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1 **Primary drivers of multidecadal spatial and temporal patterns of shoreline**  
2 **change derived from optical satellite imagery**

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11

12 **Highlights**

- 13 • 1984-2020 satellite-derived shorelines (SDS) collected along 269 km of sandy coast  
14 • Gradients in longshore drift control shoreline trends away from estuary mouths  
15 • Space-averaged SDS interannual variability is correlated with some climate indices  
16 • Sectors downdrift of inlets and estuary mouths are affected by internal dynamics  
17 • SDS can guide the development and application of shoreline change models

18 **Abstract**

19 Understanding and predicting shoreline change along sandy coasts requires continuous (in both time  
20 and space) long-term (decades) shoreline data at good spatial (e.g. 100s of metres) and temporal  
21 (e.g. months) resolution. Publicly available satellite imagery can now provide such time series.  
22 However, satellite-derived shorelines (SDS) are associated with uncertainties, particularly at high-  
23 energy meso-macrotidal coasts, which challenge the assessment of long-term trends and interannual

24 variability. In this paper we address the 1984-2020 time- and space-evolution of 269 km of high-  
25 energy meso-macrotidal sandy coast in southwest France using uncertain (no tide and runup  
26 correction) SDS data. The shoreline trends are validated with field data collected over the period  
27 2008-2019. Over 1984-2020, the shoreline eroded by 0.55 m/yr with maximum erosion (accretion)  
28 reaching 15.61 m/yr (6.94 m/yr), with the largest changes observed along coasts adjacent to the inlet  
29 and estuary mouths. We show that, away from the presence of ebb-tide deltas and swash bars  
30 affecting offshore wave transformation and nearshore circulation, the long-term shoreline trend is  
31 well explained by the gradients in longshore drift computed from a regional wave hindcast and an  
32 empirical longshore transport formula. By averaging the yearly SDS along the entire coastline, we  
33 find that interannual shoreline variability is well correlated with the winter West Europe Pressure  
34 Anomaly (WEPA), which outscores the other conventional teleconnection pattern indices. WEPA  
35 even explains more than 80% of the space-averaged shoreline variability over the recent period  
36 2014-2020 when more and higher quality satellite images are available. A more local assessment of  
37 the links between climate indices and shoreline response shows that correlation with all climate  
38 indices dramatically drops downdrift of the large-scale estuary mouths and inlets. This suggests that  
39 along this 10-20 km stretch of downdrift coast, shoreline response is controlled factors internal to  
40 the estuary mouth / inlet system. The rest of the coast is mostly controlled by factors external to the  
41 system, which are primarily the variability in winter-mean wave height correlated to winter WEPA  
42 index. Overall, we demonstrate that an adapted space-averaging of uncorrected (noisy) SDS dataset  
43 can allow addressing the time- and space variability of shoreline change and their primary drivers  
44 including large-scale climate patterns of atmospheric variability. We also advocate that such SDS  
45 analysis can be performed along any coastline in the world in order to guide future model  
46 development and application.

47 **Keywords:** satellite-derived shoreline; chronic erosion; interannual shoreline variability; wave climate  
48 indices; internal and external controls; inlet and estuary mouth

49

**51 1. Introduction**

52 Climate change, declining sediment supply, and global population growth in the coastal zone are  
53 projected to result in unprecedented socio-economic losses and environmental changes in the  
54 coming decades (Oppenheimer et al., 2019). This is particularly the case of sandy beaches  
55 (approximately one-third of the global ice-free coastline, Luijendijk et al., 2018) which are highly  
56 dynamic and provide outstanding recreation, tourism and ecosystem services, while acting as energy  
57 buffers in an increasingly stormy environment. Erosion has therefore become one of the biggest  
58 threats to coastal zones globally, both in developed (e.g. Southern California, Vitousek et al., 2017a)  
59 and less developed (e.g. North Africa Hzami et al., 2021) regions of the world, which calls for  
60 improved understanding of past and future shoreline evolution and its drivers. This motivated the  
61 recent development of a wealth of reduced-complexity, computationally cheap, shoreline models  
62 (e.g. Vitousek et al., 2017b; Robinet et al., 2018; Antonilez et al., 2019; Tran and Barthélemy, 2020)  
63 able to simulate shoreline change on timescales of decades of coastlines extending up to 10s to 100s  
64 of kilometres. However, model performance heavily relies on training datasets on similar spatial and  
65 temporal scales, and comparisons between multiple models on additional datasets are strongly  
66 needed (Montano et al., 2020).

67 Free-of-charge publicly available optical satellite imagery can now be used to provide short-term to  
68 multi-decadal shoreline data from the local to the global scale using different techniques (e.g. Liu et  
69 al., 2017; Duarte et al., 2018; Toure et al., 2019; Sánchez-García et al., 2020; Bishop-Taylor et al.,  
70 2021). On microtidal beaches, satellite-derived shoreline (SDS) errors are typically under 10 m (e.g.  
71 Vos et al., 2019a; Bishop-Taylor et al., 2019; Cuttler et al., 2020). Therefore in such environments SDS  
72 can be used to improve the understanding of, for instance, embayed beach rotation (Di Luccio et al.,  
73 2019) or the dominant timescales of shoreline variability (Vos et al., 2019a). However, SDS accuracy  
74 dramatically worsens at high-energy and/or meso to macrotidal low-gradient beaches with errors

75 potentially exceeding 30 m (Castelle et al., 2021) due to the action of breaking waves affecting the  
76 total water level at the coast and blurring the dry sand / water limit. Recently, Castelle et al. (2021)  
77 investigated the uncertainties associated with SDS on a high-energy meso-macrotidal beach in  
78 southwest France. They proposed a new total water level threshold accounting for wave runup  
79 which, combined with a horizontal correction of shoreline position based on average beach slope  
80 estimated from *in situ* data, halves shoreline error (decreasing to around 10 m) and doubles the  
81 number of usable satellite images, thus dramatically improving shoreline reconstruction. However,  
82 and despite fair remotely-sensed beach slope datasets can now be generated (Vos et al., 2020), long-  
83 term breaking wave condition hindcast is challenging to generate and such runup correction ideally  
84 needs detailed wave modelling combined with accurate bathymetric data, particularly in complex  
85 coastal settings (e.g., sheltered zones, offshore bathymetric anomalies affecting wave  
86 transformation).

87 Global assessment of long-term sandy shoreline trends at 500-m spaced transects has been  
88 performed using annual composite of cloud-free images (Luijendijk et al., 2018), i.e. disregarding tide  
89 and runup correction. Despite the apparent simplicity of the composite SDS approach (in contrast to  
90 the synoptic SDS approach), the spatially-averaged, regional analyses provided fairly accurate insights  
91 into chronic shoreline trends for sandy beaches across the globe (Luijendijk et al., 2018). The ability  
92 of SDS without tide and runup correction to provide accurate long-term shoreline trends along entire  
93 stretches of coast with contrasting evolution pathways has not been fully validated, particularly at  
94 high-energy meso-macrotidal environments. In addition, the strong links between interannual  
95 shoreline response and large-scale climate patterns of atmospheric variability has been explored only  
96 locally, based *in situ* monitoring program (e.g. Dodet et al., 2019). The recent work of Vos *et al.*  
97 (2022) is a notable exception, where SDS anomaly around the Pacific Basin was computed during  
98 extreme (El Niño/Southern Oscillation) ENSO index phases (multivariate index larger than half of its  
99 standard deviation). The authors found significant and coherent regional variability in coastal  
100 response to ENSO. The space-averaging of uncorrected (noisy) SDS datasets could, by smoothing the

101 errors, allow addressing the regional variability of the links between shoreline response and different  
102 modes of climate variability. However, this has never been tested.

103 The southwest coast of France is made of high-energy meso-macrotidal beaches. The coast has been  
104 eroding over the last decades although erosion and accretion can alternate in both time and space  
105 particularly near large-scale tidal inlets and estuary mouths (Castelle et al., 2018a). So far, continuous  
106 large-scale (~250 km) long-term (~70 years) shoreline analysis along this coast has only been  
107 performed at low-frequency (~10 years) using historical orthophotos (Bernon et al., 2016; Castelle et  
108 al., 2018a), while high-frequency (daily to monthly) data (<20 years) are limited to a couple of sites  
109 (e.g. Coco et al., 2014; Biauxque and Sénéchal, 2019; Castelle et al., 2020). In this paper 269 km of  
110 sandy coast in southwest France are studied using, uncorrected, SDS data from 1984 to 2020. We  
111 explore if time- and/or space-averaging of such SDS data can be used to describe shoreline change,  
112 including long-term trends and interannual variability, and their primary driver. To do so, we validate  
113 the SDS trends with *in situ* data and further use wave hindcast, longshore drift estimations and  
114 climate indices to link the observed changes with external forcing. We will show that the processing  
115 of such SDS data can provide new insight into shoreline response and their primary, thus indicating  
116 guidelines for future model development and application.

## 117 **2. Study area: the sandy coast of Nouvelle-Aquitaine**

118 The present study focuses on a large sector of the sandy coast of the Nouvelle-Aquitaine region,  
119 southwest France, from the mouth of the Adour River in the south to the south of Oléron Island in  
120 the north (Figure 1a). The role of the inherited geology on coastline shape and landscape is  
121 extensively described in Castelle et al. (2018a). The coast is disrupted by two major inlets  
122 (Maumusson and Arcachon), associated with two prominent updrift sandspits (Gatseau and Cap  
123 Ferret), and one large estuary mouth (Gironde). The coast is mostly composed of relatively straight  
124 sandy beaches backed by coastal dunes (Figure 1d, Bossard and Nicolae Lerma, 2020), with only a  
125 few, isolated, coastal towns built on the dune although with limited coastal defences (e.g. Royan,

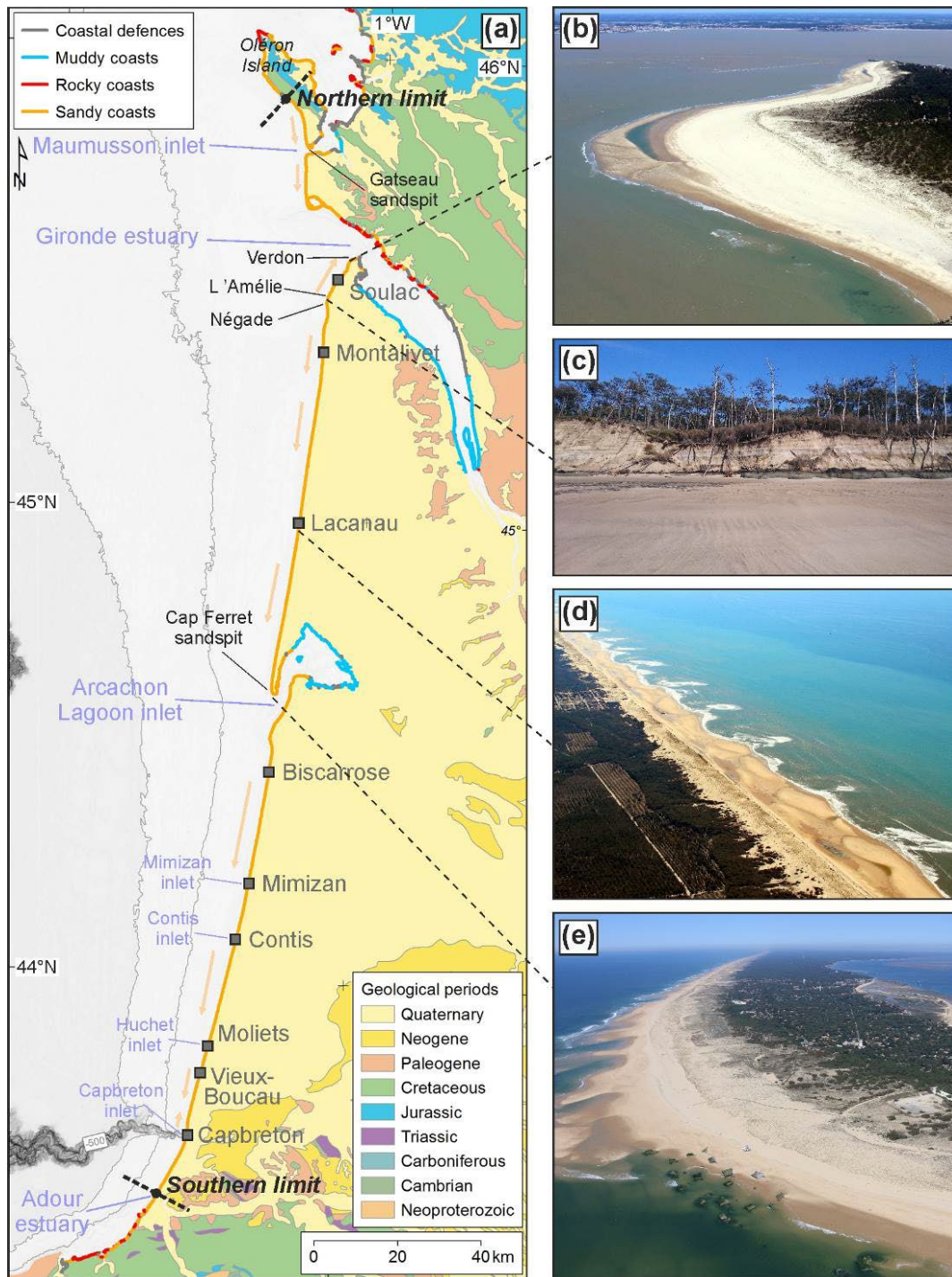
126 Soulac, Montalivet, Lacanau, Mimizan, Capbreton, Figure 1a). The coast is also slightly disrupted by  
127 the small-scale wave-dominated inlets of Mimizan, Contis-les-Bains, Capbreton and Huchet, with only  
128 the latter being not trained by jetties. In the south of the study area, the jetties and groins of the  
129 coastal town of Capbreton, the Capbreton submarine canyon, and the northern training wall of the  
130 Adour river mouth also disrupt the sediment pathways.

131 Beaches are made of fine to medium quartz sand slightly coarsening southwards. It is a meso-  
132 macrotidal environment with the tidal range increasing northwards due to the widening continental  
133 shelf (Le Cann, 1990), with the highest astronomical tide peaking around 6.5 m in the north. The  
134 coast is exposed to an energetic wave climate generated by extratropical cyclones tracking eastwards  
135 in the North Atlantic Ocean, driving waves predominantly with a west to northwest incidence. While  
136 offshore significant wave height  $H_s$  can exceed 10 m during severe storms, the monthly-averaged  $H_s$   
137 in the centre of the study area ranges from 1.11 m in July to 2.4 m in January (Castelle et al., 2017a).  
138 Winter-mean incident wave energy shows dramatic interannual variability enforced by natural large-  
139 scale climate modes of atmospheric variability, primarily the West Europe Pressure Anomaly  
140 (Castelle et al., 2017b). Overall, the wave height at breaking slightly increases southwards because of  
141 the narrowing continental shelf reducing the bottom friction and resulting in less offshore energy  
142 dissipation of the incoming ocean waves. The dominant west-northwest wave climate drives a net  
143 southerly longshore drift (Bertin et al., 2008; Idier et al., 2013), except locally at northwest-facing  
144 sectors where the longshore drift reverses. The longshore drift also locally reverses north of  
145 Capbreton owing to offshore wave refraction across the Capbreton canyon (Abadie et al., 2006;  
146 Mazieres et al., 2014).

147 Castelle et al. (2018a) used 15 geo-referenced orthomosaics photos between 1950 to 2014 from  
148 which shoreline position was manually retrieved using as proxy the dune foot and the limit of the  
149 vegetated foredune in eroding and accreting sectors, respectively. The authors showed that,  
150 averaged across the entire sandy coast, the shoreline has eroded by 1.12 m/yr at a relatively steady

151 rate. Maximum rates of shoreline change are observed along sectors adjacent to the inlets and  
152 estuary mouths. In these sectors, erosion and accretion typically alternate over time on the timescale  
153 of decades (e.g. Cap Ferret sandspit, Figure 1e). Computed shoreline change rates range from -11  
154 m/yr (+6 m/yr) in eroding (accreting) sectors, which is evidenced by the coastal landscape in rapidly  
155 chronically accreting (e.g. Cape Verdon sector, Figure 1b) and eroding (e.g. Cap Négade, Figure 1c)  
156 sectors. Although not captured by the, low-frequency, historical orthophoto analysis in Castelle et al.  
157 (2018a), observation along the coast also shows occasional dramatic shoreline erosion driven by  
158 severe winters. The most striking example is the winter of 2013/2014, characterised by extreme  
159 storm clustering (Davies, 2015), which drove widespread erosion along the Atlantic coast of Europe  
160 (Masselink et al., 2016), including the southwest coast of France (Castelle et al., 2015).





161

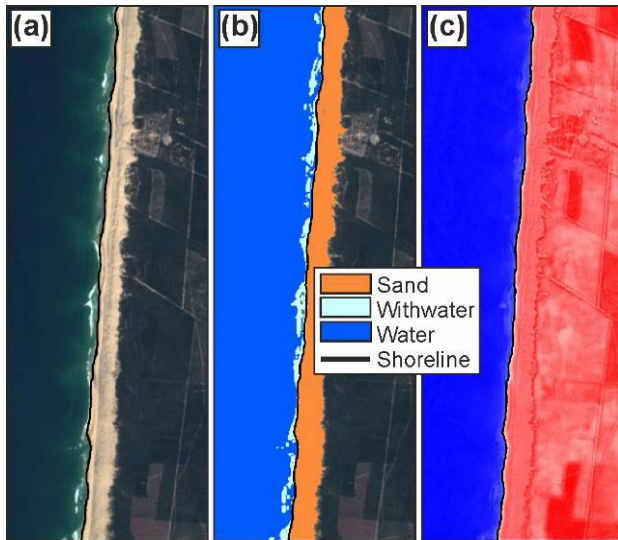
162 Figure 1. Study area (delimited by the southern and northern black dashed segments) mostly  
 163 composed of sandy coasts, with indication of the inherited geology. The grey squares show the  
 164 location of the small coastal towns with their seafront more or less built on the coastal dune, and the  
 165 alongshore arrows show the net longshore drift patterns. The right-hand photos display some  
 166 representative coastal settings: (b) accreting sector south of Cape Verdon (@Observatoire de la Côte  
 167 de Nouvelle-Aquitaine); (c) chronically eroding Cape Négade where the dune has disappeared (Ph.

168 B. Castelle); (d) typical landscape of long and straight beach-dune systems (@Observatoire de la Côte  
169 de Nouvelle-Aquitaine); (e) the tip of the Cap Ferret sandspit, adjacent to the Arcachon Lagoon inlet,  
170 which has a long history of alternatively eroding and accreting phases as evidenced by the Second  
171 World War German bunkers, formerly built on the top of the coastal dune, now lost to coastal  
172 erosion (@Observatoire de la Côte de Nouvelle-Aquitaine).

### 173 **3. Methods**

#### 174 **3.1 *Shoreline detection from publicly available satellite images***

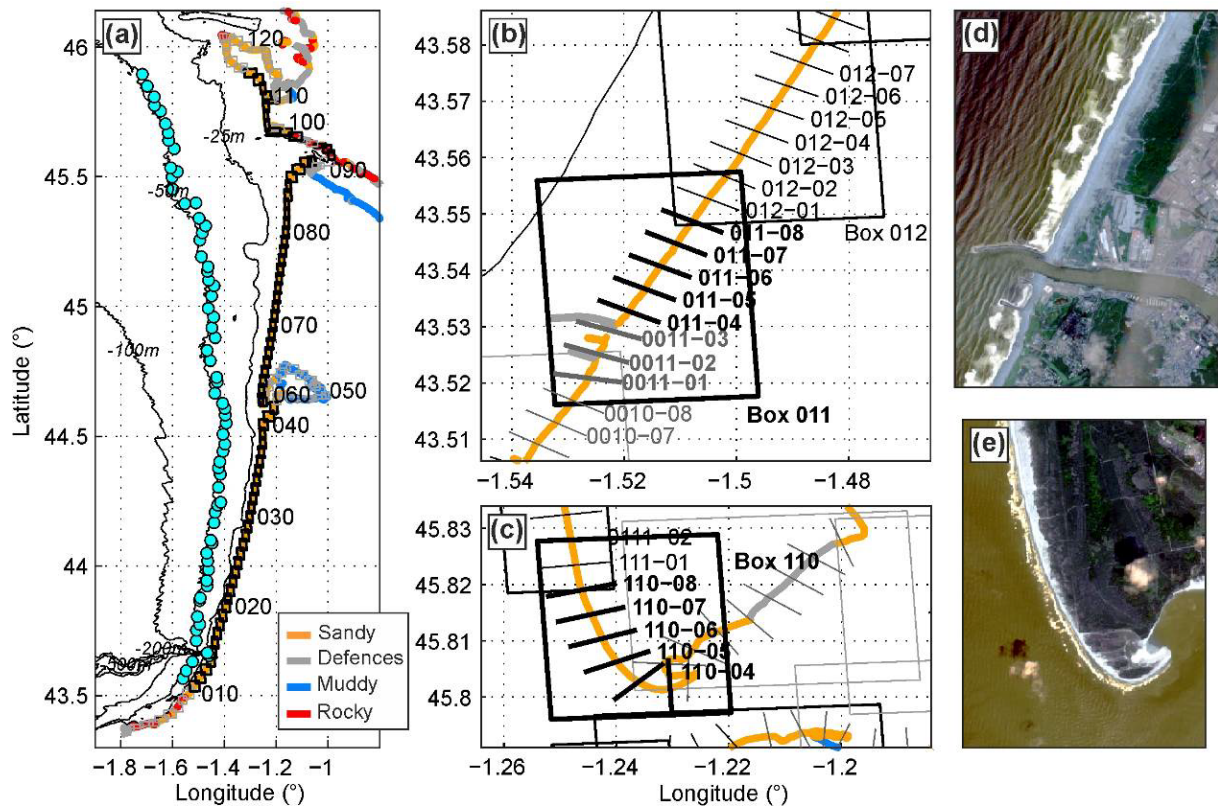
175 We used the CoastSat toolkit developed by Vos et al. (2019a, 2019b). The toolkit allows extracting  
176 waterlines from publicly available optical satellite data through Google Earth Engine, namely Landsat  
177 5, 7 & 8 (L5, L7, L8, 30-m spatial resolution) and Sentinel-2 (S2, 10-m spatial resolution) images. In  
178 brief, for a given RGB (+ infrared) satellite image (Figure 2a), image classification into four classes is  
179 performed based on a Neural Network classifier (Figure 2b) which, combined with a global threshold  
180 on the Modified Normalised Difference Water Index (MNDWI), provides a waterline using a sub-pixel  
181 resolution contouring algorithm (Figure 2c). For an extensive description of the CoastSat toolkit, the  
182 reader is referred to Vos et al. (2019b). Following Castelle et al. (2021) who used CoastSat at Truc  
183 Vert beach on this coast, images with cloud cover larger than 50% were automatically disregarded.  
184 Additional images were manually removed by visual inspection when the algorithm failed to depict  
185 shoreline position due to e.g. flawed detection of the water/sand limit in the saturated intertidal  
186 domain or shadows cast by clouds affecting waterline detection. Contrary to Castelle et al. (2021),  
187 tide and runup SDS correction was not performed because accurate runup estimation was not  
188 possible at many sectors affected by offshore wave refraction / breaking that strongly affect  
189 nearshore breaking wave conditions. Disregarding such correction and thus using off-the-shelf  
190 CoastSat toolkit also allowed us to explore if and how spatial or temporal averaging can provide  
191 accurate and new information on shoreline change along this coast.



192

193 Figure 2. Outputs from the CoastSat toolkit of Vos (2019b): (a) RGB image of a stretch of coast north  
 194 of Lacanau (S2 on April 18, 2020); (b) corresponding output of image classification where each pixel is  
 195 labelled as ‘sand’, ‘water’, ‘white-water’ or ‘other’; (c) corresponding pseudocolour image of the  
 196 MNDWI pixel values. In all panels, the black line indicates the waterline detected by CoastSat.

197 The southwest coast of France was subdivided into boxes to which satellite images were cropped and  
 198 processed with CoastSat. A total of 126, approximately 20% overlapping, boxes were designed (area  
 199 ranging from 5.53 km<sup>2</sup> to 14.65 km<sup>2</sup>, with a mean of 9.34 km<sup>2</sup>) ranging from the Spanish border to the  
 200 entire Oléron Island (Figure 3a). The resulting 512-km shoreline baseline is made of 1024 500-m-  
 201 spaced cross-shore transects. Each box contains eight central transects used for analysis (Figure  
 202 3b,c), the other transects overlapping those in the two neighbouring boxes. In order to focus on open  
 203 sandy coast sectors, we disregarded the beaches (1) of the Basque coast south of the Adour River  
 204 mouth, (2) inside the Arcachon Lagoon, (3) in predominantly muddy, trained or rocky sectors within  
 205 the Gironde estuary mouth and (4) in Oléron island sectors which are sheltered from ocean waves  
 206 and/or with thin beaches mostly perched on rocky basement, thus with limited dynamics (Figure 3a).  
 207 Overall, 269 km of sandy shoreline (538 transects) were analysed, for a total of 104,444 individual  
 208 shoreline positions between April 12, 1984 and December 31, 2020.



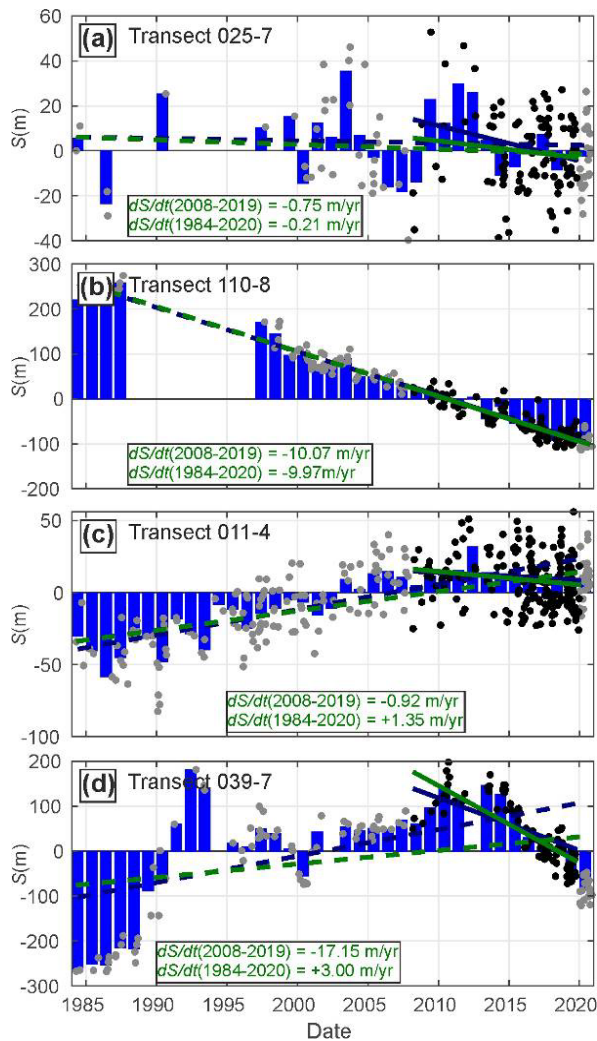
209

210 Figure 3. (a) Location map of the southwest coast of France, with colour indicating shoreline type,  
 211 and with the bathymetry contoured. The boxes (numbered) indicate Coastsat image extraction zones  
 212 along the entire coast with the cyan dots indicating the corresponding wave hindcast grid points in  
 213 approximately 50-m depth where wave time series were extracted. The thick black boxes show the  
 214 boxes used in the present analysis. Middle and right-hand panels show a zoom onto boxes 011 and  
 215 110 and examples of corresponding satellite image. (b,c) Each box consists of eight 500-m spaced  
 216 cross-shore transects, with in each thick black box the greyish transects disregarded from the analysis  
 217 (e.g. outside of the domain, located in a sheltered area). S2 images on (d) June 22, 2020 and (e) June  
 218 13, 2019.

219 **3.2 Satellite-derived shoreline trend computation and validation**

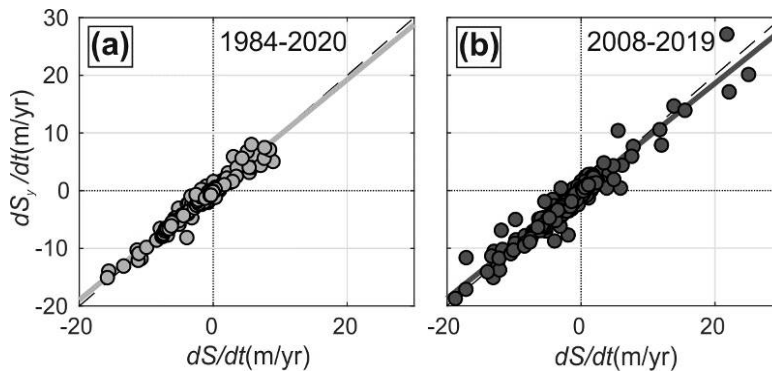
220 At each transect, time series of shoreline deviation from the mean was retrieved from the CoastSat-  
 221 derived shoreline position  $S$ . Given that shoreline trends are sometimes based on the entire  
 222 shoreline time series (e.g. Vos et al., 2019), or sometimes from annual composite images (Luijendijk  
 223 et al., 2018), two approaches for computing long-term shoreline trends were tested here: by linearly

224 regressing (1) raw  $S$  giving trend  $dS/dt$  and (2) yearly-mean SDS  $S_y$  giving trend  $dS_y/dt$ . Figure 4  
225 shows examples of  $S$  time series at representative transects showing contrasting variability in both  
226 pattern and amplitude, e.g. from a quasi-steady erosion (Figure 4b) to strong interannual variability  
227 with an amplitude of 100s of metres and net accreting long-term trend (Figure 4d). Trends from the  
228 two methods are shown for two different periods, i.e. the entire 1984-2020 time series and for the  
229 2008-2019 period which will be used for validation with field data. The two methods show similar  
230 results, with a root-mean-square error RMSE and coefficient of determination  $R^2$  of 0.59 m/yr and  
231 0.95, respectively, for the 1984-2020 period (Figure 5a), changing to 1.06 m/yr and 0.92 for the 2008-  
232 2019 period (Figure 5b). In the following, long-term trend using raw  $S$  is used throughout ( $dS/dt$ ).  
233 We also computed the  $S$  standard deviation around the long-term trend  $\sigma_e$ , which is composed of all  
234 the components of errors and variability, namely : seasonal and particularly interannual variability  
235 and SDS detection uncertainties (e.g. shoreline detection algorithm, tide effects) .



236

237 Figure 4. Time series of SDS position deviation from the mean at different representative transects  
 238 along the coast (a) 025-7 south of Contis, (b) 110-8 near the southern tip of Oléron Island, (c) 011-4  
 239 immediately to the north of the Adour estuary training wall and (d) 039-7 between Biscarrosse and  
 240 the Arcachon Lagoon inlet. In each panel blue bars show yearly mean ( $S_y$ ) and the dots show  
 241 individual ( $S$ ) shoreline data (grey <2008, black  $\geq$ 2018). The dotted (solid) lines depict the long-term  
 242 trend  $dS/dt$  (in green) ( $dS_y/dt$  (in dark blue)) computed on the entire 1984-2020 (limited 2008-  
 243 2019) period, with the 2008-2019 period corresponding to the available *in situ* data collected for  
 244 validation. Raw shoreline trend values  $dS/dt$  are given in each panel.

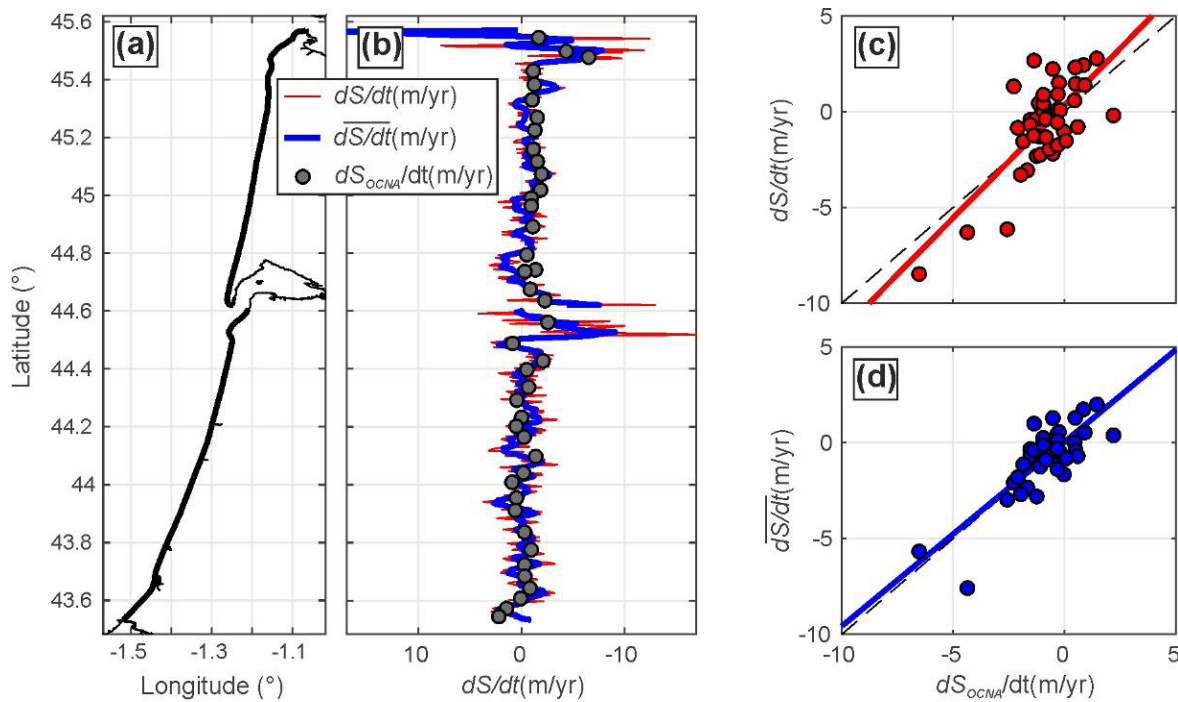


245

246 Figure 5. Long-term shoreline trend computed using yearly-mean shoreline  $dS_y/dt$  versus that  
 247 computed using raw shorelines  $dS/dt$  over the (a) 1984-2020 and (b) 2008-2019 periods

248 In order to validate the SDS trends, we used the field dataset described in Nicolae Lerma et al. (2022)  
 249 collected by the Observatoire de la Côte de Nouvelle-Aquitaine (OCNA) between 2008 and 2019 and  
 250 we computed the SDS trends over the same period. The dataset consists of 11 years of beach-dune  
 251 profiles along 41 transects surveyed yearly in spring between the Adour River mouth in the south,  
 252 and the Gironde estuary mouth in the north (Figure 6a,b), completed by interspersed autumn LiDAR  
 253 surveys (2014, 2016, 2017, 2018, 2019). The *in situ* shoreline  $S_{OCNA}$  was extracted from this dataset  
 254 as the intersection of the beach-dune profile with elevation  $z = 6$  m NGF, which roughly corresponds  
 255 to the time and space average dune foot elevation along the coast (Nicolae Lerma et al., 2019).  
 256 Figure 6b shows the comparison between observed trend  $dS_{OCNA}/dt$  and SDS trend  $dS/dt$  and its  
 257 2500-m moving average  $\overline{dS/dt}$ . Trends are in fair agreement, with RMSE 1.61 m/yr and  $R^2 = 0.54$  for  
 258 the raw trends ( $dS/dt$ , Figure 6c), and RMSE = 1.05 m/yr and  $R^2 = 0.64$  for its 2500-m moving average  
 259 ( $\overline{dS/dt}$ , Figure 6d). It is important to note that: (1)  $S_{OCNA}$  and  $S$  are not based on the same shoreline  
 260 proxy and thus trends are not robustly comparable ; (2)  $S_{OCNA}$  is collected at single transects and is  
 261 thus affected by the presence of alongshore-non uniform features such as megacusp embayments  
 262 cutting the dune with a cross-shore amplitude locally exceeding 20 m (Castelle et al., 2015), which  
 263 result in shoreline estimation uncertainties. Additional tests were performed using lower *in situ*  
 264 shoreline proxies, including the MSL shoreline which should be close to the, time-averaged, SDS  
 265 proxy. However, the tests showed that the agreement between the trends computed from  $S_{OCNA}$

266 and  $S$  worsens. The two primary reasons are that: (1) the presence of rip channels in the lower  
 267 profile results in an increased alongshore beach non-uniformity and thus increased  $S_{OCNA}$   
 268 uncertainties ; (2) beach slope progressively decreases seaward, which also results in more uncertain  
 269 shoreline detection from the intersection of the beach profile with a given elevation datum.  
 270 Therefore, the comparison shown in Figure 6 between the trends derived from  $S$  and  $S_{OCNA}$  (using  
 271  $z = 6 \text{ m}$  NGF) is fair and can be considered as a validation of our computed SDS trends.



272  
 273 Figure 6. (a) Zoom onto the southern part of the study area where OCNA *in situ* profiles have been  
 274 collected for validation of shoreline trends, with the thick black shoreline indicating the sections used  
 275 for analysis. (b) Spatial distribution of 2008-2019 shoreline change trend  $dS/dt$  and its 2500-m  
 276 moving average  $\overline{dS/dt}$ , with the grey dots showing the measured shoreline trends at the OCNA  
 277 transects  $dS_{OCNA}/dt$ . (c)  $dS/dt$  and (d)  $\overline{dS/dt}$  versus  $dS_{OCNA}/dt$ .

### 278 3.3 Wave data, climate indices and longshore drift computation

279 We used wave data from a regional wave hindcast (Boudière et al., 2013; Michaud et al., 2015),  
 280 which showed excellent skill against interspersed buoy measurements (see Castelle et al., 2020 for  
 281 details). For each box, hourly time series (2012-2020) of wave conditions was extracted at the grid



282 point the closest to both the box and to the 50-m isobath (cyan dots in Figure 3a). Significant wave  
 283 height  $H_s$ , peak period  $T_p$  and angle of incidence  $\theta$  in water depth  $h_0 \approx 50$  m were transformed into  
 284 wave conditions at breaking  $H_{sb}, T_{pb}, \theta_b$  in water depth  $h_b$  (Figure 7) using the Larson et al. (2010)  
 285 empirical formula which assumes nearly shore-parallel offshore bathymetric iso-contours. The local  
 286 orientation of the shoreline baseline-normal transect was used to compute the wave angle at  
 287 breaking  $\alpha_b$  (Figure 7). These breaking wave conditions were used to force an empirical longshore  
 288 transport model (Kaczmarek et al., 2015) which is based on an estimation of the mean longshore  
 289 current  $V$ :

290 
$$V = 0.25k_v\sqrt{\gamma g H_{sb}} \sin 2\alpha_b \quad (1)$$

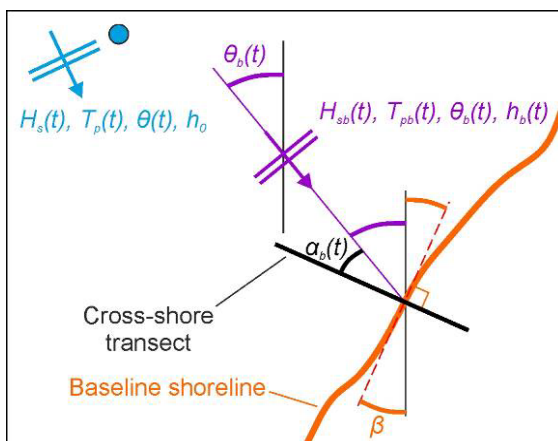
291 where  $g$  is the gravitational acceleration,  $\gamma = 0.78$  is the breaker parameter and  $k_v = 2.9$  is a free  
 292 parameter previously validated in the north of the study area (Bertin et al., 2008). The longshore  
 293 sand transport  $Q_{lst}$  is then computed at each wave time step depending on  $H_{sb}^2 V$  as:

294 
$$Q_{lst} = 0.23H_{sb}^2 V, \text{ if } H_{sb}^2 V < 0.15 \quad (2)$$

295 
$$Q_{lst} = 0.2300225 + 0.008H_{sb}^2 V, \text{ if } H_{sb}^2 V > 0.15 \quad (3)$$

296 Hourly hindcast (2012-2020)  $Q_{sit}$  was then time averaged for each transect to compute the spatial  
 297 distribution of the longshore drift  $Q_s$ . Alongshore gradients of  $Q_s$  are then computed and further  
 298 compared with shoreline trends  $dS/dt$ .

299



300 Figure 7. Schematics of longshore drift computation approach: wave hindcast data ( $H_s, T_p, \theta$ ) in  
301 water depth  $h_0 \approx 50$  m are transformed into breaking wave conditions ( $H_{sb}, T_{pb}, \theta_b, h_b$ ) using  
302 Larson et al. (2010) from which breaking wave angle to the shore  $\alpha_b$  can be computed according to  
303 local transect orientation.

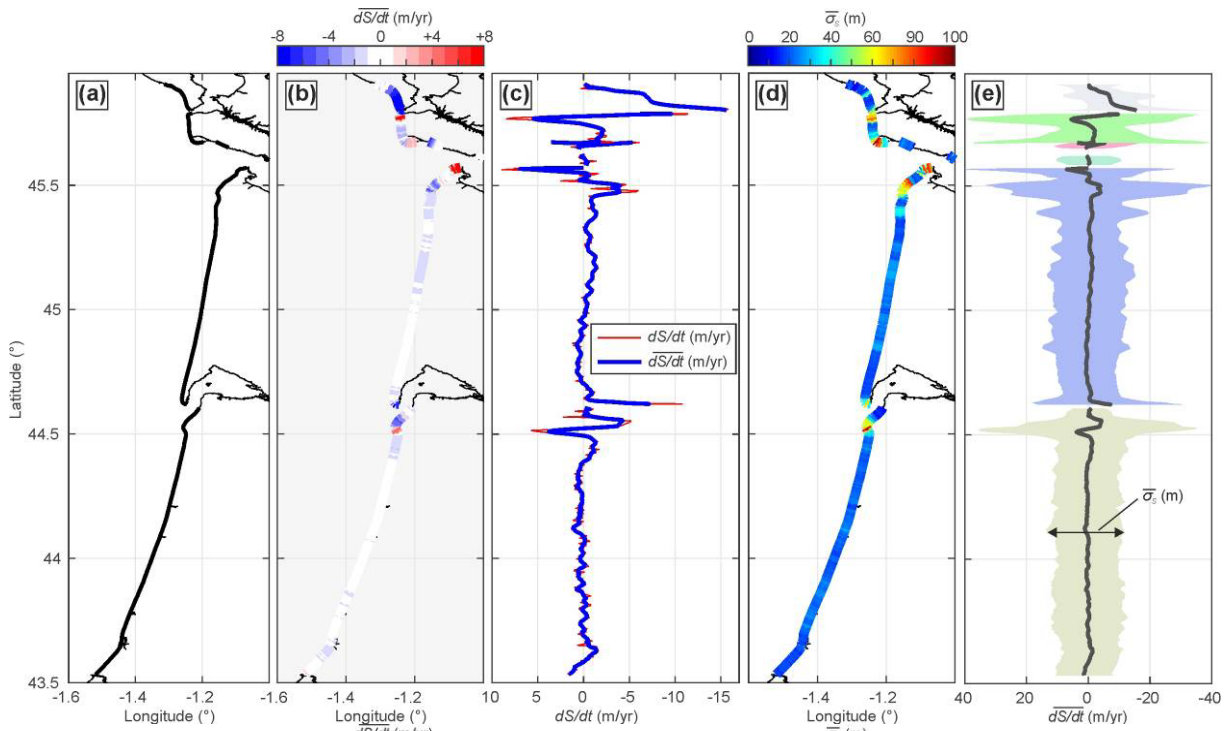
304 Correlation between SDS interannual variability and large-scale climate modes of atmospheric  
305 variability was also explored. Previous work indicates that the winter (DJFM) West Europe Pressure  
306 Anomaly (WEPA, Castelle et al., 2017b), defined as the normalised gradient of sea-level pressure  
307 between Valentia (Ireland) and Santa Cruz de Tenerife (Canary Islands, Spain) stations, is the primary  
308 climate index explaining the interannual variability of e.g. winter wave activity, beach volume  
309 changes, precipitation and river discharge in the Bay of Biscay (e.g. Dodet et al., 2019; Jalon-Rojas et  
310 al., 2021). A positive winter WEPA corresponds to an intensified and southward shifted Icelandic low  
311 / Azores high dipole driving severe storms funnelling high-energy waves towards the west coast of  
312 Europe southward of  $52^\circ$  N down to the Moroccan coast (Castelle et al., 2017b, Malagon et al., 2017).  
313 The normalised 1942-2020 WEPA time series was computed from *in situ* sea level pressure data  
314 measured at the Valentia and Santa Cruz de Tenerife weather stations. In addition, winter-mean  
315 values of the conventional teleconnection indices in this region of the world, North Atlantic  
316 Oscillation (NAO), Scandinavia (SCAND) and East Atlantic (EA) indices, were also used here. These  
317 climate indices, which represent primary intrinsic modes of variability in atmospheric circulation, are  
318 derived from rotated EOF analysis of the monthly mean standardized 500-mb height anomalies  
319 hindcast in the Northern Hemisphere (Barnston and Livezey, 1987). Amongst these three indices, the  
320 NAO has long been known to be the dominant mode of variability in the North Atlantic climate  
321 (Hurrell, 1995). Similar to WEPA, a positive NAO reflects an intensified Icelandic low / Azores high  
322 dipole, but without southward shift, which limits its influence on winter wave energy in the Bay of  
323 Biscay (Castelle et al., 2017b). These indices were downloaded from the National Oceanic and  
324 Atmospheric Administration (NOAA) Climate Prediction Centre ([www.cpc.ncep.noaa.gov](http://www.cpc.ncep.noaa.gov)).

325 **4. Results**

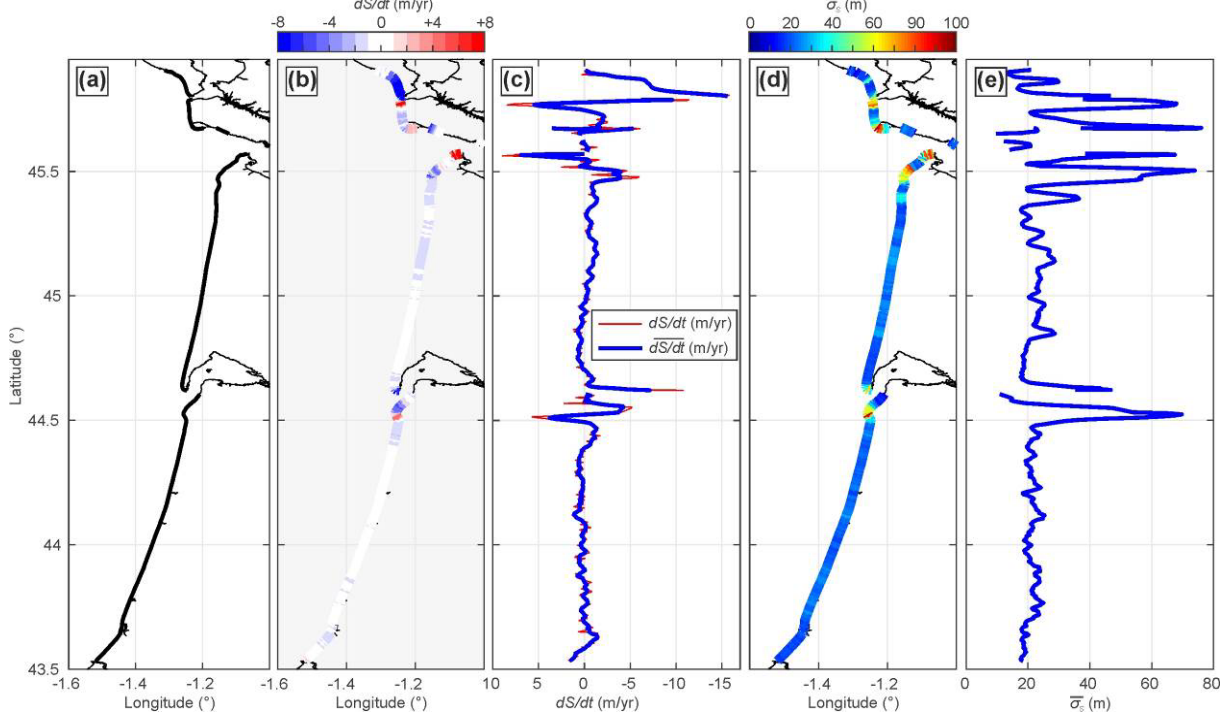
326 **4.1 Spatial distribution of shoreline change trends and gradients in longshore drift**

327 Figure 8 shows the spatial distribution shoreline change rate over the period 1984-2020 along 269  
328 km of sandy shoreline (Figure 8a). Shoreline change rate shows a large spatial variability (Figure 8b,c)  
329 with, on average, the shoreline eroding by 0.55 m/yr. The 2500-m moving average shoreline change  
330 rate  $\overline{dS/dt}$  peaks at 6.94 m/yr (accretion near Verdon, Figure 1a) and drops to 15.61 m/yr (erosion at  
331 Gatseau sandspit, Figure 1a), with the largest changes observed along coasts adjacent to inlet and  
332 estuary mouths, although with contrasting patterns depending on both the inlet/estuarine system  
333 and downdrift or updrift location (Figure 8b,c). Shoreline standard deviation around the long-term  
334 trend  $\sigma_s$  is also maximised near inlets and estuary mouths (Figure 8d,e), further indicating that  
335 shoreline interannual variability is the largest in these sectors.

336



337



338 Figure 8. 1984-2020 SDS statistics: (a) Sandy shoreline used in the analysis (thick black line); (b) 2500-  
 339 m moving averaged shoreline change trend  $\overline{dS/dt}$  coloured; (c) raw shoreline change trend (thin red,  
 340  $dS/dt$ ) and its 2500-m moving average (thick blue,  $\overline{dS/dt}$ ); (d) 2500-m moving averaged shoreline  
 341 standard deviation around the trend  $\overline{\sigma_S}$ ; (e)  $\overline{\sigma_S}$ .

342 The relationship between long-term shoreline change rate and longshore drift gradient was explored.

343 In some of the areas adjacent to tidal inlets and estuary mouths, the presence of ebb tidal shoals and

344 swash bars deeply affects the incident wave field and, in turn, breaking wave conditions. For such

345 regions the underlying assumptions of the Larson et al. (2010) empirical formula are not tenable.

346 Accordingly, the longshore drift computation and subsequent longshore drift analysis were restricted

347 to the coastline shown in Figure 10a. The latitudinal distribution of shoreline change rate  $\overline{dS/dt}$ ,

348 longshore drift  $Q_s$  and gradient of longshore drift  $dQ_s/dx$  are shown in Figures 10b, 10c and 10d,

349 respectively. Consistent with previous work (Idier et al., 2013), the longshore drift is mainly directed

350 southwards, except locally at northwest-facing sectors. The resulting gradients are weak, except

351 where shoreline orientation varies substantially, i.e. near inlets and estuary mouth (Figure 10d).

352 Figure 10e-h shows that along the southern coast of Oléron island (Figure 10e) and the Gironde coast

353 (Figure 10g), where some of the largest shoreline trends are observed, there is a statistically

354 significant relationship (p-value < 0.05) between  $\overline{dS/dt}$  and  $dQ_s/dx$  ( $R^2 = 0.92$  and  $R^2 = 0.50$ ,

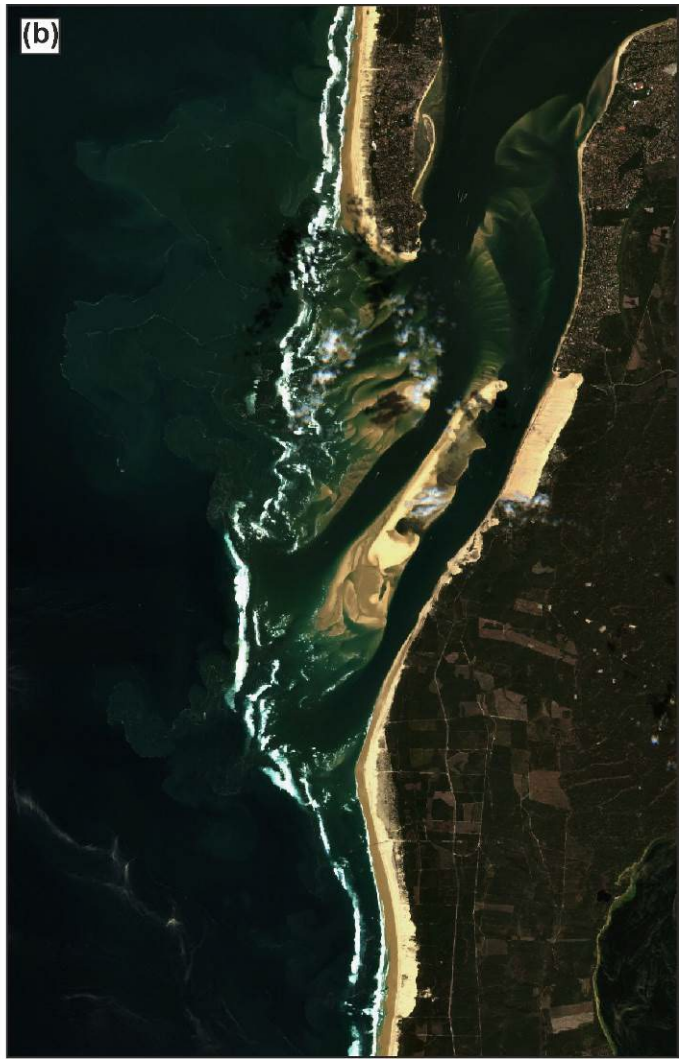
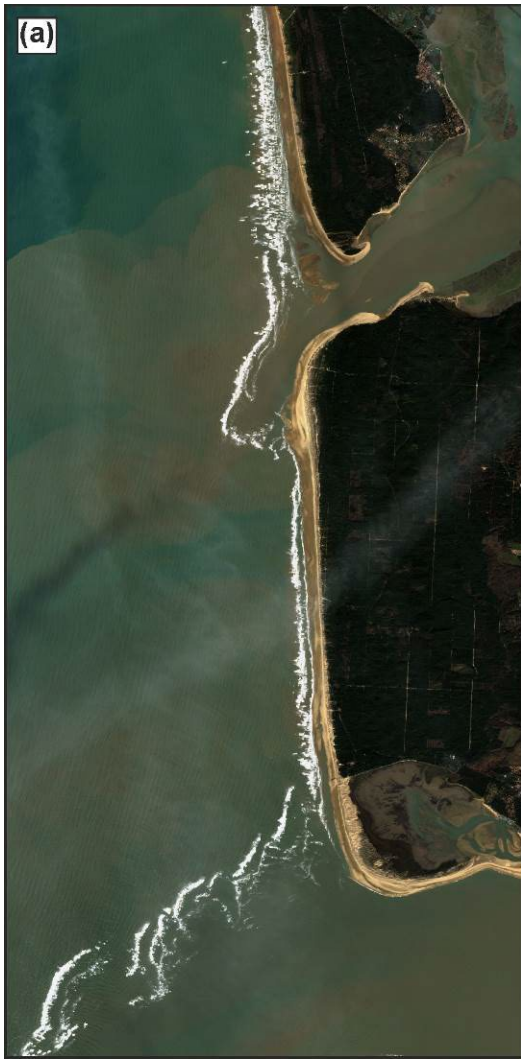
355 respectively). Along the Landes coast (Figure 10h) the southerly longshore drift is quasi-homogenous

356 (Figure 10c,d), resulting in a mostly stable shoreline position, and thus a weak correlation between

357  $\overline{dS/dt}$  and  $dQ_s/dx$ . Despite the statistical relationships are much weaker in Figure 10f,h, similar

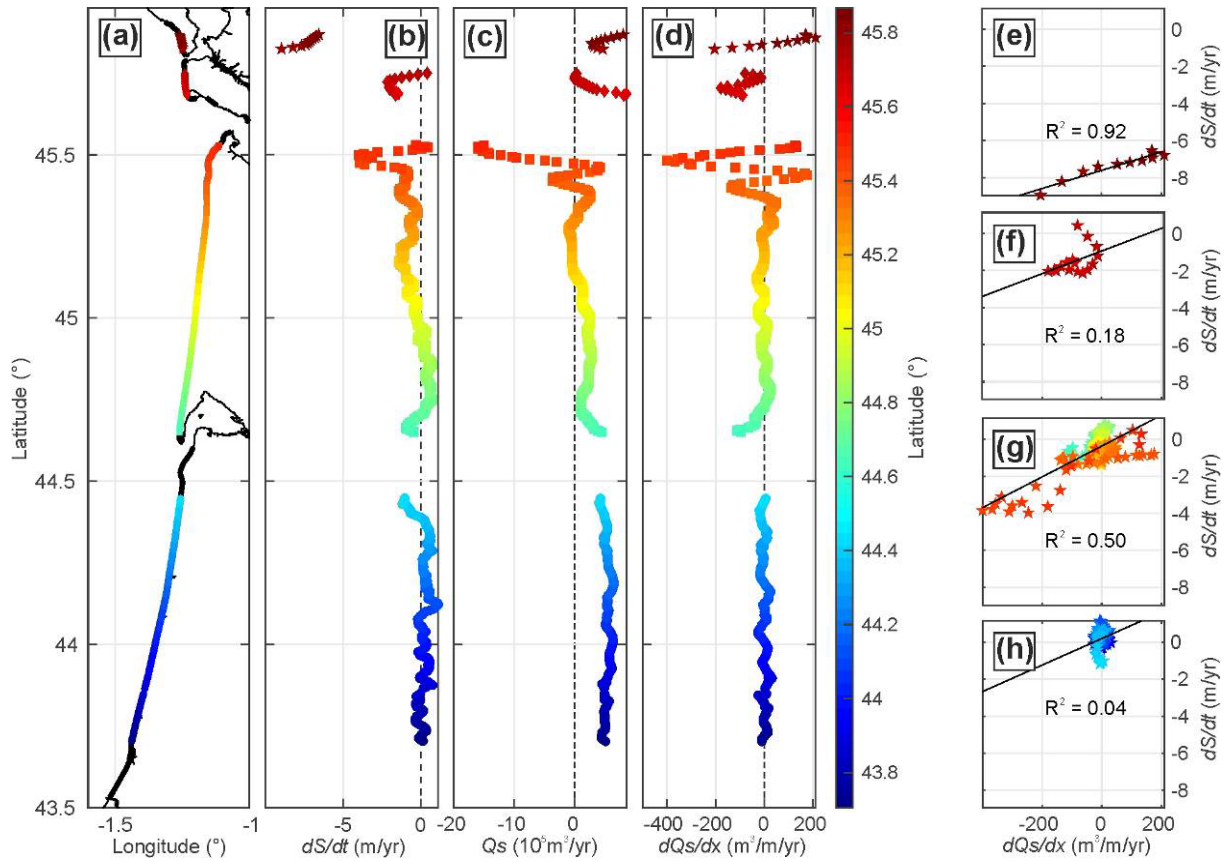
358 linear relationships are found with  $\overline{dS/dt} \approx 7.10^{-3} dQ_s/dx$  for the four sub-sectors, which will be

359 further discussed in Section 5.



360

361 Figure 9. Satellite images showing complex offshore wave transformation and breaking wave  
362 patterns around (a) Maumusson inlet (S2 image on January 24, 2019) and (b) Arcachon Lagoon inlet  
363 (S2 image on April 19, 2018).



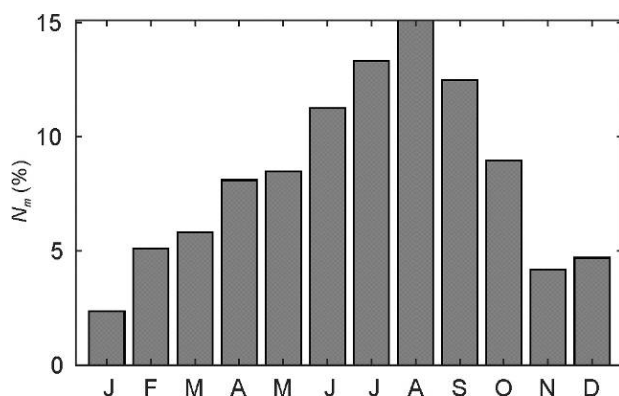
364

365 Figure 10. 1984-2020 SDS change trends and longshore drift characteristics: (a) shoreline sectors  
 366 addressed here; (d) 2500-m moving average shoreline trend  $\overline{dS/dt}$  (c) computed longshore drift  $Q_s$   
 367 (negative southwards) and (d) its alongshore gradients  $dQ_s/dx$ ; (e-h)  $\overline{dS/dt}$  versus  $dQ_s/dx$  for the  
 368 four sub-sectors and corresponding coefficient of determination  $R^2$ . Shoreline latitude is coloured in  
 369 all panels.

#### 370 4.2 Time evolution of spatially-averaged shoreline position

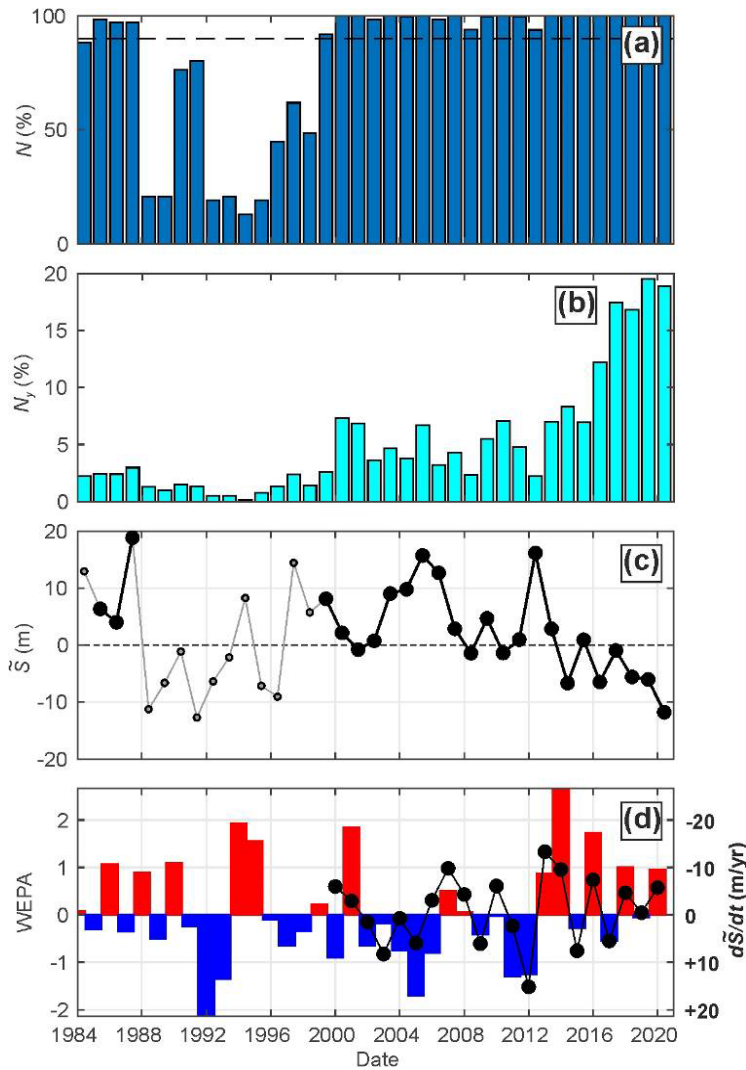
371 In Section 4.1 we found that the space- and time-averaged erosion along the 269 km of sandy coast is  
 372 0.55 m/yr, however the interannual variability was not explored. Previous work at specific sites along  
 373 this coast and more broadly along the Atlantic coast of Europe (Dodet et al., 2019) showed large  
 374 interannual shoreline variability that is well correlated with some climate indices. However, the  
 375 hypothesis that this can apply to entire stretches of coastline has never been investigated. To further  
 376 test this hypothesis, we addressed the evolution of the yearly shoreline position around the mean  $\bar{S}$ ,  
 377 averaged along the entire 269-km coast, and compared it with some dominant winter (DJFM) climate

378 indices in this region. We used the yearly-mean, and not the mean from April 1 to November 30  
 379 which would be more consistent to address the impact of winter wave conditions on shoreline  
 380 change, because some existing shoreline datasets are based on yearly composites (Luijendijk et al.,  
 381 2018). This approach is also supported by the fact that most of the cloud-free satellite images in  
 382 southwest France are collected in spring-summer-fall. This is shown in Figure 11 that displays the  
 383 monthly percentage of satellite images used over 1984-2000, with 82% of the yearly SDS data  
 384 collected between April 1 and November 30. The yearly mean shoreline is therefore close to the  
 385 AMJJASON mean shoreline position. The yearly mean shorelines were systematically computed at  
 386 each transect, with their 1984-2021 average further removed to obtain yearly shoreline position  
 387 around the mean  $\bar{S}$ . The time series of  $\bar{S}$  averaged along the entire 269-km coast is shown in Figure  
 388 12c. In order to only account for years when enough spatial coverage was obtained, we computed  
 389 the yearly percentage  $N$  of transects where SDS data are available showing that years with  
 390 consistently  $N > 90\%$  are from 1999 onwards (Figure 12a). However, it is important to note that the  
 391 space-averaged number of available images per year  $N_y$  has varied quite a lot over the years (Figure  
 392 12b) depending on the ongoing Earth observation missions, with a dramatic increase since 2016  
 393 thanks to Sentinel-2 mission. Hereafter the 1999-2020  $\bar{S}$  time series is thus used to explore the  
 394 correlation between climate indices and shoreline response.



395  
 396 Figure 11. Percentage of SDS data available per month  $N_m$  computed over 1984-2020 in southwest  
 397 France.





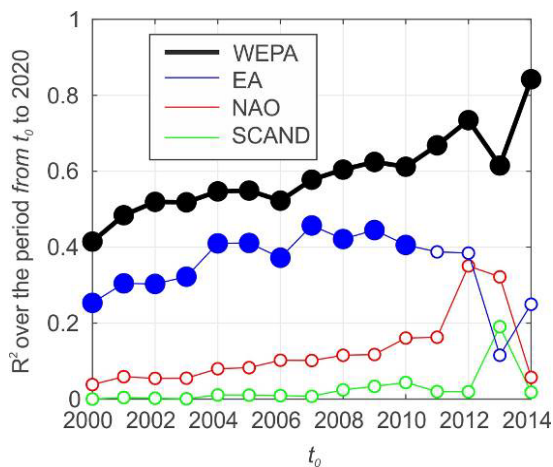
398

399 Figure 12. Time series of (a) yearly percentage  $N$  of transects where SDS data are available; (b) space-  
 400 averaged (along the entire sandy coast, Figure 8a) number of available SDS data  $N_y$ , (c) space-  
 401 averaged (along the entire sandy coast, Figure 8a) yearly-mean shoreline deviation from the mean  $\bar{S}$ ,  
 402 with the thick black dots indicating years with  $N > 90\%$ ; (d) winter WEPA climate index (coloured  
 403 bars) and superimposed  $d\bar{S}/dt$  (black dots) since 1999 showing a coefficient of determination  
 404  $R^2 = 0.42$ . Note that in (d) the  $d\bar{S}/dt$  axis is flipped, with positive WEPA generally driving shoreline  
 405 erosion ( $d\bar{S}/dt < 0$ )

406 Figure 12d shows a relationship between  $d\bar{S}/dt$  and WEPA over 1999-2020, with  $R^2 = 0.42$ , and  
 407 with erosion (accretion) observed for positive (negative) WEPA. A similar analysis was performed for  
 408 the other climate indices (not shown) indicating poorer correlation, with by decreasing skill EA ( $R^2 =$

409 0.25), NAO ( $R^2 = 0.04$ ) and SCAND ( $R^2 = 0$ ). A closer inspection of the link between WEPA and  
 410  $d\bar{S}/dt$  in Figure 12d suggests that the relationship increases when considering more recent periods  
 411 as the number of available images increases (Figure 12b) and higher resolution (10 m) satellites  
 412 operate (L8, S2).

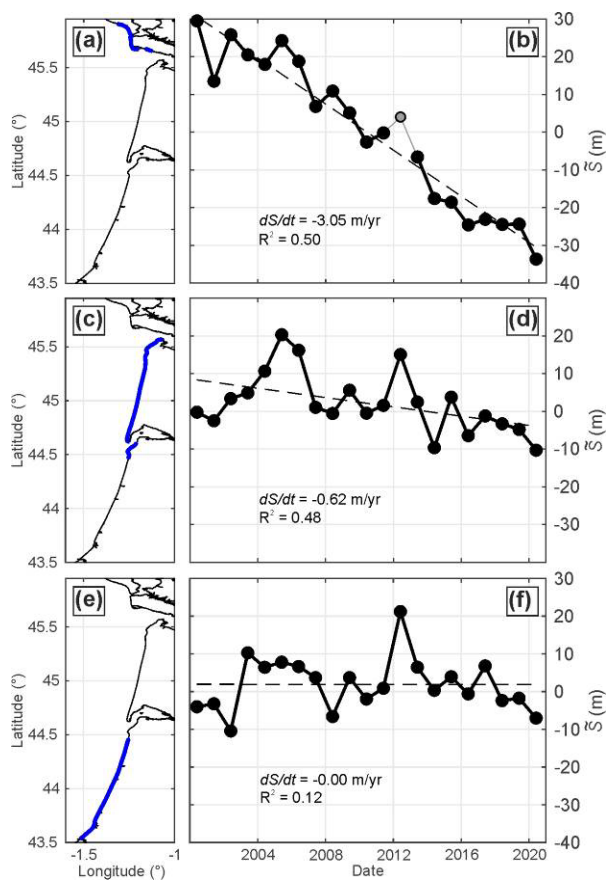
413 Figure 13 further demonstrates this increase in correlation between SDS interannual change and  
 414 winter climate indices by computing correlation between  $t_0$  and 2020, with varying  $t_0$ . Correlation is  
 415 systematically statistically significant and the largest with WEPA, once again followed by EA and NAO,  
 416 and with SCAND systematically showing poor correlation ( $R^2 < 0.2$ ). In addition  $R^2$  systematically  
 417 increases with increasing  $t_0$  which is in line with the hypothesis of larger correlation in recent years  
 418 with more and higher quality images. Importantly, between 2014 and 2020 ( $t_0 = 2014$ ),  $R^2 = 0.84$ ,  
 419 meaning that WEPA explains more than 80% of the observed space-averaged SDS interannual  
 420 response in southwest France.



421  
 422 Figure 13. Coefficient of determination  $R^2$  between yearly-mean shoreline deviation from the mean  
 423 change  $d\bar{S}/dt$  and different climate indices computed between  $t_0$  (varied) and 2020. Thick filled  
 424 circles indicate correlation statistically significant correlation ( $p < 0.05$ ).

425 This space-averaging of the yearly shoreline response masks a considerable alongshore variability.  
 426 This is emphasised in Figure 14 which divides the study area into three zones with contrasting  
 427 behaviours. North of the Gironde estuary mouth (Figure 14a), the 34-km long sector shows a time-

428 and space-averaged erosion of 3.05 m/yr with superimposed moderate (10-20 m amplitude)  
 429 interannual variability linked with WEPA ( $R^2 = 50$  over 1999-2020, Figure 14b). Further south, the  
 430 Gironde coast between the Gironde estuary in the north and Biscarrosse in the south (Figure 14c)  
 431 shows moderate erosion (0.62 m/yr) with large (20-30 m amplitude) interannual variability also  
 432 linked with WEPA ( $R^2 = 48$  over 1999-2020, Figure 14d). Further south, the Landes coast (Figure  
 433 14e) shows a stable shoreline ( $dS/dt = 0$ , Figure 14f) with moderate interannual variability (10-20 m  
 434 amplitude). Such alongshore variability will be further discussed in Section 5.



435  
 436 Figure 14. Left-hand panels: sectors (thick blue line) and in the right-hand panels their corresponding  
 437 space-averaged yearly-mean shoreline deviation from the mean  $\bar{S}$ , with the thick black dots  
 438 indicating years with  $N > 90\%$ . In the right-hand panels the dotted black line is the long-term (20-yr)  
 439 trend ( $d\bar{S}/dt$ ) and  $R^2$  the coefficient of determination with winter WEPA over 1999-2000. (a,b)  
 440 Charente-Maritime coast; (c,d) Gironde coast; (e,f) Landes coast.

441 **5. Discussion and conclusions**

442 Our SDS analysis (Figure 8) shows an overall eroding sandy coast with maximum shoreline evolutions  
443 located along sectors adjacent to the inlets and to the estuary mouth, where erosion and accretion  
444 alternate over time on the timescale of decades with an amplitude of 100s of metres. This is  
445 consistent with previous work based on historical orthophotos back to the 50s (Bernon et al., 2016;  
446 Castelle et al., 2018a). The time- and space-average shoreline evolution between 1984 and 2020  
447 indicates an overall erosion by 0.55 m/yr, which is half of the rate computed in Castelle et al. (2018a)  
448 between 1950 and 2014. However, in Castelle et al. (2018a) more than the half of the (stable) Landes  
449 coast was disregarded due to the absence of data in the 50s. Disregarding such sector in our SDS  
450 dataset shows an erosion of 0.7 m/yr, which is still under that computed over 1950-2014 in Castelle  
451 et al. (2018a), but closer to that computed between 1985 and 2014 (0.98 m/yr) in the same paper.  
452 The remaining difference may be explained by the uncertainties in both methods. Sea level rise (SLR)  
453 alone does not seem to explain such chronic large-scale erosion. For instance the Bruun rule (Bruun,  
454 1962), which is reasonable to apply along this coastline consisting of large beach-dune system with  
455 large accommodation space, predicts a SLR-driven shoreline retreat of approximately 0.14 m/yr using  
456 a SLR of 3.31 mm/yr over the last two decades and an active profile slope of 0.0235 according to  
457 D'Anna et al. (2020). The statistically significant increase of winter-mean wave height in this region  
458 associated with increased WEPA and NAO (Castelle et al., 2018b) can explain this larger observed  
459 erosion rate. Large-scale coastal sediment budget (Rosati, 2005), including variation in sediment  
460 supply by the rivers and the shelf, appears as another candidate to explain such long-term and large-  
461 scale erosive trend.

462 Long-term shoreline trend shows large spatial variability (Figure 8). Away from the tidal inlets and  
463 estuary mouths and away from stable sectors (e.g. the Landes coast in Figure 10h), long-term  
464 shoreline trends are fairly well correlated with the computed gradients in longshore drift with  
465  $\overline{dS/dt} \approx 7.10^{-3} dQ_s/dx$  (Figure 10). Following the one-line assumption that, on the long term, the  
466 profile translates parallel to itself without changing shape and with the longshore sand transport  
467 taking place uniformly over the entire beach profile from the depth of closure to the top of the dune,

468 the conservation of sediment gives  $dS/dt = (1/h)dQ_s/dx$ , with  $h$  the height of the active profile.  
469 Our computations therefore suggest an active profile height of approximately 142 m, which is much  
470 larger than that estimated at e.g. Truc Vert (around 37 m, D'Anna et al., 2021). Such difference may  
471 come from an overestimation of the longshore drift magnitude by a factor  $\approx 4$ , which is unlikely  
472 given that our values are in line with previous work building on other empirical longshore transport  
473 formula (Idier et al., 2013). Another more plausible explanation is that other processes are at work,  
474 such SLR-driven erosion, sediment supply and others implying a source/sink term such as  
475  $dS/dt = \left(\frac{1}{h}\right)\left(\frac{dQ_s}{dx} + q\right)$ . Estimating such, space- (and potentially time-) varying  $q$  or any other  
476 plausible hypothesis is out of scope.

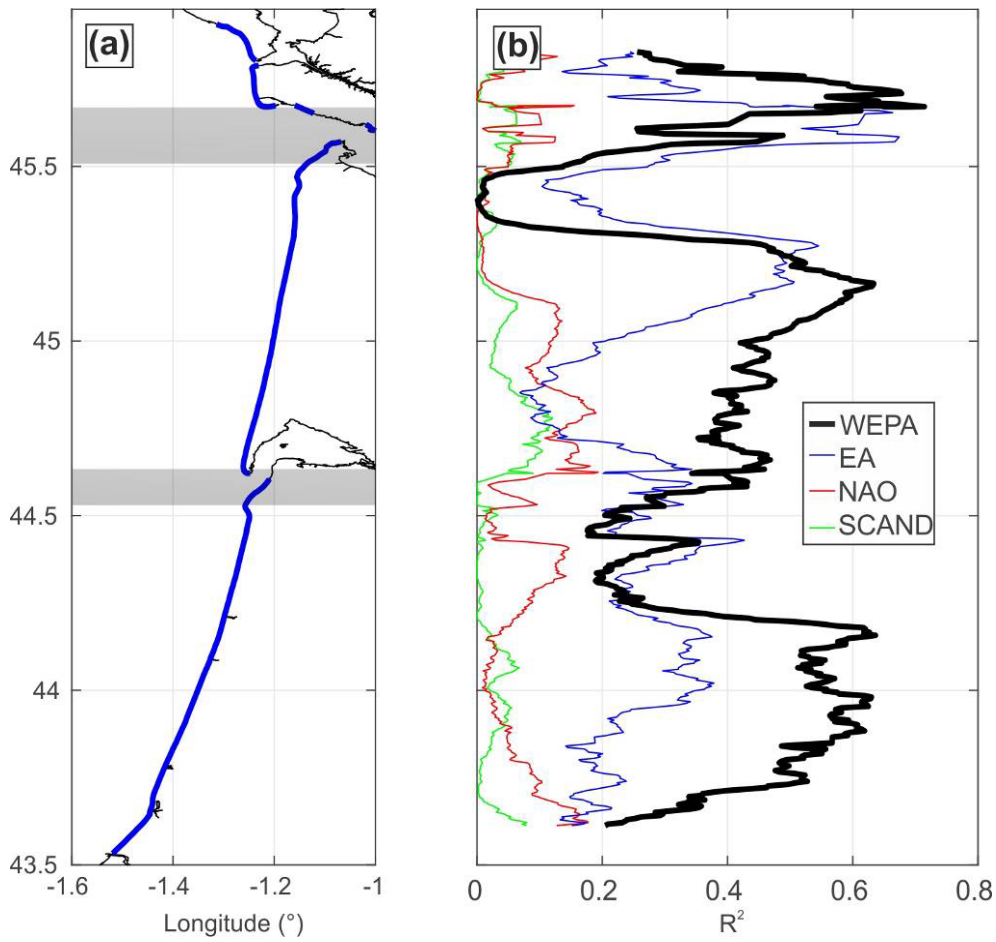
477 Despite SDS are associated with relatively large uncertainties in meso-macrotidal high-energy  
478 environments (Castelle et al., 2021), space averaging allowed unravelling different yearly shoreline  
479 response modes and the links with large-scale climate patterns of atmospheric variability (Figures 12,  
480 13 and 14). Consistent with earlier work on specific sites along the Atlantic coast of Europe (e.g.  
481 Castelle et al., 2017a; Burvingt et al., 2018; Dodet et al., 2019), interannual shoreline variability is  
482 well correlated with winter WEPA climate index. During the positive phase of WEPA, which reflects  
483 an intensified and southward shifted Icelandic low / the Azores dipole funnelling higher energy waves  
484 towards western Europe, erosion is observed (Figure 11c). The other teleconnection patterns explain  
485 only a little amount of the SDS interannual variability, with the notable exception of EA which can  
486 explain up to 40% (Figure 13). This is not surprising as the SLP-based WEPA index contains some  
487 variability of EOF-based teleconnection patterns (Scott et al., 2021), primarily NAO and EA which  
488 explain 8% and 36% of WEPA variability (Castelle et al., 2017b). Interestingly enough, in contrast with  
489 many *in situ* monitoring programs that have demonstrated the dramatic erosion caused by the  
490 winter of 2013/2014 (e.g. Blaise et al., 2015; Masselink et al., 2016; Pye and Blott, 2016; Burvingt et  
491 al., 2018; Garrote et al., 2018), the space-averaged SDS erosion during that winter is limited (Figures  
492 12c and 14). An explanation is that the SDS proxy, given that images taken at all tidal stages were

493 considered, is around the intersection of the beach profile with mean sea level elevation. As shown  
494 by the bimonthly beach monitoring program at Truc Vert, the impact of the 2013/14 winter was  
495 mostly observed at the dry beach and embryo dune with limited impact in the lower intertidal  
496 domain (Castelle et al., 2020, their figure 3 at Truc Vert, see also Nicolae Lerma et al., 2019). Limiting  
497 satellite images to higher water levels should make the 2013/14 winter impact standing up, as  
498 evidenced at Truc Vert using only near high-tide data (Castelle et al., 2021, their figure 10).

499 In our study WEPA explain > 40% of the interannual space-averaged shoreline variability over 1999-  
500 2000, a statistical relationship increasing when considering more recent periods (> 80% over 2014-  
501 2020) when the amount and quality of satellite images have both increased. In addition, over the last  
502 decade, the predominantly positive winter WEPA including some extremes like in 2013/14 (Figure  
503 11c) clearly resulted in an increased erosion with, on average, the shoreline retreating by over 20 m  
504 between 2012 and 2020 (Figure 11b). This may suggest that, in addition to SLR and large-scale  
505 sediment budget (Bruun, 1962; Rosati, 2005; Cooper et al., 2020), changes in the pattern and  
506 magnitude of winter wave height interannual variability may also impact long-term shoreline  
507 variability. This must be investigated on a longer term as such response may just be a cross-shore  
508 readjustment of the overall profile. Overall, such links between SDS interannual variability and  
509 climate indices calls for more research on the impact of climate change on wave height trends  
510 (Hemer et al., 2013; Morim et al., 2019, 2021) and on the climate modes of atmospheric variability  
511 (Smith et al., 2019, 2020).

512 The space averaging of SDS has already been found to provide unprecedented global insight into  
513 regional variability of long-term shoreline trends (Luijendijk et al., 2018). We advocate that the  
514 pursuing collection of free and publicly-available Landsat and Sentinel 10-m imagery in the next years  
515 and decades will make possible an accurate global assessment of the links between the dominant  
516 modes of climate variability on shoreline response globally, similar to what has been done for e.g.  
517 wave height (e.g. Shimura et al., 2013).

518 Figure 14 showed that the study area can be further divided into different sectors, revealing different  
519 long-term SDS trends and different relationships between winter WEPA and interannual SDS  
520 variability. To provide more insight into such alongshore variability in the correlation between  
521 climate indices and shoreline response, Figure 15 shows a similar analysis but with all climate indices  
522 (WEPA, NAO, EA and SCAND) and by applying a 20-km SDS moving averaged window over the period  
523 1999-2020. It confirms that WEPA is the dominant climate index in explaining shoreline interannual  
524 variability along most of the coast, followed by EA and well after NAO and SCAND. Results also show  
525 that correlation with WEPA (and the other indices) dramatically drops downdrift of the Gironde  
526 estuary mouth and Arcachon inlet, which is not observed updrift. This suggests that, along  $O(1-10$   
527 km) of coast downdrift of large-scale inlets and estuary mouths, shoreline response is controlled by  
528 factors internal to the estuary mouth / inlet system such as quasi-cyclic ebb-tidal delta dynamics  
529 from the timescales of months to years and decades (Cayocca, 2001; Ridderinkhof et al., 2016;  
530 Weidman and Ebert, 1993; Burvingt et al., submitted). Along the rest of the coast, even updrift fairly  
531 close to the inlet or estuary mouth, the shoreline interannual variability superimposed onto the long-  
532 term trend is controlled by factors external to the system which are primarily the variability in  
533 winter-mean wave height correlated to winter WEPA index. Noteworthy, less uncertain SDS data  
534 (e.g. through tide and/or runup correction, Vos et al., 2019a, 2020; Castelle et al., 2021) should  
535 result in more accurate correlations with the climate indices. Castelle et al. (2021) showed that, at  
536 Truc Vert beach in southwest France, interannual shoreline change correlation with WEPA increases  
537 by nearly 60% using tide and runup correction. We hypothesize that such correction could allow  
538 narrowing the moving average window and thus provide higher spatial resolution information on  
539 shoreline response. For instance, it could be used to address in more detail the internal – external  
540 control transition at the updrift sectors of the estuary and inlet mouths that is hypothesized to occur  
541 at a short (e.g. a few kilometres) distance from the mouth.



542

543 Figure 15. (a) Shoreline sector addressed here (thick blue line); (b) coefficient of determination  $R^2$   
 544 between, 10-km moving averaged, yearly-mean shoreline deviation from the mean change  $d\bar{S}/dt$   
 545 and different climate indices on the period 1999-2020.

546 The SDS analysis provided new insight into shoreline response and the primary drivers, which can  
 547 guide future numerical model application. For instance, we hypothesize that reduced complexity  
 548 models coupling cross-shore and longshore processes (e.g. Vitousek et al., 2017b; Robinet et al.,  
 549 2018; Antonilez et al., 2019) can be applied and further used for future shoreline prediction well  
 550 away from the downdrift zones of the major inlets and estuary mouths. Such models can then be  
 551 used to estimate sediment sources and sink through calibration with SDS. Further, prediction of  
 552 future shoreline change and their uncertainties will be made possible using a similar approach as  
 553 D'Anna et al. (2021).



554 A similar SDS analysis can be performed along any coastline in the world in order to guide future  
555 model development and application. In this frame, SDS are also a promising input for coastal  
556 modelling through data assimilation (Turner et al., 2021). We advocate that, by keeping the reduced-  
557 complexity model 'on the track', data assimilation will allow: (1) to both identifying the primary  
558 sources of model errors and understanding the links between time-varying free parameters and  
559 changes in environmental conditions but also (2) to impose shoreline boundary conditions at inlets  
560 and estuary mouths during hindcast thus extending their range of application.

### 561 **Acknowledgments**

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563 number ANR-21-CE01-0015. The *in situ* data used for the validation of SDS trends was collected and  
564 provided by the Observatoire de la Côte de Nouvelle-Aquitaine (OCNA). NORGAS-UG wave hindcast  
565 data provided by LOPS-Ifremer. EOF-based climate indices used in this study are publicly available for  
566 the period 1980–2017 (National Oceanic and Atmospheric Administration (NOAA) Climate Prediction  
567 Center; [www.cpc.ncep.noaa.gov](http://www.cpc.ncep.noaa.gov)). We thank Kilian Vos and the Water Research Laboratory for  
568 developing and making freely available the CoastSat toolkit.

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