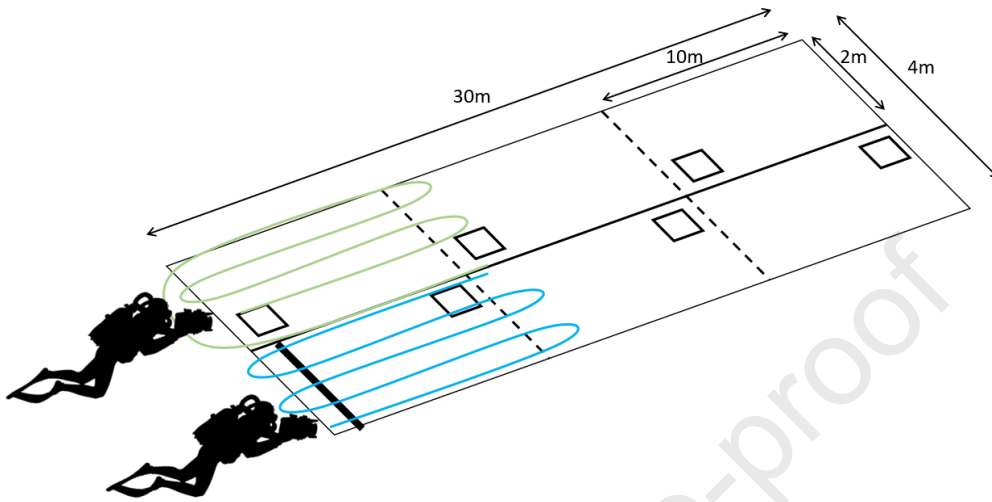


Fig. 3. Scheme of the 120 m² transect (30 m long and 4 m large) shooting. The dotted lines separate each 10 m sections. The curved lines symbolize the trajectory of divers in their respected lane during the sampling. The six squares indicate the position of quadrats (50 x 50 cm). The thick line indicates the 2 m rule.

166 2.2. Imagery acquisition

167

168 A total of 1831 and 1995 pictures were taken for Bizeux and Buharats,
 169 respectively (Fig. 3 and Fig. 4 step 1). The transect was set-out with a 30 m tape. Six
 170 quadrats (0.25 m²) were distributed along the transect and a 2 m rule was placed for
 171 an *a posteriori* calibration. Special photogrammetric markers were fixed on quadrats
 172 (8 markers) and rules (6 markers) for the 3D model construction. The depth was
 173 controlled with a dive computer (Suunto Vyper©, 10 cm precision). Each quadrat was
 174 georeferenced (in latitude and longitude) under water using a submarine geolocation
 175 system (i.e.

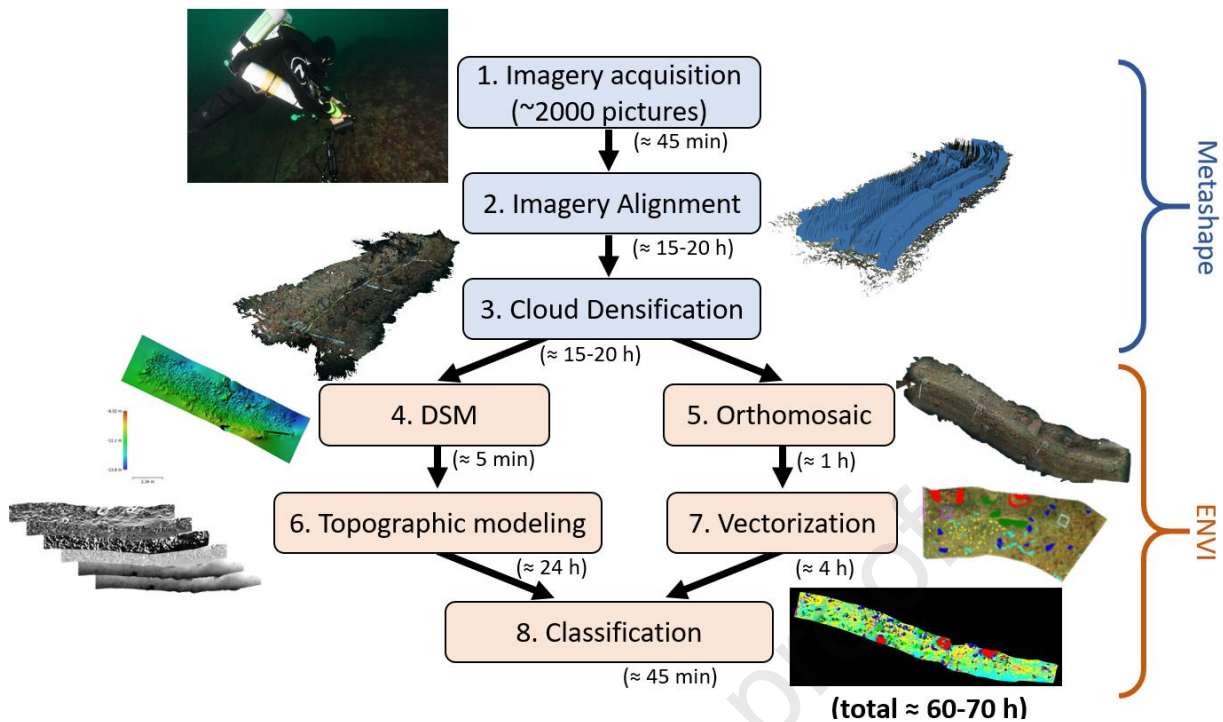


Fig. 4. Workflow of the photogrammetry to describe a 120 m² transect of benthic temperate rocky substrates from photograph acquisition to classification. The time indications represent the rough duration of each process. Software used to perform each process are indicated on the right. DSM: Digital surface model.

176 UWIS© system; 1m precision). The transect was divided in 2 lanes of 2 meters wide
 177 (one for each diver) and 3 consecutive sections of 10 m long (to secure data collection;
 178 Fig. 3). Digital single-lens reflex D7500-NIKON (set to 20.1 MegaPixel, F13, 1/250 s,
 179 ISO 400-800) with a 10-24 mm NIKON lens (set to 10 mm), placed in an ISOTA
 180 underwater housing, has been used for the multispectral imagery acquisition. Two
 181 PRO160-Subtronic strobes (set to 1/4 - 1/8 of the total power) were also used. Divers
 182 swam 1 m above the substrate and took pictures modulating their swimming speed
 183 and frequency of picture acquisition to ensure an approximately 60 % overlay between
 184 each photograph. Divers also maintained the camera roughly orthogonal to the
 185 substrate fitting as well as possible the shape of the substrate. An extra crossing was
 186 also carried on, with an oblique view, to improve the quality of the final model.

2.3. Photogrammetric model construction

187
188

189 All the process was performed using the Agisoft Metashape Software (version
190 1.6.1; see Table S1 for parametrization details), as frequently used in photogrammetry
191 investigation (Burns et al., 2015; Leon et al., 2015; Bayley et al., 2019; Marre et al.,
192 2019; Bayley and Mogg, 2020). Each lane was separated in 3 transversal segments in
193 which a georeferenced quadrat was placed. In each segment, the markers were
194 automatically detected and photographs were aligned. Chunks were then assembled
195 based on markers having a new chunk with the assembled pictures of the whole
196 transect (Fig. 4 step 2). A dense cloud process was then applied on the latter (Fig. 4
197 step 3). The coordinates (latitude, longitude, and depth) of each quadrat and the known
198 distance of the 2 m rule were manually annotated (see Table S2 for details on error
199 estimation of the 3D model). A digital surface model (hereafter DSM, free resolution)
200 followed by an orthomosaic (fixed at a 1 mm resolution) process were then performed
201 (Fig. 4 step 4 and 5).

2.4. Topographic modelling

202
203

204 The whole process was deployed under the ENVI Classic software (version 5.3).
205 The DSM built from the photogrammetric model was first imported and resized to 5
206 and 10 mm pixel resolutions (r). A topographic modelling process was applied on the
207 DSM band selecting 6 different benthic terrain variables : the slope, as the rate of
208 change in elevation over horizontal distance between pixels in degree; the aspect, as
209 the horizontal direction of the slope in degree; the profile and plan convexity,
210 respectively as the vertical and horizontal components of the curvature without unit;
211 the maximum curvature, as the largest local curvature in any direction without unit; the

212 root mean square error (RMSE), as the rate of change of the bathymetry in meters
 213 (Fig. 4 step 6 and Fig. 5).

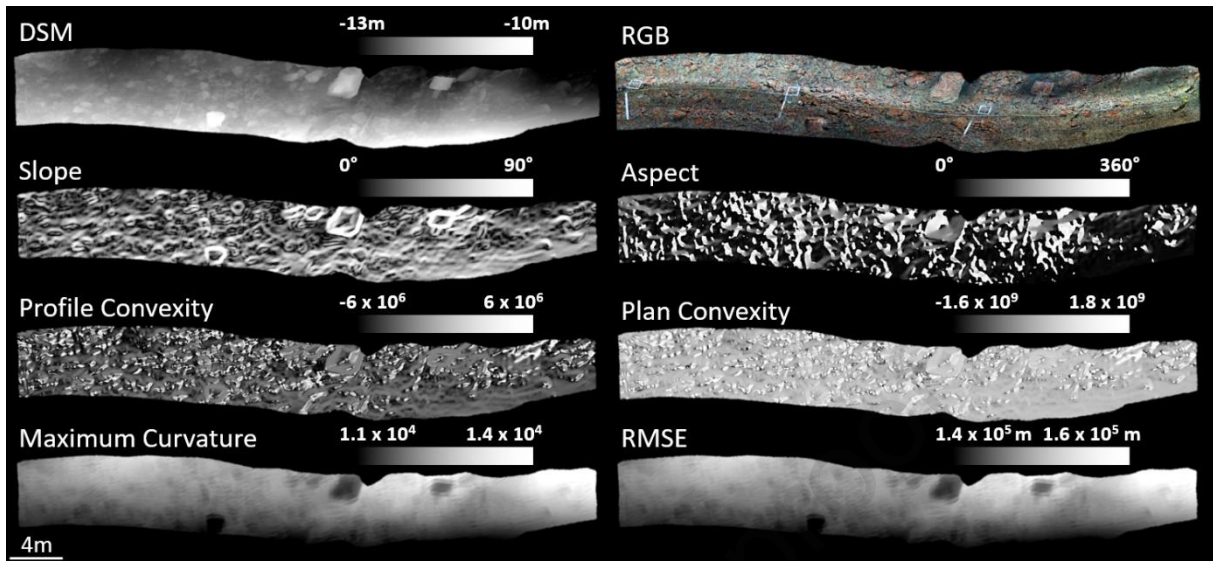


Fig.5. Pictures of the digital surface model (DSM), using average bathymetry in meters, for Bizeux (calculation window: $k = 30$ and $r = 5$ mm), orthomosaic combining red, green and blue (RGB) multispectral bands in digital numbers and the different terrain variables: the slope, aspect, profile convexity, plan convexity, maximum curvature, root mean square error (RMSE) (See details in 2.4 section).

214 These six variables were grouped under the term Terrain. Different combinations of
 215 resolution (r) and kernel size (k) were used to obtain various size of calculation
 216 windows for a multiscale approach (Table 1; Wilson et al., 2007; Porskamp et al.,
 217 2018):

218 *Table 1: The different combinations of resolution (r) and kernel size (k) to obtain the different calculation windows*

Calculation window (in cm)	Kernel size (k , in pixel)	Resolution (r , in mm)
1.5	30	5
3	30	10
6	60	10
9	90	10

219

220

2.5. Model classification

221
222

223 A supervised classification is commonly used for typological mapping. Machine
224 learners have been developed and widely used for benthic biotope classification (Collin
225 et al., 2011; Hasan et al., 2014). However, some of them can suffer from a low
226 transferability to people without specific machine learning skills. Moreover, these are
227 not well suited for high frequency monitoring because of their complexity and also as
228 they are computationally time consuming. Among various algorithms gleaned from the
229 literature, the maximum likelihood classifier, based on the probabilistic membership, is
230 described as a fast and highly transferable one (Pal and Mather, 2003; Collin et al.,
231 2019; James et al., 2020a; James et al., 2020b). This algorithm is a pixel-wise method
232 based on a Gaussian distribution of classes of interest. Pal and Mather (2003) defined
233 it as the association of a pixel to a specific class if the probability of belonging to this
234 class is higher than those of the other classes.

235 The orthomosaic based on multispectral information (RGB) was built from the
236 photogrammetric model, and then imported and staked with the DSM and Terrain
237 variables (all calculation windows). From the orthomosaic, different typological classes
238 of the substrate (bed rock, big/medium/small boulder, cobble, pebble, sand and field
239 material; Fig. 6) were visually identified (visual size estimation) and manually
240 vectorized (Fig. 4 step 7). A threshold of a minimum of 1 000 000 pixels was reached
241 for each class (500 000 for the field material class). Vectorized pixels were randomly
242 subsampled in two sets of 500 000 pixels (250 000 for field material) respectively for
243 the calibration and validation of the classification. A supervised classification process
244 was applied using the maximum likelihood algorithm and the calibration pixel set (Fig.
245 4 step 8 and 6).

246

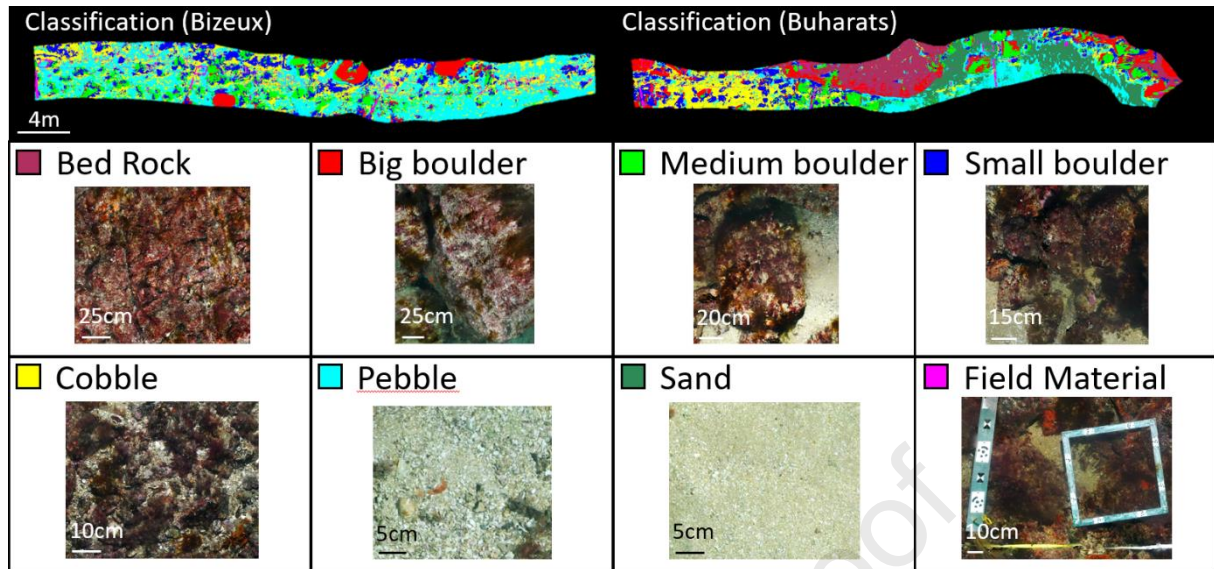


Fig.6. Classified models of transects at Bizeux and Buharats, based on multispectral (RGB), bathymetry (DSM) and all Terrain variables computed with various calculation windows. An example of each typology is given with the corresponding colour in the classification. Bed rock (homogeneous cover of rock), big ($x > 1$ m), medium ($1 \text{ m} > x > 50$ cm) and small ($50 \text{ cm} > x > 25$ cm) boulder, cobble ($25 \text{ cm} > x > 6$ cm), pebble ($6 \text{ cm} > x > 4$ mm), sand ($4 \text{ mm} > x$) and field material (2 m rule, 0.25 m^2 quadrats and transect tape) based on Blair and McPherson (1999).

247 Each combination of variables (hereafter called processing) using the association
 248 of RGB and DSM as a reference and adding Terrain for the different calculation
 249 windows (1.5, 3, 6 and 9 cm) has been calculated and compared. For each classified
 250 transect, a confusion matrix was generated to compare the resulting classes to the
 251 validation pixel set. The matrix provided information on the accuracy of both, the
 252 producer (PA; eq. 1) and the user (UA; eq. 2). The PA reflects the probability that a
 253 pixel in a given class was correctly classified, while the UA expresses the probability
 254 that a pixel predicted in a given class is really in that class (Congalton, 1991).
 255 Consequently, the PA and UA provides information about the omission error (false
 256 negative), and the commission error (false positive) respectively.

$$257 \quad PA = \text{Class}_{i(\text{Val}_i)} / \text{Val}_i \times 100 \quad (1)$$

258 With PA (in percent), $\text{Class}_{i(\text{Val}_i)}$ the number of classified pixels for the class (i) among
 259 the pixel of the validation set for the class (i), and Val_i the number of pixels of the
 260 validation set for the class (i).

$$261 \quad UA = \text{Val}_{i(\text{Class}_i)} / \text{Class}_i \times 100 \quad (2)$$

262 With UA (in percent), $\text{Val}_{i(\text{Class}_i)}$ the number of pixels of the validation set for the class
 263 (i) among the classified pixel of the class (i), and Class_i the number of pixels classified
 264 for the class (i). The overall accuracy (OA), reflecting the mean quality of the
 265 classification, can then be calculated (eq. 3).

$$266 \quad OA = \sum_{i=1}^n PA_i / n \quad (3)$$

267 With OA (in percent), n the total number of class and PA_i the producer's accuracy of
 268 the class (i).

269 2.6. Statistical analysis

270

271 The PA and UA of each processing were compared to the reference (i.e. the
 272 processing combining RGB and DSM). All statistical processes were performed using
 273 the RStudio software (version 1.4.1103; R version 4.0.4). Significance was set at a
 274 0.05 threshold using a non-parametric Kruskal-Wallis test. A Dunn test (non-parametric
 275 pairwise comparison) was applied to detect significant variables responsible for the
 276 difference. In an exploratory way, a redundancy analysis (RDA) was conducted
 277 separately on PA and UA to show the contribution of the different variables, resolutions
 278 and kernel sizes used for the classification. A total of 27 combinations of variables was
 279 used for each site. In order to obtain these combinations, the DSM and RGB
 280 information was used as a baseline, progressively incremented with the different

281 Terrain variables, obtained with the different calculation windows. For each
282 combination, the use of the different variables and calculation windows was indicated
283 (0: not used, 1: used) as well as the accuracy (PA and UA) of each class. The
284 significant predicted classes were selected progressively with the *ordiR2step* function
285 of the package 'vegan'. The RDA was conducted conserving angles between variables
286 and classes, and the significance of both the RDA and the different axes was verified
287 using the *anova.cca* function of the package 'vegan'.

288 3. Results

289

290 3.1. Overview and visual description

291

292 Two DSMs were successfully produced to map the biotope on surfaces of 120
293 m² at a fine spatial resolution of 1 cm. The topological metrics, calculated on these
294 areas, all indicated a high heterogeneity of the biotope in terms of morphology and
295 substrate typology. Geomorphologically, big boulders at Bizeux (Fig. 5) are visually
296 accompanied by high slopes, reduced maximum curvature and RMSE, and a smooth
297 convexity. Contrastingly, small boulders, cobbles, and pebbles at Bizeux are
298 associated with noisy slopes and convexity. The final classification, mapping the
299 different substrate typologies, showed that the whole surface sampled area at Bizeux
300 is covered by a mixture of boulders (big, medium and small), cobble and pebble (Fig.
301 6). The final classification at Buharats showed that this site can be visually divided into
302 4 distinct zones, with cobbles and small boulders on the left, followed by a bed rock
303 section, then by a pebble and sand basin, and with medium and big boulders to the
304 right (Fig. 6).

305 3.2. Performances of the whole classification

306

307 The OA of the classification increased respectively for Bizeux and Buharats from
 308 43.05 and 59.04 % when RGB and DSM are combined, to 79.54 and 84.76 % when
 309 all Terrain variables (calculated with all calculation windows) are added to the
 310 combination (Fig. 7).

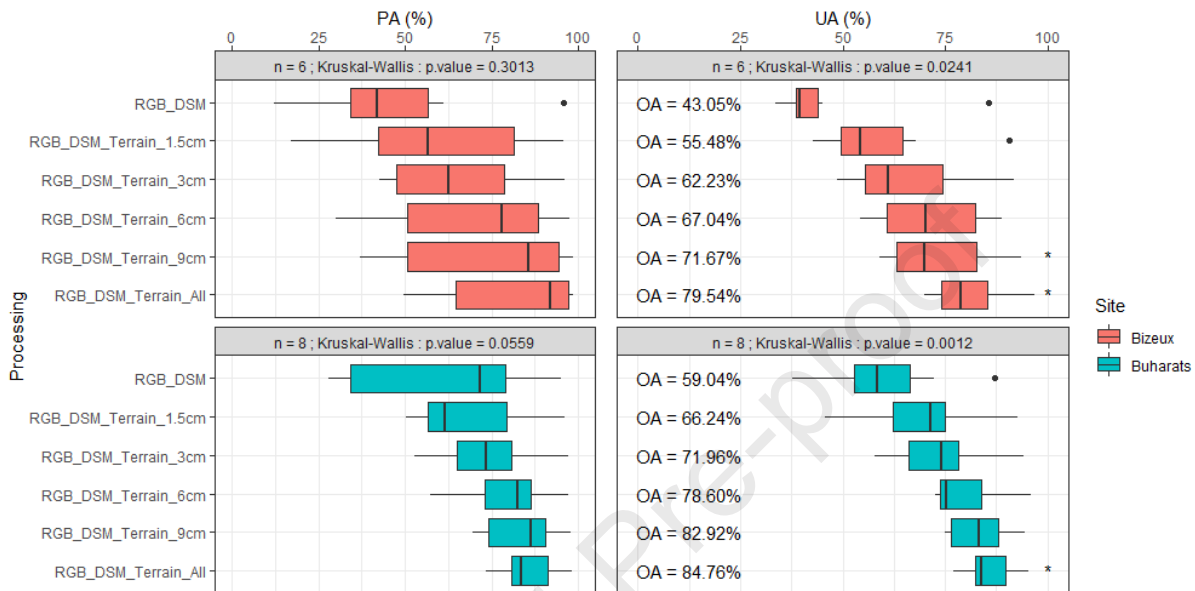


Fig.7. Boxplots (median, 25 and 75% quartiles, and outliers (dot)) showing the evolution of the accuracy of the producer (PA, left) and user (UA, right) through different processing at the sites of Bizeux (top, red) and Buharats (bottom, green). On top of each graph, the number of class used in the comparison and the p.value of the Kruskal-Wallis test are indicated. The overall accuracy (OA) is indicated for each processing. Asterisks indicate a significant difference (Dunn test, $p.value < 0.05$) between processing and the reference (i.e. Combination of RGB and DSM).

311 The same was observed for PA (omission error, false negative) and UA (commission
 312 error, false positive). The highest PA ($mean(PA_{Bizeux}) = 81.1\%$, $mean(PA_{Buharats}) = 85.6$
 313 %) and UA ($mean(UA_{Bizeux}) = 80.8\%$, $mean(UA_{Buharats}) = 85.8\%$) are observed when
 314 all variables are combined (RGB, DSM, and Terrain calculated with all calculation
 315 windows). Although the increase observed in UA is significant ($p.value_{Bizeux} = 0.024$;

316 $p.value_{Buharats} = 0.001$), this is not the case for PA ($p.value_{Bizeux} = 0.301$; $p.value_{Buharats}$
317 $= 0.056$).

318 3.3. Model performance to detect substrate classes

319

320 3.3.1. Producer's accuracy (PA)

321

322 The diagonal of the confusion matrix produced highlights the concordance of
323 the classified pixel to the ground truth class. The PA showed the highest values along
324 the diagonal of the matrix for both sites when all variables are combined (RGB, DSM,
325 and Terrain calculated with all calculation windows) (Table 2). At Bizeux, most of the
326 error (wrong classified pixels) was retrieved in small boulder and cobble classes (49.64
327 and 56.34 % of well classified pixels respectively), which are both confounded with
328 medium boulder, cobble, and pebble, plus field material for cobble (grey percentages;
329 > 5.0 %) (Table 2). At Buharats, most of the error was retrieved in small boulder and
330 pebble classes (76.49 and 73.56 % of well classified pixels respectively), which are
331 confounded with medium boulder, cobble for small boulder, and cobble and sand for
332 pebble (Table 2).

333 3.3.2. User's accuracy (UA)

334

335 The UA also showed the highest values along the diagonal of the matrix for
336 both sites when all variables are combined (RGB, DSM, and Terrain calculated with all
337 calculation windows; Table 3). At Bizeux, most of the error was retrieved for pebble,
338 medium boulder and cobble (70.09, 73.65 and 75.02 % of well classified pixels
339 respectively), which are confounded with small boulder and cobble (Table 3). At
340 Buharats, most of the error was observed for big boulder (76.93 % of well classified
341 pixels), which are confounded with bed rock and medium boulder (Table 3).

342 Table 2. Producer's accuracy (PA) for the different classes when all variables are combined (RGB, DSM, and Terrain calculated with
 343 all calculation windows) at Bizeux (top) and Buharats (down) sites. Green and red cases highlight respectively the highest (>80 %)
 344 and lowest (<80 %) percentages observed in the diagonal (classified class over ground truth class). Grey cases indicate values over
 345 5.0 % (out of the diagonal).

Classified class	Ground truth class							
	Bed Rock	Big boulder	Medium boulder	Small boulder	Cobble	Pebble	Sand	field Material
Site of Bizeux								
Big boulder	/	98.13	0.45	2.4	0	0.35	/	0
Medium boulder	/	1.56	89.5	23.84	5.77	0.83	/	0.05
Small boulder	/	0.17	4.58	49.64	5	0.56	/	0.02
Cobble	/	0	1.49	13.66	56.34	3.26	/	0.7
Pebble	/	0.14	3.79	8.48	27.69	94.51	/	0.47
field Material	/	0	0.19	1.97	5.21	0.49	/	98.76
Site of Buharats								
Bed Rock	82.97	0.32	0.09	0.28	0.77	1.8	0.89	0.03
Big boulder	15.04	98.22	7.76	1.57	2	1.26	1.74	0.16
Medium boulder	0.69	0.7	89.16	10.11	2.5	1.52	2.99	0.21
Small boulder	0.31	0.41	0.9	76.49	6.78	1.39	0.07	0.25
Cobble	0.44	0.06	0.52	8.13	82.2	6.29	2.07	0.22
Pebble	0.34	0.05	1.02	3.03	4.88	73.56	6.07	1.15
Sand	0.16	0	0.14	0.07	0.82	13.64	84.35	0.39
field Material	0.07	0.25	0.41	0.32	0.05	0.54	1.82	97.59

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348

349 Table 3. User's accuracy (UA) for the different classes when all variables are combined (RGB, DSM, and Terrain calculated with all
 350 calculation windows) at Bizeux (top) and Buharats (down) sites. Green and red cases highlight respectively the highest (>80 %) and
 351 lowest (<80 %) percentages observed in the diagonal (classified class over ground truth class). Grey cases indicate values over 5.0
 352 % (out of the diagonal).

Classified class	Ground truth class							
	Bed Rock	Big boulder	Medium boulder	Small boulder	Cobble	Pebble	Sand	field Material
Site of Bizeux								
Big boulder	/	96.84	0.44	2.37	0	0.35	/	0
Medium boulder	/	1.28	73.65	19.62	4.75	0.68	/	0.02
Small boulder	/	0.28	7.64	82.79	8.34	0.93	/	0.02
Cobble	/	0	1.98	18.19	75.02	4.34	/	0.47
Pebble	/	0.1	2.81	6.29	20.53	70.09	/	0.17
field Material	/	0	0.33	3.44	9.1	0.86	/	86.27
Site of Buharats								
Bed Rock	95.22	0.37	0.1	0.32	0.88	2.07	1.02	0.02
Big boulder	11.78	76.93	6.08	1.23	1.57	0.99	1.36	0.06
Medium boulder	0.64	0.65	82.73	9.38	2.32	1.41	2.77	0.1
Small boulder	0.36	0.47	1.04	88.45	7.84	1.61	0.08	0.14
Cobble	0.44	0.06	0.52	8.14	82.35	6.3	2.07	0.11
Pebble	0.38	0.06	1.14	3.38	5.45	82.17	6.78	0.64
Sand	0.16	0	0.14	0.07	0.83	13.73	84.88	0.2
field Material	0.13	0.48	0.78	0.61	0.1	1.03	3.48	93.38

353

3.4. Selecting relevant variables to build relevant classifications

For both producer's (Fig. 8.1) and user's (Fig. 8.2) accuracy values, the relationship between predictors (the different Terrain variables and calculation windows) and the resulting typology was analysed by redundancy analyses (RDA).

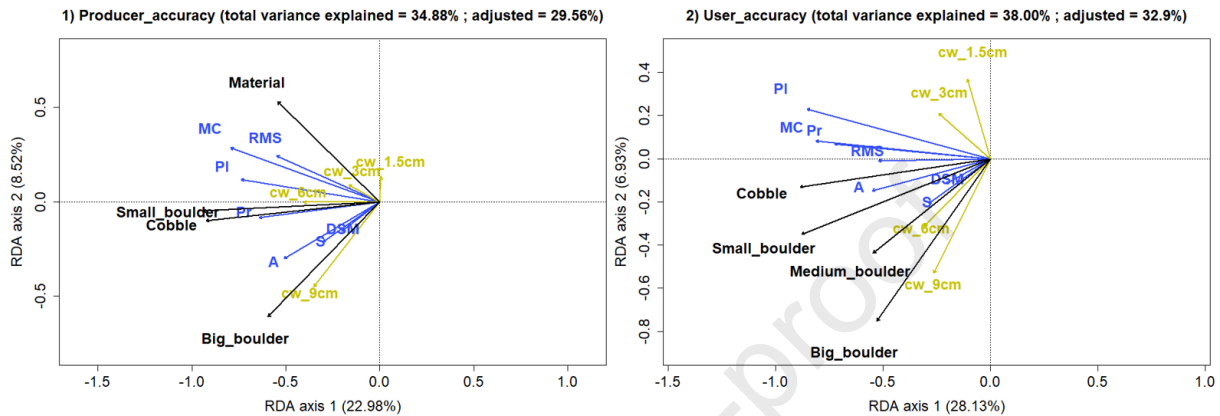


Fig. 8. Redundancy analysis (RDA) of the accuracy values of the producer (PA, graph 1) and user (UA, graph 2), showing the relationship between relevant classes (i.e. predicted typology, progressive selection; black arrows) and predictors. Predictors encompass the Terrain variables (blue) (DSM, slope (S), aspect (A), profile convexity (Pr), plan convexity (PI), maximum curvature (MC), root mean square error (RMS)) and the used calculation windows (dark yellow) (1.5 (cw_1.5cm), 3 (cw_3cm), 6 (cw_6cm), and 9 cm (cw_9cm)). Similar direction of the arrows indicates positive correlation. The total variance explained by the two significant axes (ANOVA, $p > 0.001$) is detailed in brackets for each axis. The total and adjusted variances of the RDA are indicated in brackets at the upper part of each graph.

The RDA models explained 29.56 and 32.90 % of the adjusted variance for PA and UA, respectively (Fig. 8). The progressive selection process of the PA and UA RDA models retained cobble, big and small boulder classes. The field material class was only conserved in the PA RDA model, while medium boulder was only retained in the

373 UA RDA model. Global model (integrating both axes), and the two first axes are
374 significant for PA (ANOVA; Global model: $F = 6.56$, $p.value < 0.001$; Axis 1: $F = 17.29$,
375 $p.value < 0.001$; Axis 2: $F = 6.41$, $p.value < 0.001$), and UA (ANOVA; Global model: F
376 $= 7.51$, $p.value < 0.001$; Axis 1: $F = 22.23$, $p.value < 0.001$; Axis 2: $F = 5.47$, $p.value <$
377 0.001). The axis 1 highlights correlations between the Terrain variables (i.e. slope,
378 aspect, profile convexity, plan convexity, maximum curvature, RMSE, and DSM) and
379 substrate classes (i.e. big, medium, small boulder, cobble and field material) for PA
380 and UA RDA models (Fig. 8). For both of them, the axis 2 highlights positive correlation
381 between big and medium boulders for calculation windows of 6 and 9 cm, whereas
382 negative correlation is observed for calculation windows of 1.5 and 3 cm (Fig. 8).

383 4. Discussion

384

385 In this study, we produced a fine resolution (1 cm) classification of benthic sub-
386 tidal substrates over surfaces of 120 m² (mesoscale) of temperate reefs under
387 hydrodynamic and turbid waters using photogrammetry-based methods.

388 4.1. Performance overview

389

390 Our results demonstrate that the photogrammetry approach can be used to
391 describe the substrate characteristics at scales of 120 m² with a high spatial resolution
392 of 1cm. The visual overview of the two mapping transects further highlights substrate
393 landscape differences. The Terrain variables such as slope, aspect, convexity (plan
394 and profile), maximum curvature and rugosity (RMSE) can be derived from DSM at
395 various scales. The combination of these variables with the multispectral (RGB bands)
396 information enabled a realistic and accurate ($OA > 79\%$) classification of the different
397 substrate typologies for both sites. Interestingly in our models, high OA were coupled
398 with high and balanced values of PA and UA, showing that substrate typological

399 classes are on average well identified (PA) and correctly predicted (UA) (Congalton,
400 1991). The highest PA and UA values were obtained when all variables were combined
401 (RGB, DSM, and Terrain calculated with all calculation windows), comforting the
402 importance of applying a multiscale approach to characterise typological classifications
403 relevant for the description of sub-tidal habitats (Wilson et al., 2007; Lecours et al.,
404 2015; Porskamp et al., 2018). In our study, variable redundancy can have added
405 statistical noise as no cross-correlation of variables was carried on. Further research
406 is thus needed to decipher the impacts of redundancy and turbidity on statistical noise.

407 Bizeux is probably one of the most turbid sites of the Emerald Coast, where
408 natural tidal currents are exacerbated by strong currents generated by the functioning
409 of the hydroelectric dam of the Rance (Gallon et al., 2013). Although, the potential high
410 turbidity observed at Bizeux does not seem to alter the quality of the DSM and
411 orthomosaic, a lower classification accuracy was obtained for Bizeux than for
412 Buharats. Despite this result, the final classification, we obtained for both sites, is
413 similar to the ones described in previous aerial imagery studies of habitat mapping of
414 land cover (James et al., 2020b), biogenic reefs (Collin et al., 2019), seagrass
415 meadows (James et al., 2020a), and macroalgae (Oppelt, 2012).

416 The multiscale approach described in this study is particularly cost/effective, as
417 the whole process from field work to the production of a high-resolution benthic
418 classification can be performed in 2 weeks. Most of the process is automatized, as the
419 computer controls for the 3D model building, Terrain variable calculations and
420 classifications, but for data acquisition and benthic classes vectorization.
421 Computational time can be saved by simplifying the classification, through grouping
422 different classes for example (e.g. big/medium/small boulder classes grouped in
423 boulders class). Subsequently, the substrate classes need careful definition regarding

424 the final objectives of the research, because they have a strong implication on the
425 duration of the analysis.

426 4.2. Model performance to detect substrate classes

427

428 The confusion matrices indicated that field material, big and medium boulder
429 classes appeared as the most accurately classified typologies for the two sampling
430 sites at least for PA values. However, the worst classified typologies (low PA values)
431 were small boulders (confused with medium boulder and cobble classes at both sites),
432 cobble (confused with pebble at Bizeux), and pebble (confused with sand at Buharats).
433 The UA values above 70 % reveal the concordance of the classified pixel to the ground
434 truth class. Low UA values were observed for pebble, medium boulder and cobble at
435 Bizeux, underlining the confusion shown for PA. Most of the confusion between classes
436 occurred between neighbouring granulometry, which is difficult to visually distinguish
437 during the vectorization step of the supervised classification process. A way to
438 circumvent this could be to group the neighbouring classes, while keeping ecological
439 relevance in terms of habitat for organisms.

440 4.3. Relevant variables for classification

441 The RDA analyses showed that the total and adjusted variances explained are
442 quite low and are thus discussed as exploratory results needing further research. All
443 the Terrain variables seemed to contribute to the classification of the different substrate
444 typologies, and the larger entities (i.e. big and medium boulders) were correlated with
445 the larger calculation windows (i.e. 6 and 9 cm). This highlights the key role of the
446 large-scale information for the detection of large objects. Nevertheless, this scale
447 depends on high kernel size and low resolution, having the effect to crop the borders
448 of the sampling area and in turn reduce the classified area.

4.4. Further calculation methodologies

449
450

451 In this study, the maximum likelihood classifier was investigated, as it is
452 currently used for rapid and efficient habitat descriptions (Collin et al., 2019; James et
453 al., 2020a; James et al., 2020b). However, other machine learner classifiers can be
454 used for supervised classification, such as random forest, support vector machine,
455 artificial neural network (including convolutional, Collin et al., 2011) (e.g. QUEST), as
456 well as fuzzy or unsupervised classifiers (e.g. ISODATA and k-means) (Irvin et al.,
457 1997; Pal and Mather, 2003; Schmidt and Hewitt, 2004; Rattray et al., 2009). Testing
458 and comparing different classifiers could be a way to choose the most appropriate
459 process for a given site/study, refine the classification and improve its accuracy. For
460 instance, an object based classification approach could be a relevant option,
461 particularly for marine habitats (Wahidin et al., 2015; Ierodiaconou et al., 2018).

4.5. Access to reliefs difficult to sample

462
463

464 One of the perspectives of this study would be to extend this approach to other
465 habitats, like cliffs and caves, technically difficult to characterise using LiDAR and all
466 acoustic tools operating vertically from the surface. Studying these habitats is highly
467 relevant since they shelter specifically adapted species, such as poriferans, ascidians
468 and cnidarians. This is thus not surprising that these habitats are entitled “particular
469 habitat” in the EUNIS A3.71 and A4.71 typologies (Gayet et al., 2018). Species
470 communities, found in cliff and cave walls, are similar to the ones found at deep depths,
471 characterised by adaptations to sciaphilic and specific oceanographic conditions and
472 nutrient supplies (Castric-Fey et al., 1973; Bibiloni and Gili, 1989; Barnes, 1999; Meroz-
473 Fine et al, 2005; Goffredo and Dubinsky, 2014; Sitjá and Maldonado, 2014; Quattrini
474 et al., 2015).

4.6. Toward the characterisation of benthic communities

475
476

477 The photogrammetry provides pictures, that can be analysed to identify sessile
478 organisms by photoidentification and thus further describe the benthic community
479 associated with the different substrate types. Photoidentification is less accurate than
480 traditional techniques, such as *in situ* identification or sampling and determination at
481 the laboratory but could nevertheless be useful for a fast and widespread
482 characterisation of benthic communities. In addition, photoidentification offers the
483 possibility to test *a posteriori* the responses of communities to habitat variability, and
484 potentially detect disturbances and their origin (human or natural).

5. Conclusion

485
486

487 The photogrammetry is clearly a powerful tool for a fine resolution (1cm) of the
488 substrate characterisation at mesoscale (100 m² to 1 km²). The semi-automatic
489 classification process developed here allows now a complete description of the terrain
490 characteristics. The georeferenced orthoprojection of the transect implemented in this
491 study enabled to link mesoscale fine resolution information (obtained through the
492 photogrammetric model) with a macroscale (> 1 km²) environmental context (obtained
493 by acoustic, LiDAR and satellite surveys). Jackson et al. (2020) and Rossi et al. (2021)
494 also emphasized the potential of multiscale approaches to study the responses of
495 biodiversity to environmental factors from individual to ecosystem levels using a set of
496 complementary tools (e.g. satellites, drones, LiDAR, Sonar, AUV, ROV, Camera). This
497 represents an innovative method for studying the relation between biological
498 communities and their micro/macrohhabitat through scales. As demonstrated in this
499 study, the photogrammetry can be efficient even in turbid temperate water system, and
500 is thus expected to work in a large part of sub-tidal environments. A challenge could

- 501 be now to develop photogrammetry for benthic community description per classes
502 based on (ortho)images that are collected to build up the classification.

Journal Pre-proof

503 Declaration of competing interest

504

505 The authors declare that they have no known competing financial interests or
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Table 1: The different combinations of resolution (r) and kernel size (k) to obtain the different calculation windows

Calculation window (in cm)	Kernel size (k, in pixel)	Resolution (r, in mm)
1.5	30	5
3	30	10
6	60	10
9	90	10

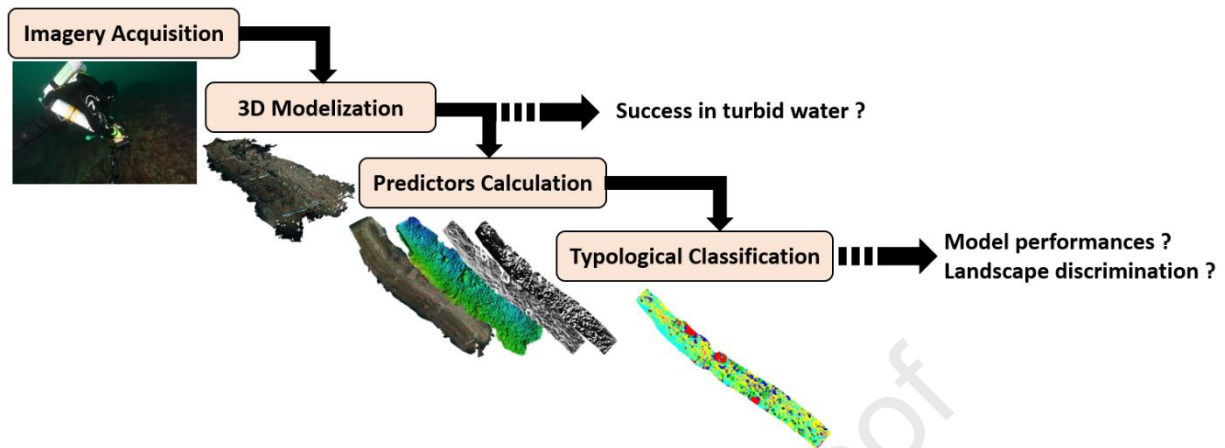
Table 2. Producer's accuracy (PA) for the different classes when all variables are combined (RGB, DSM, and Terrain calculated with all calculation windows) at Bizeux (top) and Buharats (down) sites. Green and red cases highlight respectively the highest (>80 %) and lowest (<80 %) percentages observed in the diagonal (classified class over ground truth class). Grey cases indicate values over 5.0 % (out of the diagonal).

Classified class	Ground truth class							
	Bed Rock	Big boulder	Medium boulder	Small boulder	Cobble	Pebble	Sand	field Material
Site of Bizeux								
Big boulder	/	98.13	0.45	2.4	0	0.35	/	0
Medium boulder	/	1.56	89.5	23.84	5.77	0.83	/	0.05
Small boulder	/	0.17	4.58	49.64	5	0.56	/	0.02
Cobble	/	0	1.49	13.66	56.34	3.26	/	0.7
Pebble	/	0.14	3.79	8.48	27.69	94.51	/	0.47
field Material	/	0	0.19	1.97	5.21	0.49	/	98.76
Site of Buharats								
Bed Rock	82.97	0.32	0.09	0.28	0.77	1.8	0.89	0.03
Big boulder	15.04	98.22	7.76	1.57	2	1.26	1.74	0.16
Medium boulder	0.69	0.7	89.16	10.11	2.5	1.52	2.99	0.21
Small boulder	0.31	0.41	0.9	76.49	6.78	1.39	0.07	0.25
Cobble	0.44	0.06	0.52	8.13	82.2	6.29	2.07	0.22
Pebble	0.34	0.05	1.02	3.03	4.88	73.56	6.07	1.15
Sand	0.16	0	0.14	0.07	0.82	13.64	84.35	0.39
field Material	0.07	0.25	0.41	0.32	0.05	0.54	1.82	97.59

Table 3. User's accuracy (UA) for the different classes when all variables are combined (RGB, DSM, and Terrain calculated with all calculation windows) at Bizeux (top) and Buharats (down) sites. Green and red cases highlight respectively the highest (>80 %) and lowest (<80 %) percentages observed in the diagonal (classified class over ground truth class). Grey cases indicate values over 5.0 % (out of the diagonal).

Classified class	Ground truth class							
	Bed Rock	Big boulder	Medium boulder	Small boulder	Cobble	Pebble	Sand	field Material
Site of Bizeux								
Big boulder	/	96.84	0.44	2.37	0	0.35	/	0
Medium boulder	/	1.28	73.65	19.62	4.75	0.68	/	0.02
Small boulder	/	0.28	7.64	82.79	8.34	0.93	/	0.02
Cobble	/	0	1.98	18.19	75.02	4.34	/	0.47
Pebble	/	0.1	2.81	6.29	20.53	70.09	/	0.17
field Material	/	0	0.33	3.44	9.1	0.86	/	86.27
Site of Buharats								
Bed Rock	95.22	0.37	0.1	0.32	0.88	2.07	1.02	0.02
Big boulder	11.78	76.93	6.08	1.23	1.57	0.99	1.36	0.06
Medium boulder	0.64	0.65	82.73	9.38	2.32	1.41	2.77	0.1
Small boulder	0.36	0.47	1.04	88.45	7.84	1.61	0.08	0.14
Cobble	0.44	0.06	0.52	8.14	82.35	6.3	2.07	0.11
Pebble	0.38	0.06	1.14	3.38	5.45	82.17	6.78	0.64
Sand	0.16	0	0.14	0.07	0.83	13.73	84.88	0.2
field Material	0.13	0.48	0.78	0.61	0.1	1.03	3.48	93.38

Graphical Abstract



Highlights

- Photogrammetric technique is applicable for high resolution (~1cm) mesoscale (~100m²) benthic temperate reef characterization in turbid coastal waters.
- Supervised classification provides good performance for benthic substrate mapping at a centimetre resolution.
- Resulting maps enable detection of landscape variability within and between sites.

1 **Authors agreement to the submission**

2 All authors declare being agree to the submission

3 **Author contributions**

4 Quentin Ternon, Éric Feunteun, Frédéric Ysnel, Pierre Thiriet and Antoine Collin

5 developed the study approach.

6 Quentin Ternon and Valentin Danet collected the data.

7 Quentin Ternon and Antoine Collin conducted the data analysis.

8 Quentin Ternon wrote the paper.

9 All authors participated to the manuscript revision.

10 Antoine Collin supervised the research.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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