

# Classification of underwater photogrammetry data for temperate benthic rocky reef mapping

Quentin Ternon, Valentin Danet, Pierre D Thiriet, Frédéric Ysnel, Eric

Feunteun, Antoine Collin

# ► To cite this version:

Quentin Ternon, Valentin Danet, Pierre D Thiriet, Frédéric Ysnel, Eric Feunteun, et al.. Classification of underwater photogrammetry data for temperate benthic rocky reef mapping. Estuarine, Coastal and Shelf Science, 2022, 270, pp.107833. 10.1016/j.ecss.2022.107833 . hal-03719359

# HAL Id: hal-03719359 https://hal.science/hal-03719359

Submitted on 19 Jul2022

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 2	Classification of underwater photogrammetry data for temperate benthic rocky reef mapping
3 4	Q. Ternon <sup>a,b</sup> , V. Danet <sup>a</sup> , P. Thiriet <sup>c</sup> , F. Ysnel <sup>d</sup> , E. Feunteun <sup>a,b</sup> , A. Collin <sup>e</sup>
5 6	<sup>a</sup> Museum National d'Histoire Naturelle (MNHN), Station Marine de Dinard, Centre de Recherche et d'Enseignement sur les Systèmes CÔtiers (CRESCO), 35800, Dinard, France
7 8 9	<sup>b</sup> Laboratoire Biologie des Organismes et Écosystèmes Aquatiques (UMR BOREA), MNHN, CNRS, Sorbonne Université, Université de Caen Normandie, Université des Antilles, IRD, 75231, Paris Cedex, France
10	° UMS Patrimoine Naturel, OFB, CNRS, MNHN, CRESCO, 35800, Dinard, France
11	<sup>d</sup> Université de Rennes 1, UMR BOREA, MNHN, 35042, Rennes Cedex, France
12 13	<sup>e</sup> Ecole Pratique des Hautes Etudes (EPHE), PSL Université de recherche, CNRS UMR LETG, 35800, Dinard, France
14	
15	Corresponding Author:
16	Quentin TERNON: <u>quentin.ternon@mnhn.fr</u>
17	MNHN-CRESCO, 38 rue du Port blanc, 35800, DINARD, France
18	Others Authors:
19	Valentin DANET: valentin.danet@mnhn.fr
20	Frederic YSNEL: <a href="mailto:frederic.ysnel@univ-rennes1.fr">frederic.ysnel@univ-rennes1.fr</a>
21	Éric FEUNTEUN: <u>eric.feunteun@mnhn.fr</u>
22	Pierre THIRIET: pierre.thiriet@mnhn.fr
23	Antoine COLLIN: antoine.collin@ephe.psl.eu
24	
25	Authors agreement to the submission
26	All authors declare being agree to the submission
27	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

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

- 55 mesoscale (100 m<sup>2</sup> to 1 km<sup>2</sup>) semi-automatic mapping of the fine resolution (1 cm)
- 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.

# 70 **1. Introduction**

71

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

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

and demersal habitats in relation with community composition (Fig. 1). Although, these
technologies are currently able to define the substrate at macroscale (>1 km<sup>2</sup>), with
high spatial resolution (~10 cm through acoustic, ~1 m through LiDAR and Satellite),
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).

because of water absorption (Irish and Lillycrop, 1999; Diaz et al., 2004; Bock et al., 100 2005; Collin et al., 2011; Knudby et al., 2011; Galparsoro, 2012; Collin et al. 2013; 101 Dierssen and Theberge, 2014; Zavalas et al., 2014; Calvert et al., 2015; Smith et al., 102 2015; Wahidin et al., 2015; lerodiaconou et al., 2018; Madricardo et al., 2019). LiDAR 103 and sonar surveys can provide relevant information on the terrain characteristics, 104 essential to describe and map benthic habitats (biotopes and biocenoses) (Pickrill and 105 Todd, 2003; Collin et al., 2008; Pittman et al., 2009; Brown et al., 2011; Collin et al., 106 2011; Walbridge et al., 2018). Hence, this mapping constitutes an effective baseline to 107 both target habitats of interest and evaluate the sampling effort required. More recently 108 109 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 characterisation of benthic rocky substrates and at larger scale of their associated 111 landscapes (Hatcher et al., 2020). Based on multi-view optical information (either 112 photographic or videographic), the photogrammetry has been mainly used in clear 113 water environments to describe coral reefs structure at various biological levels from 114 individuals to reefs (Burns et al., 2015; Figueira et al., 2015; Leon et al., 2015; Burns 115 et al., 2016; Ferrari et al., 2016; Anelli et al., 2017; Carlot et al., 2020; Fukunaga et al., 116 117 2020). To date, this approach has been used to describe, up to a scale of 120 m<sup>2</sup> (mesoscale), the morphology of the substrate below a centimetre resolution (Fig. 1; 118 Burns et al., 2015; Jackson et al., 2020; Marre et al., 2019; Marre, et al., 2020b). 119 However, the substrate typology (i.e. bed rock, boulders, pebbles, gravel, sand), 120 determinant for the structure and organisation of biological communities, has not been 121 derived from photogrametry in these studies. There is currently a clear need to produce 122 fine resolution (< 1 m) characterisations (geomorphology and typology) and maps of 123 temperate rocky reefs, to better understand and monitor processes involved in habitat 124

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

In this study, we propose an innovative method to produce a mesoscale (120 128 m<sup>2</sup>) fine resolution (1 cm) classification of benthic substrates in turbid waters combining 129 photogrammetry and supervised classification models. We selected two rocky 130 temperate reefs, located in the bay of Saint Malo, France, with similar topographic 131 features but characterised by different turbidity and hydrodynamic conditions. We 132 analysed the ability of the supervised classification to detect and quantify the relative 133 surface of eight substrate classes commonly used in the literature. A visual description 134 of the transect landscape (distribution patterns of the substrate types) has been 135 conducted to rapidly evaluate if differentiation of landscape patterns could be made. 136 The contribution of the spatial (terrain) and multispectral (red-green-blue, RGB) 137 predictors was investigated, and the best combination of predictors was statistically 138 examined. This research aims to develop a classification method to spatially quantify 139 the main biotope components of benthic rocky reef habitats. 140

141

2. Material and Methods

142

143 2.1. Study area

144

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

- reef of Buharats (48°40'24.08" N, 2°07'12.88" W; WGS84) located 3 km offshore, is
- more subject to marine influence but less turbid than Bizeux (Fig. 2).





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.

For each reef, a 120 m<sup>2</sup> transect (30 m long and 4 m wide ; Fig. 3) was 153 investigated in circa-littoral habitats, under the kelp belts, at depths of 13 +/- 1 m (0 m 154 corresponding to the lowest astronomical tide level). 155



Fig. 3. Scheme of the 120 m<sup>2</sup> 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.

- 2.2. Imagery acquisition 166
- 167

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



Fig. 4. Workflow of the photogrammetry to describe a 120 m<sup>2</sup> 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.

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

2.3. Photogrammetric model construction 187

188

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

202

### Topographic modelling 2.4.

203

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

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).

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

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

219

221 2.5. Model classification

222

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

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





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 m > x > 50 cm) and small (50 cm > x > 25 cm) boulder, cobble (25 cm > x > 6 cm), pebble (6 cm > x > 4 mm), sand (4 mm > x) and field material (2 m rule, 0.25 m<sup>2</sup> quadrats and transect tape) based on Blair and McPherson (1999).

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

$$PA = Class_{i(Val_i)} / Val_i \times 100$$

With PA (in percent), Class<sub>i(Vali)</sub> the number of classified pixels for the class (i) among the pixel of the validation set for the class (i), and Val<sub>i</sub> the number of pixels of the validation set for the class (i).

$$261 \quad UA = Val_{i(Class_i)} / Class_i \times 100 \tag{2}$$

With UA (in percent), Val<sub>i(Classi)</sub> the number of pixels of the validation set for the class (i) among the classified pixel of the class (i), and Class<sub>i</sub> the number of pixels classified for the class (i). The overall accuracy (OA), reflecting the mean quality of the classification, can then be calculated (eq. 3).

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

267 With OA (in percent), n the total number of class and PA<sub>i</sub> the producer's accuracy of 268 the class (i).

269 2.6. Statistical analysis 270

\_,,,

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

(1)

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

288 3. Results

289

290 3.1. Overview and visual description

291

Two DSMs were successfully produced to map the biotope on surfaces of 120 292 m<sup>2</sup> at a fine spatial resolution of 1 cm. The topological metrics, calculated on these 293 294 areas, all indicated a high heterogeneity of the biotope in terms of morphology and substrate typology. Geomorphologically, big boulders at Bizeux (Fig. 5) are visually 295 accompanied by high slopes, reduced maximum curvature and RMSE, and a smooth 296 convexity. Contrastingly, small boulders, cobbles, and pebbles at Bizeux are 297 associated with noisy slopes and convexity. The final classification, mapping the 298 different substrate typologies, showed that the whole surface sampled area at Bizeux 299 300 is covered by a mixture of boulders (bid, medium and small), cobble and pebble (Fig. 6). The final classification at Buharats showed that this site can be visually divided into 301 4 distinct zones, with cobbles and small boulders on the left, followed by a bed rock 302 section, then by a pebble and sand basin, and with medium and big boulders to the 303 right (Fig. 6). 304

305 3.2. Performances of the whole classification

306

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

The same was observed for PA (omission error, false negative) and UA (commission error, false positive). The highest PA (mean(PA<sub>Bizeux</sub>) = 81.1 %, mean(PA<sub>Buharats</sub>) = 85.6 %) and UA (mean(UA<sub>Bizeux</sub>) = 80.8 %, mean(UA<sub>Buharats</sub>) = 85.8 %) are observed when all variables are combined (RGB, DSM, and Terrain calculated with all calculation windows). Although the increase observed in UA is significant (p.value<sub>Bizeux</sub> = 0.024;

- 316 p.value<sub>Buharats</sub> = 0.001), this is not the case for PA (p.value<sub>Bizeux</sub> = 0.301; p.value<sub>Buharats</sub> = 0.056). 317
- 3.3. Model performance to detect substrate classes 318
- 320 3.3.1. Producer's accuracy (PA)
- 321

319

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

- 3.3.2. User's accuracy (UA) 333
- 334

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

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

346

347

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

352 % (out of the diagonal).

Classified class			G	round truth clas	S			
Site of Bizeux	Bed Rock	Big boulder	Medium boulder	Small boulder	Cobble	Pebble	Sand	field Material
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	Big boulder	Medium boulder	Small boulder	Cobble	Pebble	Sand	field Material
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

354 3.4. Selecting relevant variables to build relevant classifications 355 For both producer's (Fig. 8.1) and user's (Fig. 8.2) accuracy values, the relationship 356 between predictors (the different Terrain variables and calculation windows) and the 357 resulting typology was analysed by redundancy analyses (RDA).



Fig. 8. Redundancy analysis (RDA) of the accuracy values of the producer (PA, graph 359 1) and user (UA, graph 2), showing the relationship between relevant classes (i.e. 360 predicted typology, progressive selection; black arrows) and predictors. Predictors 361 362 encompass the Terrain variables (blue) (DSM, slope (S), aspect (A), profile convexity (Pr), plan convexity (PI), maximum curvature (MC), root mean square error (RMS)) 363 and the used calculation windows (dark vellow) (1.5 (cw 1.5cm), 3 (cw 3cm), 6 364 (cw\_6cm), and 9 cm (cw\_9cm)). Similar direction of the arrows indicates positive 365 correlation. The total variance explained by the two significant axes (ANOVA, p > 366 0.001) is detailed in brackets for each axe. The total and adjusted variances of the 367 RDA are indicated in brackets at the upper part of each graph. 368

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

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

- 4. Discussion 383
- 384

In this study, we produced a fine resolution (1 cm) classification of benthic sub-385 tidal substrates over surfaces of 120 m<sup>2</sup> (mesoscale) of temperate reefs under 386 hydrodynamic and turbid waters using photogrammetry-based methods. 387

4.1. 388

389

## Performance overview

Our results demonstrate that the photogrammetry approach can be used to 390 describe the substrate characteristics at scales of 120 m<sup>2</sup> with a high spatial resolution 391 of 1cm. The visual overview of the two mapping transects further highlights substrate 392 landscape differences. The Terrain variables such as slope, aspect, convexity (plan 393 394 and profile), maximum curvature and rugosity (RMSE) can be derived from DSM at various scales. The combination of these variables with the multispectral (RGB bands) 395 information enabled a realistic and accurate (OA > 79 %) classification of the different 396 397 substrate typologies for both sites. Interestingly in our models, high OA were coupled with high and balanced values of PA and UA, showing that substrate typological 398

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

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

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

the final objectives of the research, because they have a strong implication on theduration of the analysis.

426 427

## 4.2. Model performance to detect substrate classes

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

## 440 4.3. Relevant variables for classification

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

449 450

## 4.4. Further calculation methodologies

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

462

## 4.5. Access to reliefs difficult to sample

463

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

475 4.6. Toward the characterisation of benthic communities

476

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

485 5. Conclusion

486

The photogrammetry is clearly a powerful tool for a fine resolution (1cm) of the 487 substrate characterisation at mesoscale (100 m<sup>2</sup> to 1 km<sup>2</sup>). The semi-automatic 488 classification process developed here allows now a complete description of the terrain 489 characteristics. The georeferenced orthoprojection of the transect implemented in this 490 study enabled to link mesoscale fine resolution information (obtained through the 491 photogrammetric model) with a macroscale (> 1 km<sup>2</sup>) environmental context (obtained 492 by acoustic, LiDAR and satellite surveys). Jackson et al. (2020) and Rossi et al. (2021) 493 also emphasized the potential of multiscale approaches to study the responses of 494 biodiversity to environmental factors from individual to ecosystem levels using a set of 495 complementary tools (e.g. satellites, drones, LiDAR, Sonar, AUV, ROV, Camera). This 496 represents an innovative method for studying the relation between biological 497 498 communities and their micro/macrohabitat through scales. As demonstrated in this study, the photogrammetry can be efficient even in turbid temperate water system, and 499 is thus expected to work in a large part of sub-tidal environments. A challenge could 500

- 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.

- 503 Declaration of competing interest
- 504

Declaration of competing interest

505 The authors declare that they have no known competing financial interests or 506 personal relationships that could have appeared to influence the work reported in this 507 paper.

- 508 Acknowledgements
- 509

The authors would like to first thank Olivier Bianchimani from Semptentrion 510 environment company for knowledge transfer in photogrammetry, allowing to explore 511 other research perspectives at CRESCO-MNHN. Special thanks to the technical staff 512 of the CRESCO-MNHN, in particular Julien Guillaudeau, Sébastien Aubin and 513 Christophe Boinet, allowing the sampling campaign success with safety and with 514 custom material. Also, thanks to Anne Lizé from CRESCO-MNHN for having proofread 515 516 and corrected the English of the manuscript. Another thanks to Dorothée James, from the EPHE, for her initiation to the ENVI software. Authors are also grateful to Pertti 517 Arvonen, from the UWIS company, for his technical support for the geolocation system. 518 Authors finally want to thank both reviewers for taking the time to evaluate this work 519 and providing improvements to the manuscript. This study was founded by the 520 521 MARINEFF Project, developing marine infrastructure improving the ecological state of coastal water along the English Channel (Programme 2019-2022 INTERREG V-A 522 France (Manche) - Angleterre, co-financed by the FEDER). 523

# 524 References

- 525
- Anelli, M., Julitta, T., Fallati, L., Galli, P., Rossini, M., Colombo, R., 2017. Towards
- 527 new applications of underwater photogrammetry for investigating coral reef
- 528 morphology and habitat complexity in the Myeik Archipelago, Myanmar.
- 529 Geocarto Int. 1–14. https://doi.org/10.1080/10106049.2017.1408703
- 530 Barnes, D.K.A., 1999. High diversity of tropical intertidal zone sponges in
- temperature, salinity and current extremes. Afr. J. Ecol. 37, 424–434.
- 532 https://doi.org/10.1046/j.1365-2028.1999.00197.x
- Bayley, D.T.I., Mogg, A.O.M., 2020. A protocol for the large-scale analysis of reefs
- using Structure from Motion photogrammetry. Methods Ecol. Evol. 11, 1410–
- 535 1420. https://doi.org/10.1111/2041-210X.13476
- 536 Bayley, D.T.I., Mogg, A.O.M., Koldewey, H.J., Purvis, A., 2019. Capturing complexity:
- 537 field-testing the use of 'structure from motion' derived virtual models to replicate
- standard measures of reef physical structure. PeerJ 1–17.
- 539 https://doi.org/10.7717/peerj.6540
- Bibiloni, A., Uriz, M.J., Gili, J.M., 1989. Sponge Communities in Three Submarine
- 541 Caves of the Balearic Islands (Western Mediterranean): Adaptations and
- 542 Faunistic Composition. Mar. Ecol. 10, 317–334.
- 543 Blair, T.C., McPherson, J.G., 1999. Grain-size and textural classification of coarse
- sedimentary particles. J. Sediment. Res. 69, 6–19.
- 545 https://doi.org/10.2110/jsr.69.6
- Bock, M., Xofis, P., Mitchley, J., Rossner, G., Wissen, M., 2005. Object-oriented
- 547 methods for habitat mapping at multiple scales Case studies from Northern

- 548 Germany and Wye Downs, UK. J. Nat. Conserv. 13, 75–89.
- 549 https://doi.org/10.1016/j.jnc.2004.12.002
- 550 Borland, H.P., Gilby, B.L., Henderson, C.J., Leon, J.X., Schlacher, T.A., Connolly,
- 551 R.M., Pittman, S.J., Sheaves, M., Olds, A.D., 2021. The influence of seafloor
- terrain on fish and fisheries : A global synthesis. Fish Fish. 1–28.
- 553 https://doi.org/10.1111/faf.12546
- Bravo, G., Livore, J.P., Bigatti, G., 2020. The Importance of Surface Orientation in
- 555 Biodiversity Monitoring Protocols: The Case of Patagonian Rocky Reefs. Front.

556 Mar. Sci. 7, 1–12. https://doi.org/10.3389/fmars.2020.578595

- Brown, C.J., Smith, S.J., Lawton, P., Anderson, J.T., 2011. Benthic habitat mapping:
- 558 A review of progress towards improved understanding of the spatial ecology of
- the seafloor using acoustic techniques. Estuar. Coast. Shelf Sci. 92, 502–520.

560 https://doi.org/10.1016/j.ecss.2011.02.007

- 561 Burns, J., Delparte, D., Gates, R., Takabayashi, M., 2015. Integrating structure-from-
- 562 motion photogrammetry with geospatial software as a novel technique for
- quantifying 3D ecological characteristics of coral reefs. PeerJ 3, e1077.
- 564 https://doi.org/10.7717/peerj.1077
- 565 Burns, J.H.R., Delparte, D., Kapono, L., Belt, M., Gates, R.D., Takabayashi, M.,
- <sup>566</sup> 2016. Assessing the impact of acute disturbances on the structure and
- 567 composition of a coral community using innovative 3D reconstruction techniques.
- 568 Methods Oceanogr. 15–16, 49–59. https://doi.org/10.1016/j.mio.2016.04.001
- 569 Calvert, J., Strong, J.A., Service, M., McGonigle, C., Quinn, R., 2015. An evaluation
- 570 of supervised and unsupervised classification techniques for marine benthic
- habitat mapping using multibeam echosounder data. ICES J. Mar. Sci. 72,

- 572 1498–1513. https://doi.org/10.1093/icesjms/fsu223
- 573 Cameron, M.J., Lucieer, V., Barrett, N.S., Johnson, C.R., Edgar, G.J., 2014.
- 574 Understanding community-habitat associations of temperate reef fishes using
- 575 fine-resolution bathymetric measures of physical structure. Mar. Ecol. Prog. Ser.
- 576 506, 213–229. https://doi.org/10.3354/meps10788
- 577 Carlot, J., Rovère, A., Casella, E., Harris, D., Grellet-Muñoz, C., Chancerelle, Y.,
- 578 Dormy, E., Hedouin, L., Parravicini, V., 2020. Community composition predicts
- 579 photogrammetry-based structural complexity on coral reefs. Coral Reefs 39,
- 580 967–975. https://doi.org/10.1007/s00338-020-01916-8
- 581 Castric-Fey, A., Chasse, C., 1991. Factorial analysis in the ecology of rocky subtidal
- areas near brest (west brittany, france). J. Mar. Biol. Assoc. United Kingdom 71,
- 583 515–536. https://doi.org/10.1017/S0025315400053121
- 584 Castric-Fey, A., Girard-Descatoire, A., Lafargue, F., L'Hardy-Halos, M.-T., 1973.
- 585 Etagement des algues et des invertébrés sessiles dans l'Archipel de Glénan.
- 586 Helgoländer wiss. Meeresunters 24, 490–509.
- 587 Coleman, M.A., Ingleton, T., Millar, R.B., Davies, P.L., Jordan, A., Kelaher, B.P.,
- 588 2016. Remotely sensed habitat variables are poor surrogates for functional traits
- of rocky reef fish assemblages. Environ. Conserv. 43, 368–375.
- 590 https://doi.org/10.1017/S0376892916000205
- 591 Collin, A., Archambault, P., Long, B., 2011. Predicting species diversity of benthic
- communities within turbid nearshore using full-waveform bathymetric LiDAR and
- 593 machine learners. PLoS One 6, 1–16.
- 594 https://doi.org/10.1371/journal.pone.0021265

- 595 Collin, A., Archambault, P., Long, B., 2008. Mapping the shallow water seabed
- habitat with the SHOALS. IEEE Trans. Geosci. Remote Sens. 46, 2947–2955.

597 https://doi.org/10.1109/TGRS.2008.920020

- 598 Collin, A., Archambault, P., Planes, S., 2013. Bridging Ridge-to-Reef Patches :
- 599 Seamless Classification of the Coast Using Very High Resolution Satellite 5,
- 600 3583–3610. https://doi.org/10.3390/rs5073583
- 601 Collin, A., Dubois, S., James, D., Houet, T., 2019. Improving intertidal reef mapping
- using UAV surface, red edge, and near-infrared data. Drones 3, 1–12.
- 603 https://doi.org/10.3390/drones3030067
- 604 Congalton, R.G., 1991. A review of assessing the accuracy of classifications of
- remotely sensed data. Remote Sens. Environ. 37, 35–46.
- 606 https://doi.org/10.1016/0034-4257(91)90048-B
- Diaz, R.J., Solan, M., Valente, R.M., 2004. A review of approaches for classifying
- 608 benthic habitats and evaluating habitat quality. J. Environ. Manage. 73, 165–
- 609 181. https://doi.org/10.1016/j.jenvman.2004.06.004
- Dierssen, H.M., Theberge, A.E., 2014. Bathymetry: Assessment. Encycl. Nat.
- 611 Resour. Water 629–636. https://doi.org/10.1081/e-enrw-120048588
- Duckworth, A.R., 2016. Substrate type affects the abundance and size of a coral-reef
- sponge between depths. Mar. Freshw. Res. 67, 246–255.
- 614 https://doi.org/10.1071/MF14308
- Elvenes, S., Dolan, M.F.J., Buhl-Mortensen, P., Bellec, V.K., 2014. An evaluation of
- 616 compiled single-beam bathymetry data as a basis for regional sediment and
- biotope mapping. Nature 71, 867–881. https://doi.org/10.1038/278097a0

- Ferrari, R., McKinnon, D., He, H., Smith, R.N., Corke, P., González-Rivero, M.,
- Mumby, P.J., Upcroft, B., 2016. Quantifying multiscale habitat structural
- 620 complexity: A cost-effective framework for underwater 3D modelling. Remote
- 621 Sens. 8, 1–21. https://doi.org/10.3390/rs8020113
- Figueira, W., Ferrari, R., Weatherby, E., Porter, A., Hawes, S., Byrne, M., 2015.
- 623 Accuracy and precision of habitat structural complexity metrics derived from
- underwater photogrammetry. Remote Sens. 7, 16883–16900.
- 625 https://doi.org/10.3390/rs71215859
- Fukunaga, A., Burns, J.H.R., Pascoe, K.H., Kosaki, R.K., 2020. Associations
- 627 between benthic cover and habitat complexity metrics obtained from 3D
- reconstruction of coral reefs at different resolutions. Remote Sens. 12, 1–16.
- 629 https://doi.org/10.3390/rs12061011
- 630 Gallon, R.K., Ysnel, F., Feunteun, E., 2013. Optimization of an "in situ" subtidal
- rocky-shore sampling strategy for monitoring purposes. Mar. Pollut. Bull. 74,
- 632 253–263. https://doi.org/10.1016/j.marpolbul.2013.06.049
- Galparsoro, I., Guest Editor, 2012. Using EUNIS Habitat Classification for Benthic
   Mapping in European Seas. Rev. Investig. Mar. 19, 21–70.
- Gayet, G., Baptist, F., Maciejewski, L., Poncet, R., Bensettiti, F., 2018. Guide de
- 636 détermination des habitats terrestres et marins de la typologie EUNIS.
- 637 Goffredo, S., Dubinsky, Z., 2014. The mediterranean sea: Its history and present
- challenges. Mediterr. Sea Its Hist. Present Challenges 1–678.
- 639 https://doi.org/10.1007/978-94-007-6704-1
- Guinan, J., Grehan, A.J., Dolan, M.F.J., Brown, C., 2009. Quantifying relationships

- between video observations of cold-water coral cover and seafloor features in
- rockall trough, west of Ireland. Mar. Ecol. Prog. Ser. 375, 125–138.
- 643 https://doi.org/10.3354/meps07739
- Hasan, R.C., lerodiaconou, D., Laurenson, L., Schimel, A., 2014. Integrating
- 645 multibeam backscatter angular response, mosaic and bathymetry data for
- benthic habitat mapping. PLoS One 9, 1–14.
- 647 https://doi.org/10.1371/journal.pone.0097339
- Hatcher, G.A., Warrick, J.A., Ritchie, A.C., Dailey, E.T., Zawada, D.G., Kranenburg,
- 649 C., Yates, K.K., 2020. Accurate Bathymetric Maps From Underwater Digital
- Imagery Without Ground Control. Front. Mar. Sci. 7, 1–20.
- 651 https://doi.org/10.3389/fmars.2020.00525
- Holmes, K.W., Van Niel, K.P., Radford, B., Kendrick, G.A., Grove, S.L., 2008.
- 653 Modelling distribution of marine benthos from hydroacoustics and underwater
- video. Cont. Shelf Res. 28, 1800–1810. https://doi.org/10.1016/j.csr.2008.04.016
- lerodiaconou, D., Schimel, A.C.G., Kennedy, D., Monk, J., Gaylard, G., Young, M.,
- Diesing, M., Rattray, A., 2018. Combining pixel and object based image analysis
- of ultra-high resolution multibeam bathymetry and backscatter for habitat
- mapping in shallow marine waters. Mar. Geophys. Res. 39, 271–288.
- 659 https://doi.org/10.1007/s11001-017-9338-z
- Irish, J.L., Lillycrop, W.J., 1999. Scanning laser mapping of the coastal zone: The
- 661 SHOALS system. ISPRS J. Photogramm. Remote Sens. 54, 123–129.
- 662 https://doi.org/10.1016/S0924-2716(99)00003-9
- Irvin, B.J., Ventura, S.J., Slater, B.K., 1997. Fuzzy and isodata classification of
- landform elements from digital terrain data in Pleasant Valley, Wisconsin.

665	Geoderma 77, 137-154. https://doi.org/10.1016/S0016-7061(97)00019-0
666	Jackson, T.D.U., Williams, G.J., Walker-springett, G., Davies, A.J., 2020. Three-
667	dimensional digital mapping of ecosystems : a new era in spatial ecology. Proc.
668	R. Soc. B 287, 1–10. https://doi.org/10.1098/rspb.2019.2383
669	James, Dorothée, Collin, A., Houet, T., Mury, A., Gloria, H., Le, N., 2020. Towards
670	Better Mapping of Seagrass Meadows using UAV Multispectral and Topographic
671	Data. J. co 95, 1117–1121. https://doi.org/10.2112/SI95-217.1
672	James, D., Collin, A., Mury, A., Costa, S., 2020. Very high resolution land use and
673	land cover mapping using pleiades-1 stereo imagery and machine learning. Int.
674	Arch. Photogramm. Remote Sens. Spat. Inf. Sci ISPRS Arch. 43, 675–682.
675	https://doi.org/10.5194/isprs-archives-XLIII-B2-2020-675-2020
676	Keith, D.A., Ferrer-paris, J.R., Nicholson, E., Kingsford, R.T., 2020. IUCN Global
677	Ecosystem Typology 2.0: descriptive profiles for biomes and ecosystem
678	functional groups. Gland, Switzerland.
679	https://doi.org/10.2305/iucn.ch.2020.13.en
680	Knudby, A., LeDrew, E., Brenning, A., 2010. Predictive mapping of reef fish species
681	richness, diversity and biomass in Zanzibar using IKONOS imagery and
682	machine-learning techniques. Remote Sens. Environ. 114, 1230–1241.
683	https://doi.org/10.1016/j.rse.2010.01.007
684	Knudby, A., Roelfsema, C., Lyons, M., Phinn, S., Jupiter, S., 2011. Mapping fish
685	community variables by Integrating field and satellite data, object-based image
686	analysis and modeling in a traditional Fijian fisheries management area. Remote
687	Sens. 3, 460–483. https://doi.org/10.3390/rs3030460

688	Kuffner,	I.B.,	Brock.	J.C.,	Grober-Dunsmore,	R.	, Bonito.	V.E.	, Hickey	. T.D.	, Wright,
-----	----------	-------	--------	-------	------------------	----	-----------	------	----------	--------	-----------

- 689 C.W., 2007. Relationships between reef fish communities and remotely sensed
- rugosity measurements in Biscayne National Park, Florida, USA. Environ. Biol.

691 Fishes 78, 71–82. https://doi.org/10.1007/s10641-006-9078-4

- Lecours, V., Devillers, R., Schneider, D.C., Lucieer, V.L., Brown, C.J., Edinger, E.N.,
- 693 2015. Spatial scale and geographic context in benthic habitat mapping: Review

and future directions. Mar. Ecol. Prog. Ser. 535, 259–284.

- 695 https://doi.org/10.3354/meps11378
- Leon, J.X., Roelfsema, C.M., Saunders, M.I., Phinn, S.R., 2015. Measuring coral reef
- terrain roughness using "Structure-from-Motion" close-range photogrammetry.

698 Geomorphology 242, 21–28. https://doi.org/10.1016/j.geomorph.2015.01.030

Madricardo, F., Foglini, F., Campiani, E., Grande, V., Catenacci, E., Petrizzo, A.,

Kruss, A., Toso, C., Trincardi, F., 2019. Assessing the human footprint on the

sea-floor of coastal systems: the case of the Venice Lagoon, Italy. Sci. Rep. 9,

702 1–14. https://doi.org/10.1038/s41598-019-43027-7

- Marre, G., De Almeida Braga, C., Ienco, D., Luque, S., Holon, F., Deter, J., 2020a.
- 704 Deep convolutional neural networks to monitor coralligenous reefs:
- 705 Operationalizing biodiversity and ecological assessment. Ecol. Inform. 59,
- 706 101110. https://doi.org/10.1016/j.ecoinf.2020.101110
- Marre, G., Deter, J., Holon, F., Boissery, P., Luque, S., 2020b. Fine-scale automatic
- mapping of living posidonia oceanica seagrass beds with underwater
- photogrammetry. Mar. Ecol. Prog. Ser. 643, 63–74.
- 710 https://doi.org/10.3354/meps13338
- Marre, G., Holon, F., Luque, S., Boissery, P., Deter, J., 2019. Monitoring Marine

- 712 Habitats With Photogrammetry: A Cost-Effective, Accurate, Precise and High-
- 713 Resolution Reconstruction Method. Front. Mar. Sci. 6, 1–15.
- 714 https://doi.org/10.3389/fmars.2019.00276
- Meroz-Fine, E., Shefer, S., Ilan, M., 2005. Changes in morphology and physiology of
- an East Mediterranean sponge in different habitats. Mar. Biol. 147, 243–250.
- 717 https://doi.org/10.1007/s00227-004-1532-2
- Monk, J., Ierodiaconou, D., Bellgrove, A., Harvey, E., Laurenson, L., 2011. Remotely
- sensed hydroacoustics and observation data for predicting fish habitat suitability.
- 720 Cont. Shelf Res. 31, 17–27. https://doi.org/10.1016/j.csr.2010.02.012
- Monk, J., Ierodiaconou, D., Versace, V.L., Bellgrove, A., Harvey, E., Rattray, A.,
- Laurenson, L., Quinn, G.P., 2010. Habitat suitability for marine fishes using
- presence-only modelling and multibeam sonar. Mar. Ecol. Prog. Ser. 420, 157–
- 724 174. https://doi.org/10.3354/meps08858
- Moore, C.H., Harvey, E.S., Van Niel, K., 2010. The application of predicted habitat
- models to investigate the spatial ecology of demersal fish assemblages. Mar.
- 727 Biol. 157, 2717–2729. https://doi.org/10.1007/s00227-010-1531-4
- Moore, C.H., Harvey, E.S., Van Niel, K.P., 2009. Spatial prediction of demersal fish
- distributions: Enhancing our understanding of species-environment relationships.
- 730 ICES J. Mar. Sci. 66, 2068–2075. https://doi.org/10.1093/icesjms/fsp205
- 731 Oppelt, N., 2012. Hyperspectral classification approaches for intertidal macroalgae
- habitat mapping: a case study in Heligoland. Opt. Eng. 51, 111703.
- 733 https://doi.org/10.1117/1.oe.51.11.111703
- Pal, M., Mather, P.M., 2003. An assessment of the effectiveness of decision tree

- methods for land cover classification. Remote Sens. Environ. 86, 554–565.
- 736 https://doi.org/10.1016/S0034-4257(03)00132-9
- Pickrill, R.A., Todd, B.J., 2003. The multiple roles of acoustic mapping in integrated
- ocean management, Canadian Atlantic continental margin. Ocean Coast.
- 739 Manag. 46, 601–614. https://doi.org/10.1016/S0964-5691(03)00037-1
- 740 Pittman, S.J., Brown, K.A., 2011. Multi-scale approach for predicting fish species
- distributions across coral reef seascapes. PLoS One 6, 1–12.
- 742 https://doi.org/10.1371/journal.pone.0020583
- Pittman, S.J., Christensen, J.D., Caldow, C., Menza, C., Monaco, M.E., 2007.
- 744 Predictive mapping of fish species richness across shallow-water seascapes in
- the Caribbean. Ecol. Modell. 204, 9–21.
- 746 https://doi.org/10.1016/j.ecolmodel.2006.12.017
- Pittman, S.J., Costa, B.M., Battista, T.A., 2009. Using Lidar Bathymetry and Boosted
- Regression Trees to Predict the Diversity and Abundance of Fish and Corals. J.
- 749 Coast. Res. 10053, 27–38. https://doi.org/10.2112/si53-004.1
- Porskamp, P., Rattray, A., Young, M., Ierodiaconou, D., 2018. Multiscale and
- <sup>751</sup> hierarchical classification for benthic habitat mapping. Geosciences 8, 1–24.
- 752 https://doi.org/10.3390/geosciences8040119
- 753 Pygas, D.R., Ferrari, R., Figueira, W.F., 2020. Review and meta-analysis of the
- importance of remotely sensed habitat structural complexity in marine ecology.
- 755 Estuar. Coast. Shelf Sci. 235, 1–16. https://doi.org/10.1016/j.ecss.2019.106468
- 756 Quattrini, A.M., Nizinski, M.S., Chaytor, J.D., Demopoulos, A.W.J., Roark, E.B.,
- France, S.C., Moore, J.A., Heyl, T., Auster, P.J., Kinlan, B., Ruppel, C., Elliott,

758	K.P., Kennedy, B.R.C., Lobecker, E., Skarke, A., Shank, T.M., 2015. Exploration
759	of the canyon-incised continental margin of the northeastern United States
760	reveals dynamic habitats and diverse communities. PLoS One 10, 1–32.
761	https://doi.org/10.1371/journal.pone.0139904
762	Rattray, A., Ierodiaconou, D., Laurenson, L., Burq, S., Reston, M., 2009. Hydro-
763	acoustic remote sensing of benthic biological communities on the shallow South
764	East Australian continental shelf. Estuar. Coast. Shelf Sci. 84, 237–245.
765	https://doi.org/10.1016/j.ecss.2009.06.023
766	Rees, M.J., Knott, N.A., Neilson, J., Linklater, M., Osterloh, I., Jordan, A., Davis, A.R.,
767	2018. Accounting for habitat structural complexity improves the assessment of
768	performance in no-take marine reserves. Biol. Conserv. 224, 100–110.
769	https://doi.org/10.1016/j.biocon.2018.04.040
770	Rossi, P., Ponti, M., Righi, S., Castagnetti, C., Simonini, R., Mancini, F., Agrafiotis,
771	P., Bassani, L., Bruno, F., Cerrano, C., Cignoni, P., Corsini, M., Drap, P.,
772	Dubbini, M., Garrabou, J., Gori, A., Gracias, N., Ledoux, J.B., Linares, C.,
773	Mantas, P.T., Menna, F., Nocerino, E., Palma, M., Pavoni, G., Ridolfi, A., Rossi,
774	S., Skarlatos, D., Treibitz, T., Turicchia, E., Yuval, M., Capra, A., 2021. Needs
775	and Gaps in Optical Underwater Technologies and Methods for the Investigation
776	of Marine Animal Forest 3D-Structural Complexity. Front. Mar. Sci. 8, 1–9.
777	https://doi.org/10.3389/fmars.2021.591292
778	Schmidt, J., Hewitt, A., 2004. Fuzzy land element classification from DTMs based on
779	geometry and terrain position. Geoderma 121, 243–256.
780	https://doi.org/10.1016/j.geoderma.2003.10.008
781	Sekund, L., Pittman, S., 2017. Explaining island-wide geographical patterns of

- 782 Caribbean fish diversity: A multi-scale seascape ecology approach. Mar. Ecol.
- 783 38, 1–19. https://doi.org/10.1111/maec.12434
- Sitjá, C., Maldonado, M., 2014. New and rare sponges from the deep shelf of the
- Alboran Island (Alboran Sea, Western Mediterranean). Zootaxa 3760, 141–179.
- 786 https://doi.org/10.11646/zootaxa.3760.2.2
- 787 Smith, G., Yesilnacar, E., Jiang, J., Taylor, C., 2015. Marine habitat mapping
- incorporating both derivatives of LiDAR data and hydrodynamic conditions. J.
- 789 Mar. Sci. Eng. 3, 492–508. https://doi.org/10.3390/jmse3030492
- Wahidin, N., Siregar, V.P., Nababan, B., Jaya, I., Wouthuyzen, S., 2015. Object-
- 791based Image Analysis for Coral Reef Benthic Habitat Mapping with Several
- 792 Classification Algorithms. Procedia Environ. Sci. 24, 222–227.
- 793 https://doi.org/10.1016/j.proenv.2015.03.029
- Walbridge, S., Slocum, N., Pobuda, M., Wright, D.J., 2018. Unified geomorphological
- analysis workflows with benthic terrain modeler. Geosciences 8, 1–24.
- 796 https://doi.org/10.3390/geosciences8030094
- 797 Williams, J., Jordan, A., Harasti, D., Davies, P., Ingleton, T., 2019. Taking a deeper
- <sup>798</sup> look: Quantifying the differences in fish assemblages between shallow and
- mesophotic temperate rocky reefs. PLoS One 14, 1–20.
- 800 https://doi.org/10.1101/449959
- Wilson, M.F.J., O'Connell, B., Brown, C., Guinan, J.C., Grehan, A.J., 2007. Multiscale
- terrain analysis of multibeam bathymetry data for habitat mapping on the
- continental slope. Mar. Geod. 30, 3–35.
- 804 https://doi.org/10.1080/01490410701295962

- Zavalas, R., Ierodiaconou Daniel, D., Ryan, D., Rattray, A., Monk, J., 2014. Habitat
- classification of temperate marine macroalgal communities using bathymetric
- LiDAR. Remote Sens. 6, 2154–2175. https://doi.org/10.3390/rs6032154

808

Journal Prevention

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).

	Ground truth							
Classified class				class	)			
			Medium					
Site of Bizeux	Bed Rock	Big boulder	boulder	Small boulder	Cobble	Pebble	Sand	field Material
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
			Medium					
Site of Buharats	Bed Rock	Big boulder	boulder	Small boulder	Cobble	Pebble	Sand	field Material
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 along				Ground truth	)			
Classified class			Medium	class				
Site of Bizeux	Bed Rock	Big boulder	boulder	Small boulder	Cobble	Pebble	Sand	field Material
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
		. (	Medium					
Site of Buharats	Bed Rock	Big boulder	boulder	Small boulder	Cobble	Pebble	Sand	field Material
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
- (~100m<sup>2</sup>) 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.

## **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:

Journal Prevention