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# 1 Contribution of Sentinel-2 satellite images for habitat mapping 2 of the Natura 2000 site ‘Estuaire de la Loire’ (France)

3

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15

16 **Keywords:** Sentinel-2, Satellite multi-date classification, Natura 2000, Estuarine habitats, EUNIS  
17 habitat mapping, Phytosociology, Random Forest.

18

19 **Abstract**

20 Habitat mapping is an essential tool to implement the European Habitats Directive 92/43/EEC and to  
21 manage the Natura 2000 protected areas network. However, their elaboration is most often based on  
22 field surveys, which are time-consuming and expensive when dealing with large areas. In this study,  
23 we aimed to evaluate the contribution of Sentinel-2 satellite images for mapping habitats of the Natura  
24 2000 site ‘Estuaire de la Loire’. We used 1,248 phytosociological plots to establish a complete  
25 typology of the study site’s habitats. Locating these plots led us to select training areas that  
26 characterize 39 habitats to calibrate the Random Forest algorithm. We classified 11 single-date images

27 spread evenly over a year and performed a multi-date classification of 9 images. We obtained high  
28 overall accuracy between 76.47% and 87.28% for the single-date image classifications and 98.7% for  
29 multi-date image classification. Our results demonstrate that Sentinel-2 images are appropriate for  
30 accurate habitat mapping and constitute a relevant tool to identify and conserve habitats of community  
31 interest.

32

### 33 **1. Introduction**

34 Preserving habitats is a major challenge for European nature conservation policies (Bijlsma et al.,  
35 2019). The implementation of the Habitats Directive 92/43/CEE (HabDir) especially permitted to  
36 target the most threatened habitats for which the European Union (EU) is committed to ensuring the  
37 maintain or the restoration to a favorable state of conservation (Art. 2 of HabDir) (Evans &  
38 Arvela 2011; Schaminée et al., 2016). Moreover, the Directive imposes applying measures of  
39 conservation and assessing the state of these habitats regularly. More specifically, naming protected  
40 areas led to the creation of the Natura 2000 network for which it is necessary to gather information on  
41 the habitats' distribution and surface areas (Evans, 2012).

42 To meet this goal, the EU member states need precise, simple and reproducible methods. Mapping  
43 represents an excellent tool to evaluate the habitat distribution and surface areas (Bunce et al., 2013).  
44 Currently, mapping methodologies are mainly based on field surveys and photo-interpretation (Ichter  
45 et al., 2014). These methods require roaming all the study areas to gather data on the vegetation and  
46 environmental factors characterizing the habitats. However, this type of mapping becomes quickly  
47 very time-consuming, costly and therefore difficult to implement in large and difficult-to-access  
48 territories (Kopeć et al., 2016; Moran et al., 2017). This is especially the case when mapping wetlands,  
49 which tend to be inaccessible because of numerous canals and flooded areas. (Harris et al., 2015;  
50 Zlinszky et al., 2014). Furthermore, this type of work is often subjective, which is why the  
51 cartographic productions can greatly vary from one operator to the other (Cherrill, 2014; Raab et al.,  
52 2018; Ullerud et al., 2018).

53 Approaches based on remote sensing currently offer many opportunities for cost-effective, rapid and  
54 reproducible mapping (Corbane et al., 2015; Vanden Borre et al., 2011). More and more studies show  
55 that remote sensing is increasingly used for mapping natural environments (Lang et al., 2015). For  
56 example, this is the case for studies on the mapping of alkaline peatland habitats in Poland using  
57 Rapid-Eye satellite images (Stenzel et al., 2014) or on mapping Belgian heathland habitats using  
58 hyperspectral airborne imagery (Haest et al., 2017). The quality of the remote sensing-based image  
59 classification depends on the characteristics of the images used, like the number of available spectral  
60 bands, the spatial resolution or the sensor's acquisition frequency. The Sentinel-2 satellite  
61 constellation produces 13-band multispectral images in the visible and infrared frequency range with a  
62 minimum spatial resolution of 100 m<sup>2</sup> and a high revisit frequency (several images per month). These  
63 characteristics are a good compromise for mapping wetland vegetation, in particular through multi-  
64 date classifications (Rapinel et al., 2019; Vrieling et al., 2018). To overcome these obstacles, remote  
65 sensing is a pertinent tool for identifying and locating habitats and, more broadly, areas with  
66 conservation issues. In this context, this study aims to assess the contribution of Sentinel-2 satellite  
67 images to mapping habitats in the Loire estuary by (1) developing an exhaustive typology of habitats  
68 from ground reference data and by (2) testing the accuracy of single-date and multi-date Sentinel-2  
69 image classification using the Random Forest algorithm.

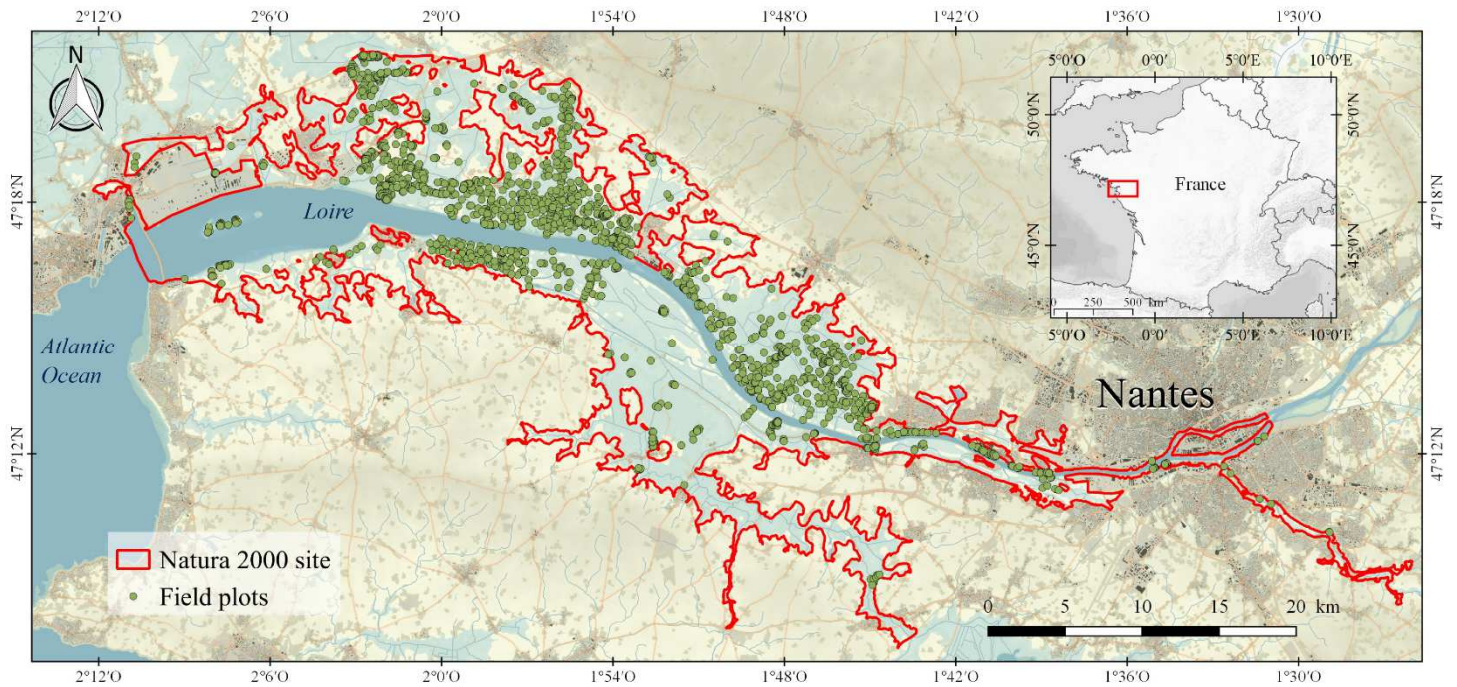
70

## 71 **2. Materials and Methods**

### 72 *2.1 Study area*

73 The Natura 2000 site 'Estuaire de la Loire', located in western France (47° 15'N, 1° 54'O) (Fig. 1), is  
74 an estuary formed by the Loire's alluvial plain which covers an area of 26,000 ha. It is a tidal wetland  
75 site of major ecological importance, hence its designation in 2004 as a Natura 2000 site (FR5200621 –  
76 Estuaire de la Loire). The site is recognized for the diversity of its ecosystems, from coastal habitats  
77 of dunes and salt marshes to agropastoral habitats of freshwater marshes and woodland habitats. The

78 large variety of habitats is mostly linked to flood frequency and duration, variations in exposure to  
79 salinity, as well as agricultural management (mainly mowing and grazing).



81 **Fig. 1.** Location of the Natura 2000 site 'Estuaire de la Loire' and available ground data.

82

### 83 *2.2 Typology of habitat types*

84 We used two habitat classification systems to establish the typology: EUNIS  
85 (European Union Nature Information System), which represents the most complete habitat repository  
86 in Europe, covering both marine and terrestrial environments (Chytrý et al., 2020; Evans, 2012) and  
87 the Interpretation Manual of European Union Habitats-EUR28 (European Commission, 2013), which  
88 includes definitions of the habitats of community interest in annex 1 of HabDir.

89 The typological units of these habitat repositories are mostly defined by vegetation classifications  
90 derived from sigmatist phytosociology (Gayet et al., 2018; Rodwell et al., 2018). We established the  
91 study site's habitat typology by identifying field vegetation plots which were collected using the  
92 sigmatist phytosociological method. A vegetation plot corresponds to the list of plant species  
93 inventoried inside areas with a floristically homogeneous composition (Dengler et al. 2008). The cover

94 of each species is visually estimated and quantified according to the Braun-Blanquet's scale (Braun-  
95 Blanquet, 1932).

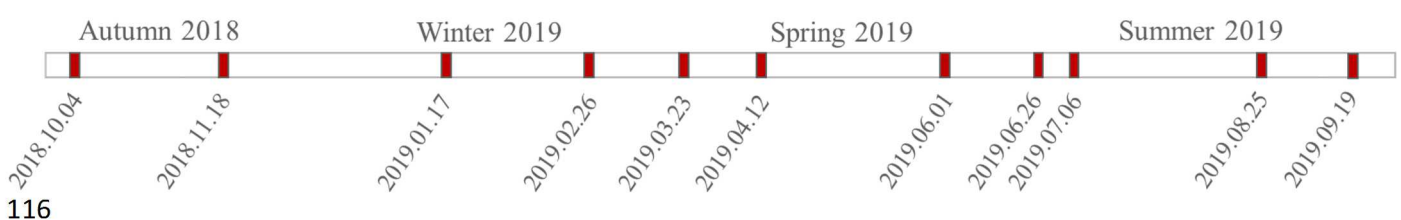
96 We used 1,248 phytosociological vegetation plots to obtain a representative sampling of the diversity  
97 of habitat types present in the study site (Fig. 1). A total of 989 phytosociological vegetation plots  
98 were collected from the bibliography (scientific publications, PhD theses, impact studies, vegetation  
99 maps...) and we collected in the field 259 phytosociological vegetation plots for this study. This  
100 dataset is constituted of vegetation plots that were collected from 2010 to 2019. Older vegetation plots  
101 were not selected because of a too long-time gap between field and satellite data. Most bibliographical  
102 vegetation plots were located precisely (horizontal accuracy <5 m) and those collected during this  
103 study were georeferenced using a differential GPS (GPS GeoXH™ from Trimble Geo-Explorer®,  
104 horizontal accuracy <1 m).

105 Firstly, we assigned vegetation plots to a phytosociological unit based on the descriptions contained in  
106 the Prodrome of French Vegetation (Bioret et al., 2013). Secondly, phytosociological units were  
107 related to EUNIS and EUR28 habitat types. This step (hereafter call "crosswalks") has been carried  
108 out using the French repository of habitats and vegetation typologies HABREF (Clair et al., 2019).

109

### 110 *2.3 Acquisition of Sentinel-2 images*

111 Covering the entire site requires using two Sentinel-2 image tiles (tiles' identification numbers:  
112 T30TWT and T30TXT). We looked for images without cloud cover and regularly distributed along an  
113 annual cycle of vegetation. Overall, we used 22 Sentinel-2 images (Level-2A – product-Bottom of  
114 Atmosphere (BOA) reflectance), corresponding to 11 acquisition dates from autumn 2018 to summer  
115 2019 (Fig. 2).



116

117 **Fig. 2.** Acquisition dates of Sentinel-2 images during an annual cycle of vegetation.

118

#### 119 *2.4 Image preparation and vegetation indices calculations*

120 Sentinel-2 images are distributed with three spectral bands at 60m spatial resolution (B1, B9 and B10),  
121 six bands at 20m spatial resolution (B5, B6, B7, B8A, B11 and B12) and four bands at 10m spatial  
122 resolution (B2, B3, B4 and B8) (Table 1). For each date, we only selected the bands with a spatial  
123 resolution of 10m and 20m (the 60m bands were mostly intended for the atmospheric corrections). We  
124 stacked the bands with the same spatial resolution and the 20m bands were interpolated on a 10m grid  
125 using the bilinear approach. Finally, all bands were stacked to form an image of 10 spectral bands with  
126 a 10-meter spatial resolution.

127 **Table 1** Sentinel-2 band characteristics

Sentinel-2 bands	Spectral region	Central wavelength (nm)	Bandwidth (nm)	Resolution (m)
B1	Coastal aerosol	442.7	21	60
B2	Blue	492.4	66	10
B3	Green	559.8	36	10
B4	Red	664.6	31	10
B5	Red-edge 1	704.1	15	20
B6	Red-edge 2	740.5	15	20
B7	Red-edge 3	782.8	20	20
B8	Near-infrared	832.8	106	10
B8A	Near-infrared narrow	864.7	21	20
B9	Water vapour	945.1	20	60
B10	Shortwave-infrared - Cirrus	1373.5	31	60
B11	Shortwave-infrared 1	1613.7	91	20
128 B12	Shortwave-infrared 2	2202.4	175	20

129

#### 130 **Calculating vegetation indices**

131 Remote sensing spectral indices are based on the combination of spectral bands to highlight  
132 biophysical characteristics of land surfaces. They are particularly useful for multi-date classifications  
133 as they are good indicators of seasonal changes of vegetation cover (Schuster et al., 2015). In this  
134 study, we have selected a set of 12 spectral indices (Table 2) covering the full spectral domain of

135 Sentinel-2 and commonly used for vegetation mapping (Adam et al., 2010; Kaplan and Avdan, 2017;  
 136 Roberts et al., 2011; Wakulińska and Marcinkowska-Ochtyra, 2020). NDVI remains the most  
 137 commonly used index with a very sensitive response to green vegetation thanks to its pigment  
 138 absorption ratio in the red range of electromagnetic spectrum and cell reflectance in the near-infrared  
 139 range (NIR), but it remains sensitive to effects of soil color, soil brightness and atmospheric effects.  
 140 GNDVI differs from NDVI by establishing a ratio between the NIR and the green range. SAVI  
 141 considers the effects of the soil more, which theoretically improves NDVI while EVI focuses more on  
 142 atmospheric effects. The red-edge curve is more specifically targeted with MCARI. NDWI targets  
 143 leave with the NIR and shortwave-infrared (SWIR) ratio sensitive to water content in leaves. Each  
 144 index is therefore part of the overall answer to the problem of identifying habitat types, answer given  
 145 by the combination of these indices. They are then stacked with the ten retained Sentinel-2 spectral  
 146 bands to provide a file with 22 layers (12 indices and 10 spectral bands) for each date.

147 **Table 2** List of vegetation indices calculated using Sentinel-2 spectral bands.

Vegetation index	Formulation	Sentinel-2 bands used	References
NDVI	$(\text{NIR} - \text{R}) / (\text{NIR} + \text{R})$	$(\text{B8} - \text{B4}) / (\text{B8} + \text{B4})$	Rouse et al., 1973
NDWI	$(\text{NIR} - \text{SWIR1}) / (\text{NIR} + \text{SWIR1})$	$(\text{B8} - \text{B11}) / (\text{B8} + \text{B11})$	Gao, 1996
GNDVI	$(\text{NIR} - \text{G}) / (\text{NIR} + \text{G})$	$(\text{B8} - \text{B3}) / (\text{B8} + \text{B3})$	Gitelson et al., 1996
IReCI	$(\text{NIR} - \text{R}) / (\text{RE1} / \text{RE2})$	$(\text{B8} - \text{B4}) * (\text{B5} / \text{B6})$	Frampton et al., 2013
PSSRa	$\text{NIR} / \text{R}$	$\text{B8} / \text{B4}$	Blackburn, 1998
NDI45	$(\text{RE1} - \text{R}) / (\text{RE1} + \text{R})$	$(\text{B5} - \text{B4}) / (\text{B5} + \text{B4})$	Delegido et al., 2011
EVI	$2.5 * (\text{NIR} - \text{R}) / ((\text{NIR} + 6 * \text{R} - 7.5 * \text{B}) + 1)$	$2.5 * (\text{B8} - \text{B4}) / ((\text{B8} + 6 * \text{B4} - 7.5 * \text{B2}) + 1)$	Huete et al., 2002
SAVI	$((\text{NIR} - \text{R}) / (\text{NIR} + \text{R} + 0.428)) * (1 + 0.428)$	$(\text{B8} - \text{B4}) / (\text{B8} + \text{B4} + 0.428) * (1.0 + 0.428)$	Huete, 1988
MCARI	$[(\text{RE1} - \text{R}) - 0.2 (\text{RE1} - \text{G})] * (\text{RE1} - \text{R})$	$((\text{B5} - \text{B4}) - 0.2 * (\text{B5} - \text{B3})) * (\text{B5} / \text{B4})$	Daughtry et al., 2000
CRE	$((\text{NIR} / \text{RE1}) - 1.0)$	$((\text{B8} / \text{B5}) - 1.0)$	Gitelson et al., 2006
S2REP	$705 + 35 * (((\text{NIR} + \text{R}) / 2) - \text{RE1}) / (\text{RE2} - \text{RE1}))$	$705 + 35 * (((\text{B8} + \text{B4}) / 2) - \text{B5}) / (\text{B6} - \text{B5}))$	Frampton et al., 2013
MTCI	$(\text{RE2} - \text{RE1}) / (\text{RE1} - \text{R})$	$(\text{B6} - \text{B5}) / (\text{B5} - \text{B4})$	Dash and Curran, 2004

*B, G, R, RE1, RE2, NIR, SWIR1, represent blue, green, red, red-edge 1, red-edge 2, near-infrared and and shortwave-infrared 1 spectral bands.*

*NDVI: Normalised Difference Vegetation Index*

*NDWI: Normalized Difference Water Index*

*GNDVI: Green Normalised Difference Vegetation Index*

*IReCI: Inverted Red-Edge Chlorophyll Index*

*PSSRa: Pigment Specific Simple Ratio*

1, *NDI45: Normalized difference index 4 and 5*

*EVI: Enhanced Vegetation Index*

*SAVI: Soil Adjusted Vegetation Index*

*MCARI: Modified chlorophyll absorption in reflectance index*

*CRE: Chlorophyll Red-Edge index*

*S2REP: Sentinel-2 red-edge position*

*MTCI: MERIS Terrestrial Chlorophyll Index*

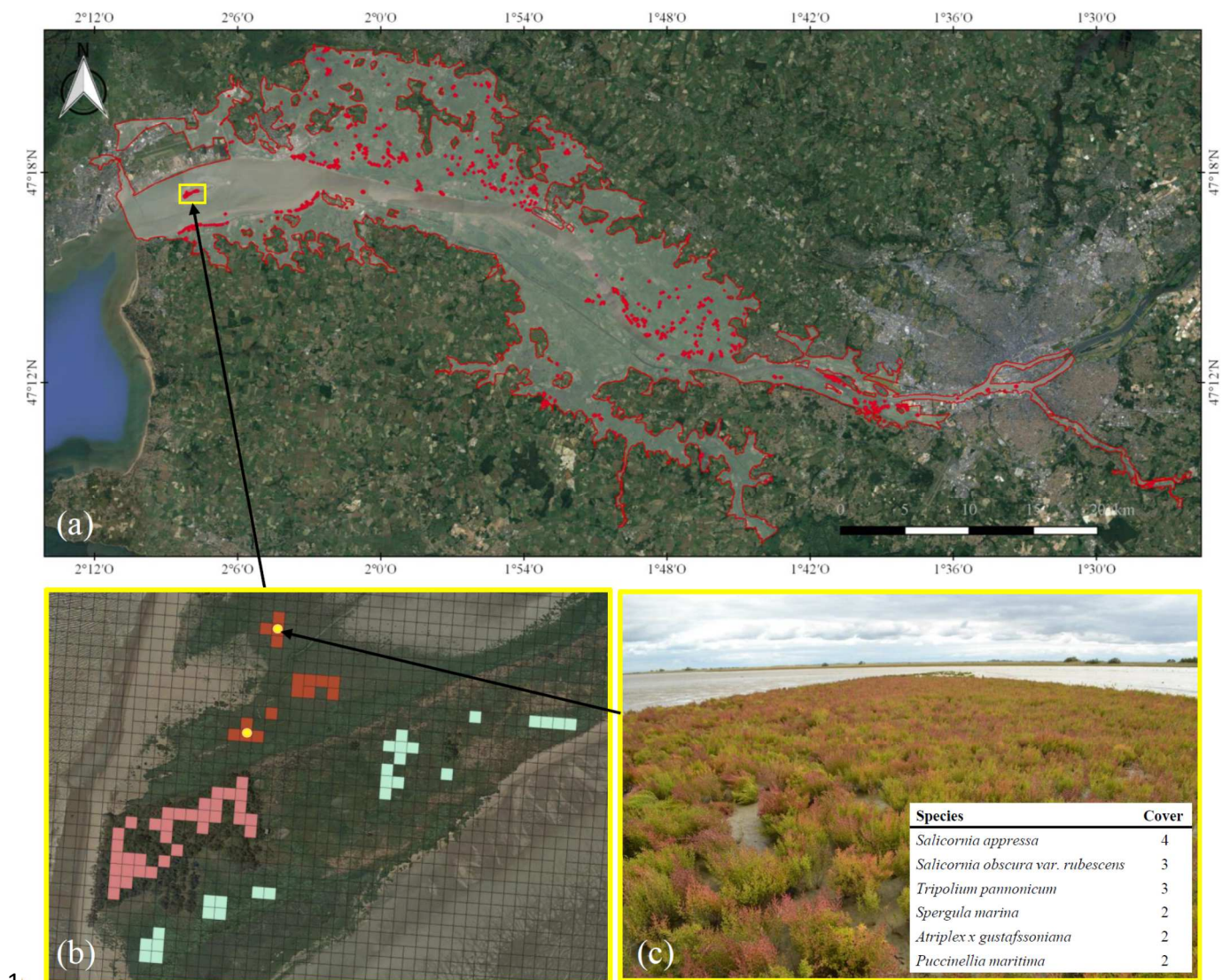
149 Finally, we cropped the images according to the study area's limits and we excluded artificial areas  
 150 using auxiliary thematic layers integrating roads, built-up and cultivated areas as suggested by Inglada  
 151 et al. (2017) and Rapinel et al. (2015).

152



153 2.5 Selection of training data

154 We vectorized a Sentinel-2 image to build a vector grid consisting of 100m<sup>2</sup> polygons (10\*10m) used  
 155 as support to select training areas. We superimposed this grid on a very high spatial resolution image  
 156 from spring 2018 (Google Earth: Images CNES ©/Airbus, Maxar Technologies©). Based on the  
 157 location of the phytosociological vegetation plots, we individually and manually selected polygons  
 158 covering visually homogenous vegetation units ('pure' pixels) (Fig. 3). The training areas had to  
 159 respect a criterion of physiognomic and colorimetric homogeneity so as not to select mixed habitats  
 160 (mosaic) or pixels overlapping several typological units.



162 **Fig. 3.** Methodological process to select training data. (a) very high spatial resolution image of the  
 163 study area (the red marked pixels indicate the training data's location). (b) Zoom on a part of the study

164 area with the vector grid displayed and the polygons selected for three EUNIS habitats (red:  
165 EUNIS A2.551; pink: EUNIS F9.3131; sea green: EUNIS A2.511). The yellow dots correspond to the  
166 phytosociological vegetation plot locations. (c) A phytosociological vegetation plot and photograph of  
167 habitat EUNIS A2.551 acquired during fieldwork.

168 We used a study of the spatio-temporal dynamics of vegetation in the Loire estuary (Le Dez et al.,  
169 2017) to determine the level of stability of plant communities in the study area. For plant communities  
170 with a high degree of stability (e.g. woodlands, forests and some types of meadows), we selected  
171 training areas using data up to the year 2010. On the other hand, for highly dynamic plant  
172 communities, we have only kept the plots collected during the year of acquisition of satellite images  
173 (e.g. annual salt marshes vegetation (A2.551 – ‘*Salicornia*, *Suaeda* and *Salsola* pioneer salt marshes’)  
174 or reedbeds on regularly submerged banks (C3.27 – ‘*Halophile Scirpus*, *Bolboschoenus* and  
175 *Schoenoplectus* beds’). In addition, during the pixel selection phase by photo-interpretation, we  
176 checked that the pixels viewed and the habitat categories identified in the typology were consistent so  
177 as not to take training samples in locations where the vegetation might have changed.

178 Finally, we selected additional pixels for some habitat categories that were easily recognizable by  
179 photo-interpretation and for which we had little field data (e.g. C3.21 – ‘*Phragmites australis* beds’ or  
180 G1.1111 – ‘Western European white willow forests’).

181 We made sure to select a number of training data that was proportional to the area covered by each  
182 habitat on the study site (Colditz 2015; Raab et al., 2018).

183

## 184 2.6 Classification method

### 185 2.6.1 Choosing the classification algorithm

186 We used the Random Forest (RF) algorithm (Breiman 2001) to classify the habitats. RF is a machine  
187 learning classifier commonly used in remote sensing and many studies showed that it could produce  
188 accurate maps of vegetation and habitats types, including from Sentinel-2 (Marzialetti et al., 2019;

189 Rapinel et al., 2020; Wittke et al., 2019). RF is especially known to be fast (requiring little calculation  
190 effort) and able to process asymmetric data with many predictive variables (Millard and Richardson,  
191 2015; Sławik et al., 2019). In RF model, the original training data are randomly sampled-with-  
192 replacement generating bootstrap samples. Each decision tree in RF is trained on an 'in bag' sample of  
193 the original training data. The remaining sample ('out of bag' sample) is used to be predicted by all the  
194 decision trees that allowed to evaluate the outcome (known as OOB score). For our analyses, we set  
195 the number of trees to 2,000 and the number of randomly sampled variables as candidates for each  
196 split to six.

197 We used the overall accuracy index (OA) and the Kappa coefficient to evaluate the overall quality of  
198 classification models (Smits et al., 1999; Stehman, 1997). We produced confusion matrices  
199 representing errors by class after each modeling and we calculated the producer's, as well as the user's  
200 accuracy (respectively PA and UA), for each habitat (Congalton, 1991). These accuracy assessment  
201 metrics are commonly used in remote sensing (Belgiu and Csillik, 2018; Calleja et al., 2019; Rana and  
202 Venkata Suryanarayana, 2020). After processing each image, we applied the model produced from the  
203 training areas to the entire image to create a predictive habitat classification of the entire study area.

204

#### 205 *2.6.2 Selection of the most important variables for multi-date image classification*

206 From the 11 Sentinel-2 image acquisition dates, we identified the most important variables  
207 (acquisition dates, spectral bands and vegetation indices) to classify habitats of the Natura 2000 site. It  
208 is possible to select the best variables using automatized methods as suggested by the Recursive  
209 Feature Elimination algorithm (Radecka et al., 2019; Rapinel et al., 2019). However, we chose to  
210 develop our supervised methodology by first assessing which of the 11 image acquisitions were  
211 relevant for separating habitat classes. The general objective is to first integrate seasonal phenological  
212 variations for all the habitats in the study site. Vegetation growth stages differ among plant  
213 communities which is an important characteristic to be used for classification. Thus, the images must

214 include vegetation changes starting with the development of the earliest plant communities until those  
215 appearing the latest (mainly from early spring to autumn for this site).

216 First, we performed an RF classification for each of the 11 dates and we assessed the overall quality of  
217 the classification models using OA. We wanted to only keep the acquisition dates of the images with  
218 the highest performance, so we set an accuracy threshold at 80% (OA=0.8). Above this percentage, we  
219 considered the classification result as satisfying, as suggested by Rapinel et al. (2014) and Zlinszky et  
220 al. (2014). All images over this threshold (OA>0.8) were retained while those below (OA<0.8) were  
221 excluded because we considered their performance as too low.

222 Secondly, we tested the importance of the spectral variables (spectral bands and vegetation indices)  
223 using the measures of mean decrease Gini (MDG) obtained from the RF algorithm classification  
224 (Hubert-Moy et al., 2020; Li et al., 2019). For each selected date (OA>80%), we selected the five best  
225 performing variables (spectral bands, vegetation indices) based on MDG (Grabska et al., 2019).  
226 Finally, we stacked all these variables (five best performing bands and/or indices of the dates with  
227 OA>80%) to build the multi-date feature dataset.

228

### 229 *2.7 Software:*

230 We used the R software (version 3.6.2) (R Development Core Team, 2019) for our analyses, with the  
231 packages ‘randomForest’ (version 4.6-14) (Liaw & Wiener, 2002), ‘rgdal’ (version 1.4-8) (Bivand et  
232 al., 2015) and ‘raster’ (version 3.0-7) (Hijmans, 2015). The results were visualized in QGIS 3.4.8  
233 (QGIS Development Team, 2019).

234

## 235 **3. Results**

236

### 237 *3.1. Typology of habitats*

238 *3.1.1. Complete typology of habitats in the Natura 2000 site*

239 The complete typology brings together all the habitats identified on the study site. They are presented  
240 in Appendix A. Overall, we characterized 74 phytosociological units based on phytosociological plots'  
241 identification.

242 The crosswalk of phytosociological units with EUNIS habitat types led us to identify 62 habitats.

243 Waterbodies and reed bed habitats and grassland habitats were the most diversified with 19 and 15  
244 habitats respectively. Two grassland habitats are made of a mosaic of EUNIS habitats (E2.1xE2.5 &  
245 E3.44xA2.5) linked to vegetation plots with an intermediate floristic composition between several  
246 vegetation communities (transitional vegetation). Marine habitats are also diversified with 14 EUNIS  
247 habitats inventoried. Woodland and forest habitats, as well as shrubs and thicket habitats are more  
248 unified with respectively 7 and 6 EUNIS habitats. Finally, cultivated plots constitute the last EUNIS  
249 habitat in our typology.

250 The crosswalk with EUR28 habitat types led us to determine 15 habitats of community interest (HCI)  
251 including 3 that are considered as a priority. All the marine habitats are HCIs and represent half of the  
252 total number of HCIs with 7 EUR28 habitats, including 1 priority. The other HCIs include waterbodies  
253 and reed bed habitats (4 HCIs, of which 1 is a priority), grassland habitats (2 HCIs), woodland and  
254 forest habitats (2 HCIs, of which 1 is a priority) and shrub and thicket habitats (1 HCI).

255

256 *3.1.2. Typology retained for the classifications after selection of the training data*

257 The typology retained to classify the images is presented in Table 3. It includes all phytosociological  
258 units for which training areas could be selected. The other phytosociological units did not cover  
259 enough surface area to compose 'pure' pixels; therefore, they could not be integrated into this  
260 typology.

261 Ultimately, only 44 of the 74 phytosociological units identified could be included in the final  
262 typology. This result corresponds to 39 EUNIS habitats out of the 62 identified and 9 EUR28 habitats  
263 out of the 15 identified in the Natura 2000 site.

264 **Table 3** Habitat typology used for image classification (habitats for which pixels could be selected).  
265 ‘Nb pixels’ corresponds to the number of pixels selected as training area for the image classification.  
266 The EUR28 habitats marked in bold correspond to priority habitats of community interest in HabDir.  
267 Fields marked with an asterisk correspond to non-vegetated or artificialized areas. They were assigned  
268 to habitat typologies based on the biotope using the criteria of the French EUNIS habitat determination  
269 guide (Gayet et al., 2018) and the ‘Cahiers d’habitats’ (Bensettiti et al., 2001–2005).

270

Physiognomic units	Phytosociological units	Nb pixels	EUNIS habitats	EUR 28 habitats
Marine habitats	*Sandy shore comprising clean sands (coarse, medium or fine-grained) and muddy sands	47	A2.2 - Littoral sand and muddy sand	1130 - Estuaries
	*Muddy shores of fine particulate sediment, mostly in the silt and clay fraction	195	A2.3 - Littoral mud	
	<i>Thero</i> – <i>Salicornietalia dolichostachyae</i> Tüxen ex Boulet & Géhu 2004	92	A2.551 - <i>Salicornia</i> , <i>Suaeda</i> and <i>Salsola</i> pioneer saltmarshes	1310 - <i>Salicornia</i> and other annuals colonising mud and sand
	<i>Parapholido strigosae</i> – <i>Hordeetum marini</i> (Géhu et al. 1975) Géhu & de Foucault 1978	66	A2.553 - Atlantic <i>Sagina maritima</i> communities	
	<i>Puccinellietum maritimae</i> Christiansen 1927	92	A2.542 - Atlantic lower shore communities	
	<i>Glauco maritimi</i> – <i>Juncion maritimi</i> Géhu & Géhu-Franck ex Géhu in Bardat et al. 2004	21	A2.531 - Atlantic upper shore communities	1330 - Atlantic salt meadows ( <i>Glauco-Puccinellietalia maritimae</i> )
	<i>Agropyron pungentis</i> Géhu 1968	152	A2.511 - Atlantic saltmarsh and drift rough grass communities	
	<i>Alopecurion utriculati</i> Zeidler 1954	777	A2.523 - Mediterranean short <i>Juncus</i> , <i>Carex</i> , <i>Hordeum</i> and <i>Trifolium</i> saltmeadows	1410 - Mediterranean salt meadows ( <i>Juncetalia maritimi</i> )
	<i>Ranunculo ophioglossifolii</i> – <i>Oenanthion fistulosae</i> de Foucault in de Foucault & Catteau 2012	97		
	Waterbodies and reedbeds habitats	*Open fresh or brackish waterbodies	96	C - Inland surface waters
*Loire river subject to the tid		125	X01 - Estuaries	
<i>Glycerietum fluitantis</i> Nowinski 1930		119	C3.1 - Species-rich helophyte beds	
<i>Phragmitetum communis</i> Saviè 1926 and <i>Astero tripolii</i> – <i>Phragmitetum communis</i> Jeschke ex Křišch 1974		390	C3.21 - <i>Phragmites australis</i> beds	
<i>Glycerietum aquaticae</i> Nowinski 1930		307	C3.251 - Sweetgrass beds	
<i>Scirpion maritimi</i> Dahl & Hadač 1941		185	C3.27 - Halophile <i>Scirpus</i> , <i>Bolboschoenus</i> and <i>Schoenoplectus</i> beds	
*Mud bottoms of waterbodies		15	C3.6 - Unvegetated or sparsely vegetated shores with soft or mobile sediments	
<i>Galio palustris</i> – <i>Caricetum ripariae</i> Bal-Tul., Mucina, Ellmauer & B.Walln. in G.Grabherr & Mucina 1993	48	D5.21 - Beds of large <i>Carex</i> spp.		
Grasslands habitats	<i>Thero</i> – <i>Airion</i> Tüxen ex Oberdorfer 1957	113	E1.91 - Dwarf annual siliceous grassland	
	Mesophile hay meadows ( <i>Cynosurion cristati</i> Tüxen 1947; <i>Lolium perennis</i> – <i>Plantaginior majoris</i> G. Sissingh 1969)	311	E2.1 - Permanent mesotrophic pastures and aftermath-grazed meadows	
	<i>Cynosurion cristati</i> Tüxen 1947 X Grp des <i>Sisymbrietea officinalis</i>	81	E2.1 - Permanent mesotrophic pastures and aftermath-grazed meadows X E5.1 - Anthropogenic herb stands	
	*Land occupied by heavily fertilised or reseeded permanent grasslands	45	E2.6 - Agriculturally-improved, re-seeded and heavily fertilised grassland, including sports fields and grass lawns	
	<i>Oenanthion fistulosae</i> de Foucault 2008	141		
	<i>Bromion racemosi</i> Tüxen ex de Foucault 2008	246	E3.41 - Atlantic and sub-Atlantic humid meadows	
	<i>Ranunculo repentis</i> – <i>Cynosurion cristati</i> Passarge 1969	46		
	Wet and humid meadows dominated by <i>Juncus effusus</i>	23	E3.417 - Soft rush meadows	
	Hygrophilic pastures regularly flooded by the oligohaline water of Loire River and dominated by <i>Agrostis stolonifera</i>	125		
	Meso-hygrophilic pastures regularly flooded by the oligohaline water of Loire River and dominated by <i>Agrostis stolonifera</i>	121	E3.44 - Flood swards and related communities	
	Pastures regularly flooded by the oligohaline water of Loire River and dominated by <i>Juncus inflexus</i>	101	E3.441 - Tall rush pastures	
	Hygrophilic pastures regularly flooded by the brackish water of Loire River and dominated by <i>Agrostis stolonifera</i>	113	E3.44 - Flood swards and related communities X A2.5 - Coastal saltmarshes and saline reedbeds	
	Meso-hygrophilic pastures regularly flooded by the brackish water of Loire River and dominated by <i>Agrostis stolonifera</i>	41		
<i>Juncion acutiflori</i> Braun-Blanquet in Braun-Blanquet & Tüxen 1952	20	E3.512 - Acidocline purple moorgrass meadows	6410 - <i>Molinia</i> meadows on calcareous, peaty or clayey-siltladen soils ( <i>Molinion caeruleae</i> )	
<i>Sisymbrietea officinalis</i> Korneck 1974 and <i>Convolvulo arvensis</i> – <i>Agropyron repentis</i> Görs 1966	33	E5.1 - Anthropogenic herb stands		
<i>Achilleo ptarmicae</i> – <i>Cirsion palustris</i> Julve & Gillet ex de Foucault 2011	19	E5.412 - Western nemoral river bank tall-herb communities dominated by <i>Filipendula</i>	6430 - Hydrophilous tall herb fringe communities of plains and of the montane to alpine levels	
Scrubs and thickets habitats	<i>Solano dulcamarae</i> – <i>Tamaricetum gallicae</i> de Foucault 2008	34	F9.3131 - West Mediterranean tamarisk thickets	92D0 - Southern riparian galleries and thickets ( <i>Nerio - Tamaricetea</i> and <i>Securinegion tinctoriae</i> )
	Species-poor <i>Prunus spinosa</i> or <i>Rubus</i> spp. thickets	91	F3.111 - Blackthorn-bramble scrub	
	<i>Salicetum triandro</i> – <i>viminalis</i> (Tüxen 1931) Lohmeyer 1952 ex Moor 1958	174	F9.121 - lmond willow-osier scrub	
	Low woods and scrubs dominated by <i>Salix atrocinerea</i>	68	F9.2 - <i>Salix</i> carr and fen scrub	
Woodland and forest habitats	<i>Salicion albae</i> Soó 1930	134	G1.1111 - Western European white willow forests	91E0 - Alluvial forests with <i>Alnus glutinosa</i> and <i>Fraxinus excelsior</i> ( <i>Alno-Padion</i> , <i>Alnion incanae</i> , <i>Salicion albae</i> )
	<i>Alnion glutinoso - incanae</i> Oberdorfer 1953	23	G1.211 - <i>Fraxinus</i> - <i>Alnus</i> woods of rivulets and springs	
	<i>Ulmoe laevis</i> – <i>Fraxinetum angustifoliae</i> (Breton) Rameau & Schmitt ex J.-M. Royer, Felzines, Misset & Thévenin 2006	89	G1.22 - Mixed <i>Quercus</i> - <i>Ulmus</i> - <i>Fraxinus</i> woodland of great rivers	91F0 - Riparian mixed forests of <i>Quercus robur</i> , <i>Ulmus laevis</i> and <i>Ulmus minor</i> , <i>Fraxinus excelsior</i> or <i>Fraxinus angustifolia</i> , along the great rivers ( <i>Ulmion minoris</i> )
	Meso-hygrophilic forests dominated by <i>Quercus robur</i> and <i>Fraxino excelsioris</i> – <i>Quercion roboris</i> Rameau 1996	269	G1.A1 - <i>Quercus</i> - <i>Fraxinus</i> - <i>Carpinus</i> betulus woodland on eutrophic and mesotrophic soils	
	Plantations of species, hybrids or cultivars of the deciduous genus <i>Populus</i>	136	G1.C1 - <i>Populus</i> plantations	
Plantations of Palaearctic conifers of genus <i>Pinus</i>	113	G3.F12 - Native pine plantations		
Cultured agricultural habitats	Cereal crops	65	II.1 - Intensive unmixed crops	

272 The number of training pixels per typological unit varies from 15 (mud bottoms of waterbodies) to 777

273 (*Alopecurion utriculati* Zeidler 1954). Overall, 5,564 training pixels were selected for all the data.

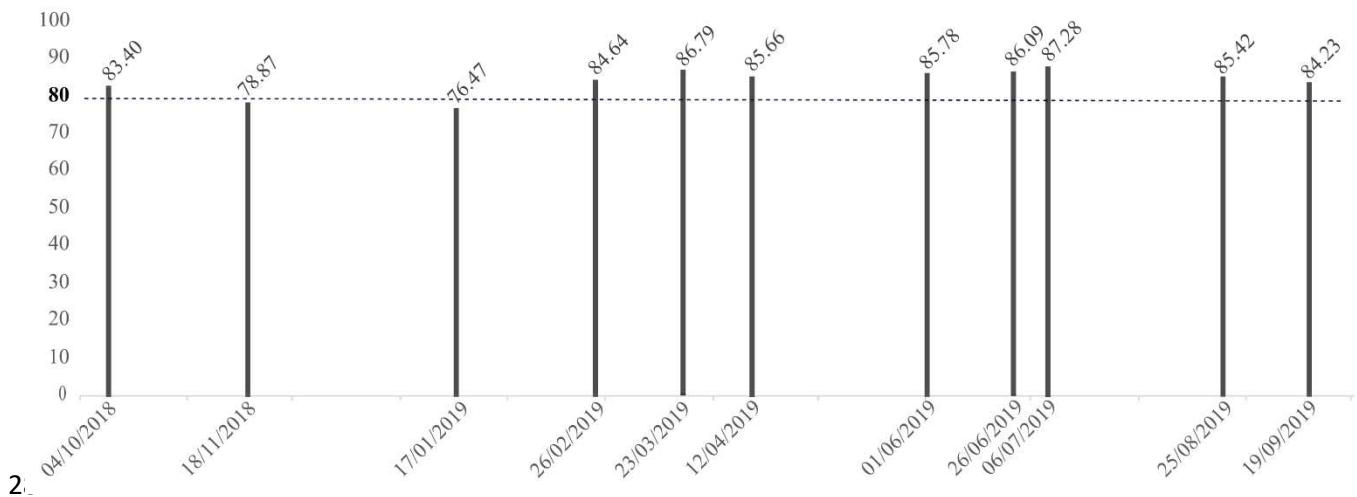
274

275 3.2 Analyses of single date images

276 Overall accuracy indices of the single classification of the Sentinel-2 images for the 11 selected dates

277 are presented in Fig. 4. Images acquired during spring and summer gave the best results (OA>85%).

278 The highest accuracy was obtained with the image of July 6, 2019 (OA=87.28%). The classifications  
 279 of the images taken at the end of winter and in autumn present slightly lower results (80 % < OA  
 280 <85%). The less accurate classifications are from the late autumn and winter images (OA <80%).



282 **Fig. 4.** Overall accuracy indices of the single date classifications of Sentinel-2 images for the 11 dates.  
 283 The dotted line shows the 80% threshold used to select the best-performing dates.

284

### 285 *3.3 Selected variables to build the multi-date feature dataset*

286 Based on the results of the single-image classifications, we selected images of nine dates that had an  
 287 overall accuracy higher than 80% (Fig. 4). For each of these dates, we kept the five variables (spectral  
 288 bands and vegetation indices) that contribute most to the classification result according to MDG  
 289 (Table 4, Appendix B). In total, six different spectral bands and four vegetation indices were included  
 290 in the multi-date feature dataset. The spectral bands B11 and B12 (SWIR) were systematically present  
 291 for the nine dates, while the bands B5 (red-edge), B3 (green) and B2 (blue) are only present for six,  
 292 four and two dates respectively and the band B8A (near-infrared narrow) only for one date. Regarding  
 293 vegetation indices, GNDVI and MTCI are present for seven and four dates respectively, whereas  
 294 NDWI and EVI both appear for two dates. In total, 45 variables were retained and stacked to build the  
 295 multi-date feature dataset.



296

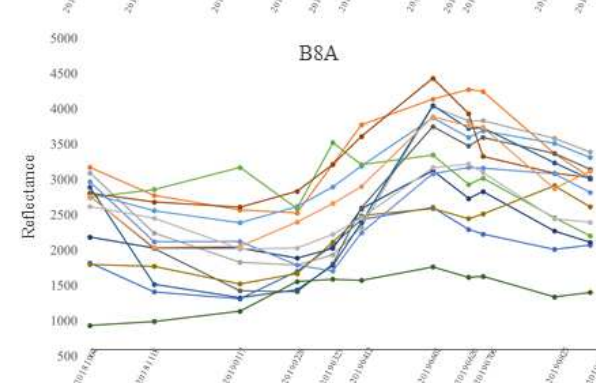
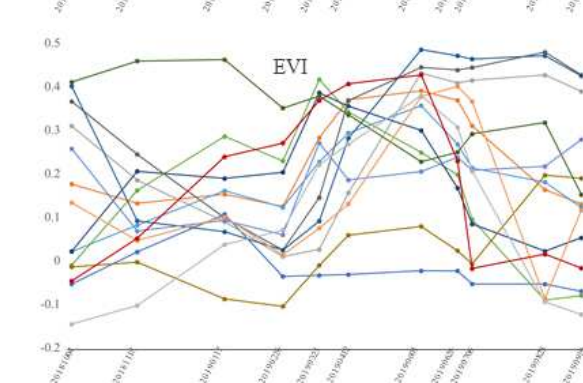
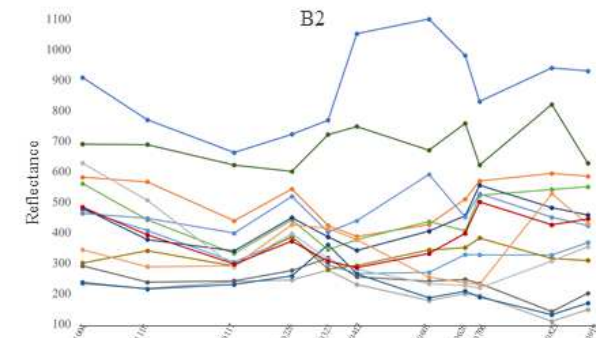
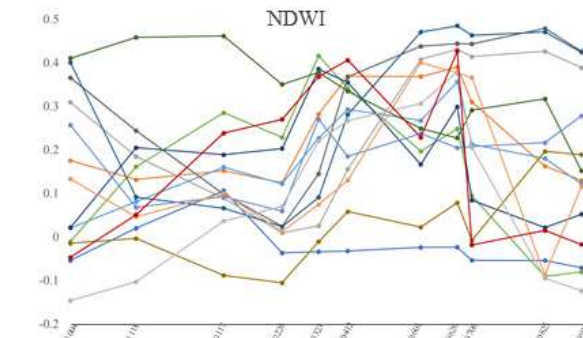
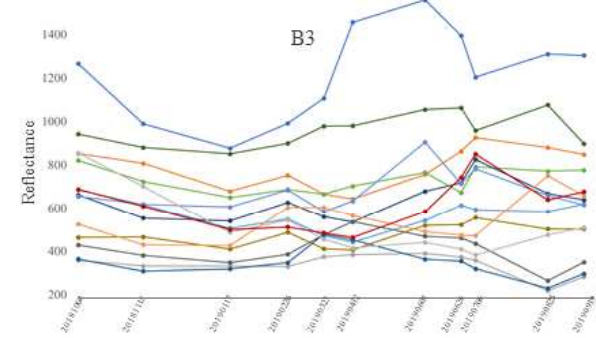
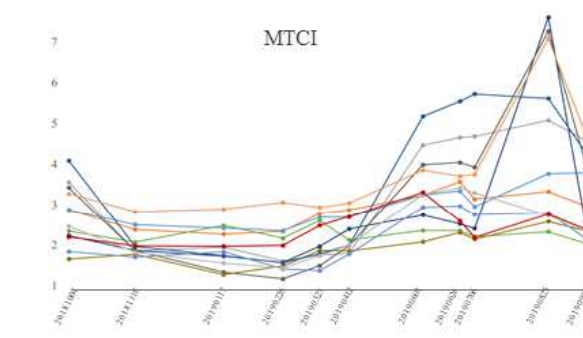
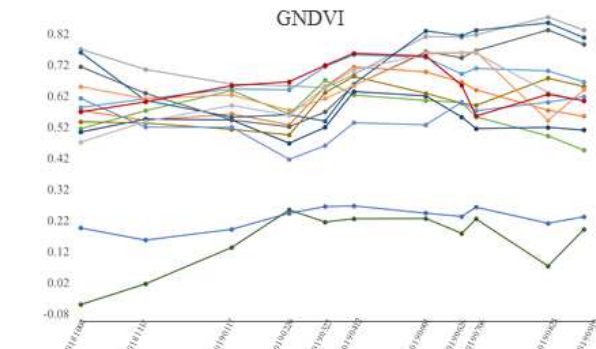
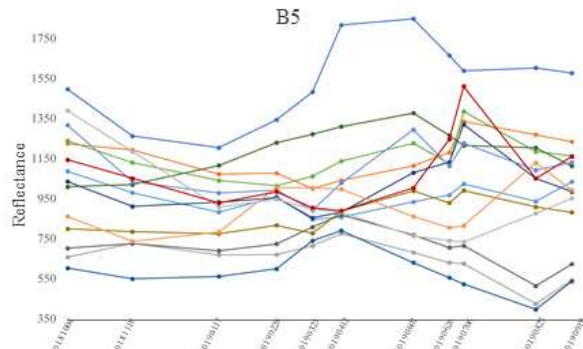
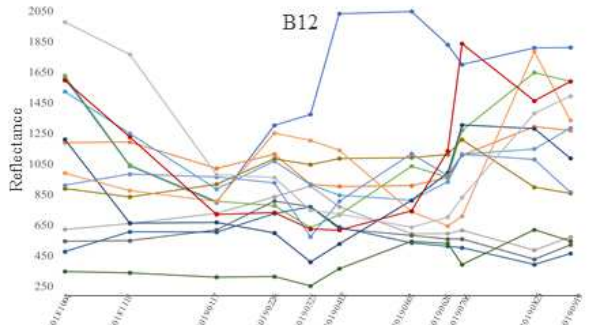
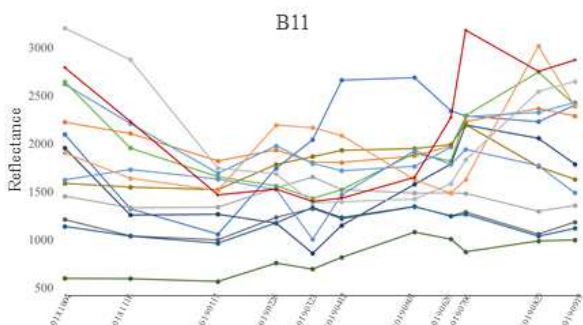
297 **Table 4** List of the five variables that contributed most to the single-date image classification (spectral  
 298 bands and vegetation indices) according to MDG for each date. The number indicates the variable's  
 299 order of importance according to MDG for each date (the most contributing variables are indicated by  
 300 the lowest numbers - for more details, see Appendix B).

	20181004	20190226	20190323	20190412	20190601	20190626	20190706	20190825	20190919
<b>B11</b>	1	2	2	1	1	1	1	1	1
<b>B12</b>	2	1	1	2	2	3	2	2	2
<b>B5</b>		3	3		4	2	3	3	
<b>GNDVI</b>	5	5	4	4			5	5	5
<b>MTCI</b>		4		3	3	5			
<b>B3</b>	4		5	5					4
<b>NDWI</b>	3								3
<b>B2</b>						4		4	
<b>EVI</b>							4		
<b>B8A</b>					5				

302

303 Fig. 5 shows the seasonal variations of the main variables (Table 4) for habitat discrimination. The  
 304 GNDVI index and B2 (blue) and B3 (green) spectral bands allow good discrimination of habitats A2.2  
 305 'Littoral sand and muddy sand' and A2.3 - 'Littoral mud' all year long. On the contrary, the  
 306 phenological profiles of the other habitats cannot be easily distinguished over the period studied.  
 307 Overall, temporal profiles have more similar values during wintertime. The main reflectance and  
 308 intensity variations of the indices are observed in spring and summer. More precisely, it is the  
 309 temporal shifts in spectral responses that allow the distinction of habitats. For example,  
 310 habitats A2.523 - 'Mediterranean short *Juncus*, *Carex*, *Hordeum* and *Trifolium* salt meadows' and  
 311 A2.511 - 'Atlantic salt marsh and drift rough grass communities' show similar profiles on some bands  
 312 (B11 and B12) and some indices (NDWI and EVI). However, they peak at different dates (June 26,  
 313 2019, for A2.523 and August 25, 2019, for A2.51) because of mowing taking place at different times.

314



- A2.2
- A2.511
- G1.211
- E3.512
- A2.553
- A2.542
- G1.1111
- F9.3131
- G1.22
- A2.3
- A2.551
- E5.412
- A2.531
- A2.523

316 **Fig. 5.** Seasonal variations of the most important variables (Table 4) for habitat discrimination in the  
317 study site. Only the spectral profiles of EUNIS habitats characterizing habitats of community interest  
318 are represented. The curves are plotted from the average for all training pixels for each habitat.

319

### 320 *3.4 Multi-date classification*

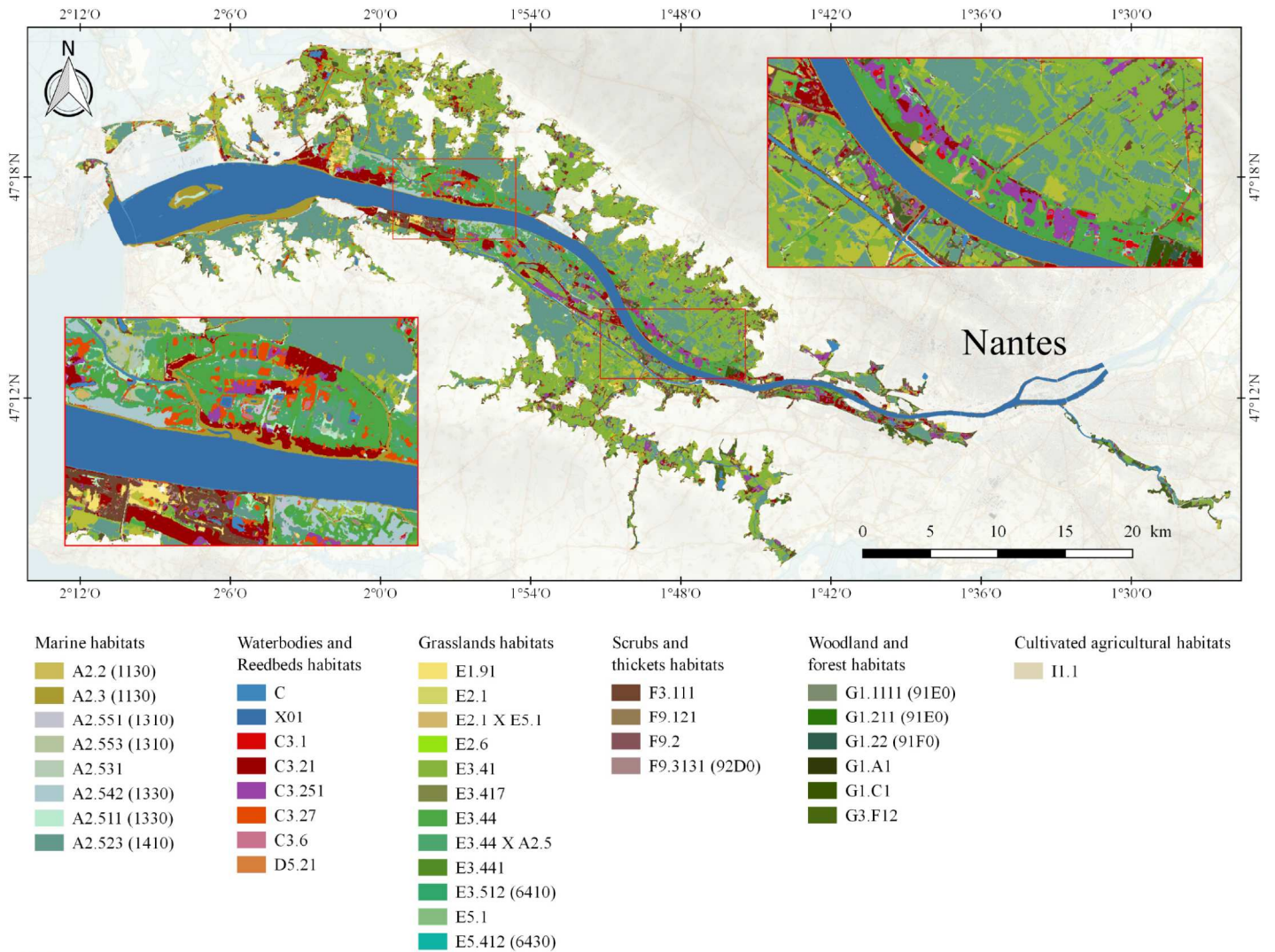
321 The confusion matrix showing the results of the RF classification of the multi-date feature dataset is  
322 presented in Table 5. The predictive habitat map obtained after running the RF model on all pixels of  
323 the investigation area is shown in Fig. 6. The results are presented at the EUNIS habitats level after  
324 merging the phytosociological units corresponding to the same habitat category, following the  
325 crosswalks in Table 3.

326 The overall evaluation of the model shows highly satisfying results with an overall accuracy of 98.7%  
327 and a kappa coefficient of 0.99. The producer's accuracy is 100% for 19 habitats out of the 39 in the  
328 EUNIS habitat typology. The other habitats present moderate errors leading us to obtain a producer's  
329 accuracy higher than 90%, except for EUNIS habitats D5.21, E3.512 and F9.2 with a PA of 87.5%,  
330 75% and 89.7% respectively. These results indicate that these habitats tend to be underrepresented in  
331 the predicted habitat map (Fig. 6).

332 In the same way, the user's accuracy is highly satisfying with 21 habitats with 100% UA whereas  
333 other habitats still present an accuracy higher than 90% UA. These slight confusions lead to an  
334 overrepresentation of habitats in the predicted map (Fig. 6).

335 Figure 7 shows that habitats with a high number of training areas obtain a very high estimated  
336 producer's accuracy (PA). This is the case for habitat A2.523 – 'Mediterranean short *Juncus*, *Carex*,  
337 *Hordeum* and *Trifolium* salt meadows' with 874 training pixels and a 99.4% PA or habitat E3.41 –  
338 'Atlantic and sub-Atlantic humid meadows' with 706 pixels and a 99.6% PA. Conversely, habitats  
339 with a lower PA have fewer training areas, such as habitat E3.512 – 'Acidocline purple moor grass  
340 meadows' with 20 training and a 75% PA or habitat D5.21 – 'Beds of large *Carex spp.*' with 48





351 **Fig. 6.** Predicted map of the 39 EUNIS habitats in the Natura 2000 site 'Estuaire de la Loire'. The  
 352 codes correspond to EUNIS habitat identifiers and crosswalks with EUR28 habitats are indicated in  
 353 brackets. For details of the full habitat headings, see Table 3.



367 Reed beds are frequently near the river, in areas that are regularly flooded by the tides. Among reed  
368 bed habitats, habitat C3.21 – ‘*Phragmites australis* beds’ is dominating (977 ha) and regularly  
369 distributed in tidal marshes throughout the site. Habitat C3.27 – ‘Halophile *Scirpus*, *Bolboschoenus*  
370 and *Schoenoplectus beds*’ colonizes the downstream areas (510 ha) while habitat C3.251 – ‘sweetgrass  
371 beds’, intolerant to salt, succeeds it when going upstream (747 ha).

372 Grassland habitats also cover large areas (10,400 ha) and are distributed mostly upstream and on the  
373 margins of the site, i.e., in areas that are less subjected to saltwater intrusions. Thickets and forests are  
374 rarer and cover smaller areas with 1,471 ha and 1,027 ha respectively. These habitats usually do not  
375 tolerate salt, hence their location on the most upstream areas of the Natura 2000 site.

376

## 377 **4. Discussion**

### 378 *4.1 The Importance of field data*

379 Using a large amount of field data is paramount to ensure high accuracy in the classification of  
380 remotely sensed images (Calleja et al., 2019; Yeo et al., 2020). Several authors insist on using a wide  
381 range of vegetation plots to establish a complete typology of habitats (Chytrý et al., 2016; Rodwell et  
382 al., 2018). In this study, we relied on a large phytosociological plots dataset which led us to develop a  
383 complete and accurate typology of the study site. Beyond confirming the diversity of the habitats  
384 present at the Natura 2000 site, we used these field plots to calibrate the RF algorithm for image  
385 classification. Indeed, these field data are essential to locate and precisely sample the training areas to  
386 optimize image classification (Millard and Richardson, 2015). We conducted this step pixel by pixel  
387 by selecting only visually homogenous areas. The number of training pixels per habitat varies and  
388 depends on the number of field plots and habitat homogeneity. In general, the most widespread  
389 habitats are characterized by more training pixels to assess their variability at the scale of the study site  
390 (Colditz, 2015; Raab et al., 2018).

391 Most of the plots we used are derived from bibliographical data and were collected through an  
392 important work of synthesis of the studies previously conducted on site (impact studies, vegetation  
393 maps...). Accessing preexisting data is essential to develop a robust typology and to calibrate  
394 classification algorithms. Thus, it is essential to centralize and share field plots, and especially to  
395 implement common databases (Gautreau and Noucher, 2013), such as the European Vegetation  
396 Archive which gathers thousands of vegetation plots across Europe (Chytrý et al., 2016).

397 However, despite compiling numerous phytosociological vegetation plots, we could only use a part to  
398 calibrate the classifier. Indeed, several habitats could not be selected inside Sentinel-2 pixels because  
399 the images' spatial resolution was insufficient to integrate habitats of small surface areas. This led us  
400 to only use a partial typology of habitats compared to the initial typology established from all the  
401 plots. For example, aquatic vegetation (i.e. *Lemnetalia minoris* or *Hydrocharition morsus-ranae*),  
402 which are uncommon and occupy small areas, could not be represented in the final map. To overcome  
403 this problem, other remote sensing images could be tested, such as high spatial resolution data (Gavish  
404 et al., 2018; Strasser and Lang, 2015). For example, Espel et al. (2020) used very fine-scale resolution  
405 Pléiades satellite imagery (50cm) to map aquatic vegetation in France.

406

## 407 *4.2 Single-date image classification*

### 408 *4.2.1 Determining the most favorable image acquisition dates*

409 Analysis of mono-temporal Sentinel-2 imagery showed that it is possible to obtain a satisfying level of  
410 classification when using only one acquisition date. This is particularly the case for the image of July  
411 6, 2019, for which we obtained an overall accuracy of 87.74%. Analysis of the overall accuracy (OA)  
412 obtained for each date led us to determine the most favorable times of the year to get good  
413 discrimination of the habitats. Even if the overall accuracy differences are small between dates  
414 ( $\Delta=11\%$ ), images acquired in spring and summer noticeably give the best results. This time of year is  
415 especially marked by rapid phenological variations in vegetation (appearance of leaves, flowering).  
416 Those variations are linked to the increase in day length and temperatures (Meier, 1997), as well as to



417 the receding water from winter flooding due in particular to evapotranspiration and the hydraulic  
418 management of marshes (Reed, 1993). During this period of maximum vegetation growth, the plants'  
419 expression of pigment content is most pronounced, favoring habitat discrimination (Addabbo et al.,  
420 2016). These observations are consistent with the results of recent studies for vegetation mapping from  
421 series of remote sensing images on floodplain meadows (Rapinel et al., 2019) or salt marsh vegetation  
422 (Vrieling et al., 2018).

423

#### 424 *4.2.2 Determination of the most favorable spectral bands and indices*

425 In this study, most habitats are characterized by vegetation whose spectral response is determined by  
426 plants' biochemical and biophysical properties (Peñuelas and Filella, 1998). Over time, variations of  
427 reflectance values and indices reflect plants' phytosociological changes (pigment composition, plants'  
428 internal tissue structure) allow us to differentiate habitats according to their floristic composition (Cole  
429 et al., 2014). MDG led us to highlight the most contributing variables for habitat mapping of the study  
430 site.

431 B11 and B12 spectral bands appear as the best performing bands for all dates. These shortwave-  
432 infrared (SWIR) spectral bands are especially characterized by their sensitivity to water on the earth's  
433 surface (Middleton et al., 2012; Psomas et al., 2011) and to biochemical contents such as lignin and  
434 cellulose in plant cover (Fourty et al., 1996). SWIR bands can be particularly useful for mapping  
435 wetlands where plant communities are marked by flooding gradients (Rapinel et al., 2019). The B5  
436 band is located at the beginning of the red-edge curve (704.1 nm), and it also represents an important  
437 variable to discriminate the study site's habitats. Several studies have shown that different meadow  
438 vegetation types can be effectively discriminated using red-edge wavelengths (Pinar and Curran, 1996;  
439 Shoko and Mutanga, 2017) due to its sensitivity to variations in chlorophyll concentration (Curran et  
440 al., 1990; Sims and Gamon, 2002). SWIR and red-edge spectrum regions are interesting for mapping  
441 wetland vegetation as demonstrated by several previous studies (Dronova, 2015; Dronova et al., 2012;  
442 Franke et al., 2012). GNDVI (based on NIR (B8) and green (B3) bands) is the most important

443 vegetation index in this study. It is a variation of NDVI but is found to be more sensitive to plants'  
444 changes in chlorophyll content (Gitelson et al., 1996). For instance, GNDVI provided a good  
445 distinction between vegetated and non-vegetated habitats characterized by high and low values of the  
446 index respectively.

447 The other retained variables contribute to a lesser extent: MTCI (analysis of the red-edge curve with  
448 B4, B6 and B5), B3 (leaf green intensity), NDWI (leaf water content with B8 and B11), B2 (leaf blue-  
449 green intensity), EVI (leaf pigment content with B2, B4 and B8) and B8A (leaf structure). Overall, we  
450 notice that most available spectral bands contributed to the classifications' success. Thus, our results  
451 confirm the relevance of the different spectral regions covered by Sentinel-2 satellites for vegetation  
452 mapping (Fauvel et al., 2020; Grabska et al., 2019).

453

#### 454 *4.3 Multi-date classification*

455 While individual image analyses achieved satisfactory levels of accuracy, the multi-date classification  
456 considerably improved habitats modeling accuracy with a 98.8% OA and a 0.99 Kappa. PA and UA  
457 are at 100% for numerous habitats showing a perfect match between reference and modeled data. For  
458 the other habitats, PA and UA are still very close to 100%, thus indicating respectively low over-or  
459 under-representation in the final map.

460 Numerous authors demonstrated the accuracy improvement brought by multi-date classifications  
461 compared to single-date classifications (Belgiu and Csillik, 2018; Feret et al., 2015; Raab et al., 2018).  
462 Rapinel et al. (2019) especially highlighted the benefits of a Sentinel-2 multi-date classification to  
463 differentiate marsh plant communities according to the flood duration and management measures  
464 (mowing, grazing). In the same way, the evolution of these parameters during our study period  
465 contributed to the success of the habitat classification of the Loire estuary.

466

#### 467 *4.4 Habitat mapping by remote sensing: contributions for nature conservation*

468 Our work led us to elaborate a map of EUNIS habitats from which it is possible to highlight  
469 conservation issues, specifically those linked to the European Habitat Directive (HabDir). Even if we  
470 could not map all the habitats of community interests due to their small surface areas, we mapped 9  
471 HCIs from typological crosswalks, representing a total of 7,080 ha, i.e. 26% of the total surface area of  
472 the site. Among all the habitats, HCI 1410 ‘Mediterranean salt meadows (*Juncetalia maritimi*)’ covers  
473 the largest area (5,047 ha, 19% of the total surface area). Thus, the use of Sentinel-2 images  
474 contributes to locate and quantify the occupied areas for these habitats of the Natura 2000 site:  
475 distribution and range being two parameters retained to assess the conservation status according to  
476 Art.17 of HabDir (European Commission, 1992; DG Environment, 2017). These data are essential for  
477 managers to define conservation measures to maintain the HICs. Thus, the habitat map produced  
478 during this study meets the needs of the manager of the Natura 2000 site ‘Estuaire de la Loire’ and  
479 will be essential to preserve this natural site.

480 Overall, our results show that it is possible to obtain habitat maps quickly and at a low cost compared  
481 with conventional fieldwork (Ichter et al., 2014). This method can be transposed to other natural sites,  
482 in or outside the Natura 2000 network, which has the advantage of promoting a common and  
483 standardized methodological approach to habitat mapping. In addition, the approach we offer  
484 completely meets the European requirements as part of the reporting required by Europe for each  
485 member state. Indeed, this method could be adopted to evaluate the distribution and areas of habitats at  
486 the European scale, two parameters defined by the HabDir to assess the conservation status of HICs  
487 (Bijlsma et al., 2019; Gigante et al., 2016). Furthermore, this method can be used for long-term  
488 monitoring of habitats based on regularly produced maps (every three or four years depending on the  
489 habitat type). The approach we developed meets the need for a monitoring method which could be  
490 proposed as part of Art. 11 of HabDir on surveillance of the conservation status of HICs (Delbosc et  
491 al. 2021).

492

## 493 **5. Conclusion**

494 Our results demonstrated that Sentinel-2 images allow for accurately mapping habitats and that their  
495 spectral resolution is particularly adapted to the study of wetlands. The high revisit frequency of  
496 Sentinel-2 satellites ensures the regular acquisition of images throughout the year, allowing multi-date  
497 image classification. This method led us to obtain a highly accurate habitat map, which considerably  
498 improves the accuracy level compared to single-date image classification. However, the spatial  
499 resolution of Sentinel-2 remains insufficient to include numerous habitats that are only locally and  
500 occasionally present. In this study, only 23 out of the 62 EUNIS habitats could be mapped.  
501 Consequently, using these images can only be considered to map habitats with a surface area higher  
502 than 100 m<sup>2</sup>. Our results generally show that Sentinel-2 data are adapted to create habitat maps at a  
503 1:25 000 scale. For finer-scale mapping, Sentinel-2 could be complemented by high spatial resolution  
504 remote sensing data such as those provided by other satellites, UAV or airborne acquisitions.

505

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### 803 **Appendices**

804 **Appendix A.** Typology of habitats in the Loire Estuary. The EUR28 habitats, marked in bold,  
805 represent the priority habitats of community interest. Fields marked with an asterisk correspond to  
806 non-vegetated or artificialized areas. They were assigned to habitat typologies based on the biotope  
807 using the criteria of the French EUNIS habitat determination guide (Gayet et al., 2018) and the  
808 ‘Cahiers d’habitats’ (Bensettiti et al., 2001–2005).

Physiognomic units	Phytosociological units	EUNIS habitats	EUR 28 habitats
Marine habitats	*Sandy shore comprising clean sands (coarse, medium or fine-grained) and muddy sands	A2.2 - Littoral sand and muddy sand	1130 - Estuaries
	*Muddy shores of fine particulate sediment, mostly in the silt and clay fraction	A2.3 - Littoral mud	
	<i>Thero</i> – <i>Salicornietalia dolichostachyae</i> Tüxen ex Boulet & Géhu 2004	A2.551 - <i>Salicornia</i> , <i>Suaeda</i> and <i>Salsola</i> pioneer saltmarshes	1310 - <i>Salicornia</i> and other annuals colonising mud and sand
	<i>Parapholido strigosae</i> – <i>Hordeetum marini</i> (Géhu et al. 1975) Géhu & de Foucault 1978	A2.553 - Atlantic <i>Sagina maritima</i> communities	
	<i>Puccinellietum maritimae</i> Christiansen 1927	A2.542 - Atlantic lower shore communities	
	<i>Halimionion portulacoidis</i> Géhu 1976	A2.527 - Atlantic salt scrubs	
	<i>Armerion maritimae</i> Braun-Blanquet & De Leeuw 1936	A2.531 - Atlantic upper shore communities	1330 - Atlantic salt meadows ( <i>Glauco-Puccinellietalia maritimae</i> )
	<i>Glauco maritimi</i> – <i>Juncion maritimi</i> Géhu & Géhu-Franck ex Géhu in Bardat et al. 2004	A2.511 - Atlantic saltmarsh and drift rough grass communities	
	<i>Agropyron pungentis</i> Géhu 1968	A2.512 - Atlantic saltmarsh driftline annual communities	
	<i>Atriplicion littoralis</i> Nordhagen 1940	A2.523 - Mediterranean short <i>Juncus</i> , <i>Carex</i> , <i>Hordeum</i> and <i>Trifolium</i> saltmeadows	1410 - Mediterranean salt meadows ( <i>Juncetalia maritimi</i> )
	<i>Alopecurion utriculari</i> Zeidler 1954	B1.12 - Middle European sand beach annual communities	2110 - Embryonic shifting dunes
	<i>Ranunculo ophioglossifolii</i> – <i>Oenanthion fistulosae</i> de Foucault in de Foucault & Cateau 2012	B1.31 - Embryonic shifting dunes	2120 - Shifting dunes along the shoreline with <i>Ammophila arenaria</i> (white dunes)
<i>Atriplici laciniatae</i> – <i>Salsolion kali</i> Géhu 1975	B1.32 - White dunes	<b>2130 - Fixed coastal dunes with herbaceous vegetation (grey dunes)</b>	
<i>Honckenyo peploides</i> – <i>Elymion arenarii</i> Tüxen 1966			
<i>Amphiphilion arenariae</i> (Tüxen in Braun-Blanquet & Tüxen 1952) Géhu 1988			
<i>Euphorbio portlandicae-Helichrysion stoechadis</i> Géhu et Tx. ex Sissingh 1974	B1.42 - Biscay fixed grey dunes		
Waterbodies and reedbeds habitats	*Open fresh or brackish waterbodies	C - Inland surface waters	
	*Loire river subject to the tid	X01 - Estuaries	
	<i>Limnetalia minoris</i> Tüxen ex O. Bolòs & Masclans 1955	C1.22 - Free-floating vegetation of mesotrophic waterbodies	3150 - Natural eutrophic lakes with <i>Magnopotamion</i> or <i>Hydrocharition</i> -type vegetation
	<i>Hydrocharition morsus-ranae</i> Rübel ex Klika in Klika & Hadač 1944	C1.23 - Rooted submerged vegetation of mesotrophic waterbodies	
	<i>Potamion pectinati</i> (W. Koch 1926) Libbert 1931	C1.33 - Rooted submerged vegetation of eutrophic waterbodies	
	<i>Ranunculion aquatilis</i> H. Passarge ex Theurillat in Theurillat, Mucina & Hájek 2015	C1.24 - Rooted floating vegetation of mesotrophic waterbodies	
	<i>Nymphaeion albae</i> Oberd. 1957	C3.21 - <i>Phragmites australis</i> beds	
	<i>Phragmitetum communis</i> Savič 1926 and <i>Astero tripolii</i> – <i>Phragmitetum communis</i> Jeschke ex Kirsch 1974	C3.22 - <i>Scirpus lacustris</i> beds	
	<i>Scirpetum lacustris</i> Chouard 1924	C3.23 - Typha beds	
	<i>Typhetum latifoliae</i> Nowinski 1930 and <i>Typhetum angustifoliae</i> P.Allorge ex Pignatti 1953	C3.24 - Medium-tall non-graminoid waterside communities	
	<i>Eleocharito palustris</i> – <i>Sagittarion sagittifoliae</i> Passarge 1964 and <i>Iridetum pseudacori</i> Egger ex Brzeg & M.Wojterska 2001 and <i>Equisetetum eleocharitis</i> Nowinski 1930	C3.251 - Sweetgrass beds	
	<i>Glycerietum aquaticae</i> Nowinski 1930	C3.1 - Species-rich helophyte beds	
	<i>Glycerietum fluitantis</i> Nowinski 1930	C3.26 - <i>Phalaris arundinacea</i> beds	
	<i>Phalaridion arundinaceae</i> Kopecký 1961	C3.27 - Halophile <i>Scirpus</i> , <i>Bolboschoenus</i> and <i>Schoenoplectus</i> beds	
	<i>Scirpion maritimi</i> Dahl & Hadač 1941	C3.423 - Mediterranean amphibious crypsis swards	<b>3170 - Mediterranean temporary ponds</b>
	<i>Heleocharion schoenoidis</i> Braun-Blanquet ex Rivas Goday, Borja, Monasterio, Galiano & Rivas-Martinez 1956	C3.5 - Periodically inundated shores with pioneer and ephemeral vegetation	
	<i>Bidenton tripartitae</i> (W. Koch 1926) Nordhagen 1940 and <i>Chenopodion rubri</i> (Tüxen in Poli & J. Tüxen 1960) Hilbig & Jage 1972	C3.51 - Euro-Siberian dwarf annual amphibious swards	3130 - Oligotrophic to mesotrophic standing waters with vegetation of the <i>Littorelletea uniflorae</i> and/or <i>Isoeto-Nanojuncetea</i>
<i>Elatino triandrae</i> – <i>Damasonion alismatis</i> de Foucault 1988			
<i>Radiolion lineoidis</i> W. Pletsch 1971	C3.6 - Unvegetated or sparsely vegetated shores with soft or mobile sediments		
*Mud bottoms of waterbodies	D5.21 - Beds of large <i>Carex</i> spp.		
<i>Caricion gracilis</i> Neuhausl 1959 and <i>Carici pseudocyperii</i> - <i>Rumicion hydrolapathi</i> H. Passarge 1964			
Grasslands habitats	<i>Thero</i> – <i>Airion</i> Tüxen ex Oberdorfer 1957	E1.91 - Dwarf annual siliceous grassland	
	Mesophile hay meadows (Cynosurion cristati Tüxen 1947; Lolio perennis – Plantaginon majoris G. Sissingh 1969)	E2.1 - Permanent mesotrophic pastures and aftermath-grazed meadows	
	<i>Cynosurion cristati</i> Tüxen 1947 X Grp des <i>Sisymbrietea officinalis</i>	E2.1 - Permanent mesotrophic pastures and aftermath-grazed meadows X E5.1 - Anthropogenic herb stands	
	*Land occupied by heavily fertilised or reseeded permanent grasslands	E2.6 - Agriculturally-improved, re-seeded and heavily fertilised grassland, including sports fields and grass lawns	
	<i>Oenanthion fistulosae</i> de Foucault 2008		
	<i>Bromion racemosi</i> Tüxen ex de Foucault 2008	E3.41 - Atlantic and sub-Atlantic humid meadows and	
	<i>Ranunculo repentis</i> – <i>Cynosurion cristati</i> Passarge 1969		
	Wet and humid meadows dominated by <i>Juncus effusus</i>	E3.417 - Soft rush meadows	
	Hygrophilic pastures regularly flooded by the oligohaline water of Loire River and dominated by <i>Agrostis stolonifera</i>		
	Meso-hygrophilic pastures regularly flooded by the oligohaline water of Loire River and dominated by <i>Agrostis stolonifera</i>	E3.44 - Flood swards and related communities	
	<i>Mentho longifoliae</i> – <i>Juncion inflexi</i> Th. Müll. & Görs ex de Foucault 2008		
	<i>Potentillion anserinae</i> Tüxen 1947		
	Pastures regularly flooded by the oligohaline water of Loire River and dominated by <i>Juncus inflexus</i>	E3.441 - Tall rush pastures	
	Hygrophilic pastures regularly flooded by the brackish water of Loire River and dominated by <i>Agrostis stolonifera</i>	E3.44 - Flood swards and related communities X A2.5 - Coastal saltmarshes and saline reedbeds	
	Meso-hygrophilic pastures regularly flooded by the brackish water of Loire River and dominated by <i>Agrostis stolonifera</i>		
	<i>Juncion acutiflori</i> Braun-Blanquet in Braun-Blanquet & Tüxen 1952	E3.512 - Acidocline purple moorgrass meadows	6410 - <i>Molinia</i> meadows on calcareous, peaty or clayey-siltladen soils ( <i>Molinion caeruleae</i> )
<i>Sisymbrietea officinalis</i> Korneck 1974 and <i>Convolvulo arvensis</i> – <i>Agropyron repentis</i> Görs 1966	E5.1 - Anthropogenic herb stands		



	<i>Achilleo ptarmicae</i> – <i>Cirsion palustris</i> Julve & Gillet ex de Foucault 2011	E5.412 - Western nemoral river bank tall-herb communities dominated by <i>Filipendula</i>	6430 - Hydrophilous tall herb fringe communities of plains and of the montane to alpine levels
	<i>Convolvulion sepium</i> Tüxen in Oberdorfer 1957		
	<i>Thalicetro flavi</i> – <i>Filipendulion ulmariae</i> de Foucault in Royer et al. 2006		
	<i>Calystegio sepium</i> – <i>Althaeion officinalis</i> de Foucault 2011	E5.4112 - <i>Angelica heterocarpa</i> fluvial communities	
	<i>Aegopodion podagrariae</i> Tüxen 1967	E5.43 - Shady woodland edge fringes	
	<i>Holco mollis</i> – <i>Pteridion aquilini</i> Passarge (1994) 2002	E5.3 - <i>Pteridium aquilinum</i> fields	
Scrubs and thickets habitats	<i>Solano dulcamarae</i> – <i>Tamaricetum gallicae</i> de Foucault 2008	F9.3131 - West Mediterranean tamarisk thickets	92D0 - Southern riparian galleries and thickets ( <i>Nerio</i> - <i>Tamaricetea</i> and <i>Securinegion tinctoriae</i> )
	Species-poor <i>Prunus spinosa</i> or <i>Rubus spp.</i> thickets	F3.111 - Blackthorn-bramble scrub	
	<i>Ulici europaei</i> - <i>Cytisetum scoparii</i> Oberdorfer ex B. Foucault, Lazare & Bioret 2013	F3.14 - Temperate <i>Cytisus scoparius</i> fields	
	<i>Ulici europaei</i> – <i>Prunetum spinosae</i> Géhu & Géhu-Franck 1983	F3.15 - <i>Ulex europaeus</i> thickets	
	<i>Salicetum triandro</i> – <i>viminalis</i> (Tüxen 1931) Lohmeyer 1952 ex Moor 1958	F9.121 - Imond willow-osier scrub	
Low woods and scrubs dominated by <i>Salix atrocinerea</i>	F9.2 - <i>Salix</i> carr and fen scrub		
Woodland and forest habitats	<i>Salicion albae</i> Soó 1930	G1.1111 - Western European white willow forests	<b>91E0</b> - Alluvial forests with <i>Alnus glutinosa</i> and <i>Fraxinus excelsior</i> ( <i>Alno-Padion</i> , <i>Alnion incanae</i> , <i>Salicion albae</i> )
	<i>Alnenion glutinoso</i> - <i>incanae</i> Oberdorfer 1953	G1.211 - <i>Fraxinus</i> - <i>Alnus</i> woods of rivulets and springs	
	<i>Ulmo laevis</i> – <i>Fraxinetum angustifoliae</i> (Breton) Rameau & Schmitt ex J.-M. Royer, Felzines, Misset & Thévenin 2006	G1.22 - Mixed <i>Quercus</i> - <i>Ulmus</i> - <i>Fraxinus</i> woodland of great rivers	91F0 - Riparian mixed forests of <i>Quercus robur</i> , <i>Ulmus laevis</i> and <i>Ulmus minor</i> , <i>Fraxinus excelsior</i> or <i>Fraxinus angustifolia</i> , along the great rivers ( <i>Ulmion minoris</i> )
	Meso-hygrophilic forests dominated by <i>Quercus robur</i> and <i>Fraxino excelsioris</i> – <i>Quercion roboris</i> Rameau 1996	G1.A1 - <i>Quercus</i> - <i>Fraxinus</i> - <i>Carpinus</i> betulus woodland on eutrophic and mesotrophic soils	
	<i>Ulmus minor</i> thickets	G1.A61 - <i>Ulmus minor</i> woods	
	Plantations of species, hybrids or cultivars of the deciduous genus <i>Populus</i>	G1.C1 - <i>Populus</i> plantations	
Plantations of Palaearctic conifers of genus <i>Pinus</i>	G3.F12 - Native pine plantations		
Cultivated agricultural habitats	Cereal crops	II.1 - Intensive unmixed crops	

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824 **Appendix B.** MDG measures obtained after RF classification for the nine analyzed dates. The five  
 825 most contributing variables, which have been retained to integrate the temporal series, are marked in  
 826 bold.

