

Uncertainties in Shoreline Projections to 2100 at Truc Vert Beach (France): Role of Sea-Level Rise and Equilibrium Model Assumptions

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1 2	Uncertainties in Shoreline Projections to 2100 at Truc Vert beach (France): Role of Sea-Level Rise and Equilibrium Model Assumptions
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12	
13	Key Points:
14 15	• Ensemble-based simulations of future shoreline evolution to 2100, including sea-level rise driven erosion, are performed and analysed
16 17	• Future shoreline projections uncertainties are initially controlled by modelling assumptions and after 2060 by sea-level rise uncertainties
18 19 20	• The choice of wave-driven equilibrium modelling approach and incident wave chronology are critical to short/mid-term shoreline projections

21 Abstract

Sandy shorelines morphodynamics responds to a myriad of processes interacting at different 22 spatial and temporal scales, making shoreline predictions challenging. Shoreline modelling 23 inherits uncertainties from the primary driver boundary conditions (e.g. sea-level rise and wave 24 forcing) as well as uncertainties related to model assumptions and/or misspecifications of the 25 physics. This study presents an analysis of the uncertainties associated with future shoreline 26 27 evolution at the cross-shore transport dominated sandy beach of Truc Vert (France) over the 21st century. We explicitly resolve wave-driven shoreline change using two different equilibrium 28 modelling approaches to provide new insight into the contributions of sea-level rise, and free 29 model parameters uncertainties on future shoreline change in the frame of climate change. Based 30 31 on a Global Sensitivity Analysis, shoreline response during the first half of the century is found to be mainly sensitive to the equilibrium model parameters, with the influence of sea-level rise 32 emerging in the second half of the century (~2050 or later), under several simulated scenarios. The 33 results reveal that the seasonal and interannual variability of the predicted shoreline position is 34 sensitive to the choice of the wave-driven equilibrium-based model. Finally, we discuss the 35 importance of the chronology of wave events in future shoreline change, calling for more 36 continuous wave projection time series to further address uncertainties in future wave conditions. 37 Our contribution demonstrates that unmitigated climate change can result in shoreline retreat of 38 several tens of meters by 2100, even for sectors that have been stable or slightly accreting over the 39 last century. 40

41 **1 Introduction**

Ongoing climate change is one of the largest concerns of our time, and its largest impacts on the world's environment are yet to come. Global mean sea-level rise is accelerating since 1870, and is expected to continue rising over the 21st century, although acceleration may be avoided if the Paris Agreement 'below 2°C climate warming' target is met (Church et al., 2013; Oppenheimer et al., 2019). In addition, global wave power is adapting to the sea surface temperature since the late 1940's (Reguero et al., 2019), and is expected to change along with storminess by 2100 (Morim et al., 2020).

Sandy beaches provide precious natural, structural and social-economical resources to coastal 49 communities (Ghermandi & Nunes, 2013; Poumadère et al., 2015), and constitute about one third 50 of the ice-free coasts worldwide (Luijendijk et al., 2018). Open sandy beaches constantly evolve 51 in response to multiple environmental drivers occurring on different time scales, making sandy 52 shoreline dynamics strongly sensitive to sea-level rise and wave climate change (Ranasinghe, 53 54 2016, 2020). Meanwhile, the expected growth of population density in low-lying coastal areas during the twenty-first century (Merkens et al., 2016; Neumann et al., 2015) increases the need for 55 efficient adaptation plans of coastal communities (Oppenheimer et al., 2019). 56

The spatial heterogeneity of sea-level rise (SLR), wave-climate change, time scales of adaptation, 57 and vulnerability of coastal communities raises the need for shoreline projections with their related 58 uncertainties that provide full support to risk-informed decision making process (Hinkel et al., 59 2019; Losada et al., 2019; Toimil et al., 2018, 2020; Wainwright et al., 2015). However, limits in 60 our understanding and modelling capacity of the primary processes driving shoreline change, 61 together with the uncertainties associated to the future climate (e.g. carbon emission scenario, SLR, 62 storminess, etc.), undermine the confidence in future shoreline estimates proportionally to the time 63 scale of application (Ranasinghe, 2020; Toimil et al., 2020). Many studies focused on the effects 64 of SLR uncertainties (Athanasiou et al., 2020; Le Cozannet et al., 2016, 2019; Thiéblemont et al., 65 66 2021; Vousdoukas et al., 2020) and changes in storminess based on data extrapolation and/or empirical models (Allenbach et al., 2015; Casas-Prat et al., 2016; Toimil et al., 2017; Vousdoukas 67 et al., 2020) on future shoreline uncertainties. However, these studies do not explicitly resolve 68 69 wave-driven shoreline change, and it is advocated that new methods have to be developed to 70 predict the impacts of SLR on the coast (Cooper et al., 2020). Short- and long-term variability in wave energy, as well as the chronology of storm events, can strongly affect future shoreline 71

patterns (Besio et al., 2017; Cagigal et al., 2020; Coco et al., 2014; Dissanayake et al., 2015; 72 Vitousek et al., 2021). Recently, Cagigal et al. (2020) developed and used a stochastic climate-73 based wave emulator to generate ensembles of wave time series at several beaches, and addressed 74 shoreline response to different wave chronologies. Based on the same emulator, Vitousek et al. 75 (2021) analytically investigated the uncertainties in shoreline predictions associated to the inherent 76 77 variability of the wave climate in the context of equilibrium shoreline modelling. Kroon et al. (2020) showed the significant effects of wave-climate variability and model uncertainty on the 78 short-term (1 year) probabilistic assessment of coastline change at the Sand Engine (Netherlands). 79 The authors used a one-line model, i.e. resolving wave-driven longshore sediment transport 80 gradients and resulting shoreline evolution, as this stretch of coast is longshore transport 81 ~ dominated. 82

Currently, there are no studies addressing the time evolution of the effects that uncertainties in 83 future SLR and model parameters have on shoreline projections to the end of the 21st century while 84 explicitly resolving wave-driven shoreline response. The recent development of equilibrium 85 shoreline models opened the way to skilful simulation of wave-driven shoreline response on cross-86 shore transport dominated sites, which are ubiquitous worldwide, on time scales from hours (storm 87 events) to decades, with low computational cost (Antolínez et al., 2019; Davidson et al., 2013; 88 89 Lemos et al., 2018; Robinet et al., 2018; Splinter et al., 2014a; Vitousek et al., 2017; Yates et al., 2009). Equilibrium shoreline models are based on the principle that the shoreline dynamically 90 moves towards a time-varying equilibrium condition (Wright & Short, 1984), which can be 91 92 expressed as a function of the current shoreline position (Yates et al., 2009) or antecedent wave conditions (Davidson et al. 2013). While the two latter equilibrium formulations show similar skill 93 against shoreline observations on a multi-year timescale (Castelle et al., 2014; Montaño et al., 94

95 2020), the accuracy of one approach over the other in different wave forcing scenarios is unclear, particularly on long timescales (multi-decadal). In addition, in this type of models, sediment 96 transport processes are described by semi-empirical relationships that require site-specific 97 calibration against observed shoreline data, introducing further uncertainty (D'Anna et al., 2020; 98 Splinter et al., 2013). Implementations of cross-shore equilibrium models into probabilistic 99 100 frameworks recently showed that uncertainties in the calibration of model free parameters (D'Anna et al., 2020) and in future wave conditions (Vitousek et al., 2021) have a significant 101 impact on model predictions. In addition, recent studies found an inherent connection between the 102 103 seasonality of wave climate and shoreline model parameters that defines the frequency of shoreline response, for several beaches along the Australian coast (Ibaceta et al., 2020; Splinter et al., 2017). 104 SLR-driven shoreline retreat is often estimated using the Bruun (1962) model. This model relates 105 the rate of shoreline erosion to the SLR rate and the average slope of the active beach profile, 106 defined between the seaward and landward limits of cross-shore sediment exchange. The seaward 107 limit of the active beach profile is commonly identified by the depth of closure (Hallermaier, 108 1978). As local scale bathymetric surveys are scarce and the estimation of the depth of closure is 109 essentially empirical, the active beach profile slope is typically associated with large uncertainties 110 (Nicholls, 1998; Ranasinghe et al., 2012). 111

In this work, we aim at deepening our understanding in the role and impact of different uncertainties in shoreline projections. We perform a Global Sensitivity Analysis (GSA) (Saltelli et al., 2008) to unravel the respective contributions of SLR, depth of closure, and shoreline model free parameters uncertainties. The framework is applied to the cross-shore dominated Truc Vert beach (SW France) using two different wave-driven shoreline models, the Bruun model, and stateof-the-art SLR and wave projections for two future Representative Concentration Pathways (RCP)

118 scenarios. The likely range provided along with median SLR estimates in IPCC reports does not cover the full uncertainty range of mean sea level projections. Hence, there remains a probability 119 of up to 33% that sea-level rise exceeds the likely range. Therefore, we also assess shoreline 120 121 projections in the deterministic high-end SLR scenario, which remains unlikely but plausible and is associated with large impacts (Stammer et al 2019). The remainder of this paper includes: an 122 outline of Truc Vert beach, the data, the shoreline models, and the method (Section 2); a 123 description of the GSA input variables' probability distributions and the numerical modelling setup 124 (Section 3); and the presentation of the results (Section 4). Discussion and conclusions are 125 126 provided in Section 5 and 6, respectively.

127 2 Study site, data and method

128 2.1 Truc Vert beach

Truc Vert is a meso-macrotidal wave dominated sandy beach located in the south of the Gironde 129 coast, southwest France, which extends roughly 100 km between the Gironde river estuary and the 130 131 south of the Arcachon basin (Figure 1a,b). Truc Vert is backed by a high (~20 m) and wide (~250 m) coastal dune system (Robin et al., 2021). The wave climate is characterized by strong seasonal 132 energy fluctuations, and strong interannual winter energy variability (Castelle et al., 2018a; 133 134 Charles et al., 2012; Robinet et al., 2016), the latter associated to large-scale climate patterns of 135 atmospheric variability in the northeast Atlantic region (Castelle et al., 2017). Monthly-averaged significant wave height ranges from 1.1 m in August with dominant W-NW direction to 2.4 m in 136 January with dominant W direction. Truc Vert beach has been intensively monitored since 2003 137 with monthly to bi-monthly topographic DGPS surveys, with additional daily topographic surveys 138 and high-resolution bathymetric surveys collected during the ECORS'08 field campaign (Parisot 139 et al., 2009), see Castelle et al. (2020) for detailed description of the datasets. Since 2017, high-140 resolution digital elevation model covering 4 km of beach-dune are also derived seasonally from 141 photogrammetry of UAV images (Laporte-Fauret et al., 2019). 142

The beach morphology is highly dynamic and responds primarily to cross-shore processes driven by the temporal variability of the incident wave climate (Castelle et al., 2014; Robinet et al., 2016, 2018). Overall, this segment of coastline has been observed to be reasonably stable over the past decades (Castelle et al., 2018b), although the interannual distribution of winter wave energy may result in episodic severe beach and dune erosion (Castelle et al., 2015; Masselink et al., 2016). 149



Figure 1 (a) Location of Truc Vert beach (green), wave hindcast grid point co-located with the CANDHIS in situ wave buoy (red), and wave projections grid point (yellow); (b) Picture of Truc Vert beach and dune landscape (photo by V. Marieu); (c) 4 km alongshore-averaged beach-dune profile from merged 2008 topo-bathymetry (submerged beach) and 2018 UAV-photogrammetry digital elevation model (emerged beach and dune); (d) Mean shoreline (1.5-m beach profile elevation proxy) positions between 2011 and 2020 derived from the bimonthly topographic surveys.

157 2.2 Wave data: historical and projections

While a dataset of future waves is required to simulate future shoreline change, hindcast wave data were also needed for the present study in order to: (1) run the shoreline models on the past period and estimate the distribution of the model parameters; and (2) support the correction of the wave projection dataset.

162

2.1.1 Hindcast wave data (1994-2020)

163	Historical wave data (H_s , T_p , and D_m), from January 1994 to January 2020, was extracted from the
164	NORGAS-UG regional hindcast model (Michaud et al., 2016) at the grid point co-located with the
165	in situ CANDHIS wave buoy (44°39'9" N; 1°26'48" W) moored in ~50 m depth offshore of Truc
166	Vert beach (Figure 1a). The NORGAS-UG model covers the French Atlantic coastal area using an
167	unstructured mesh grid with resolution of 10 km offshore, increasing to 200 m nearshore. The
168	wave model was validated against several French and international wave buoy data, and showed
169	0.96-0.99 correlations coefficients, 0.15-0.21 m RMSE, and -0.02 to 0.04 m bias (Michaud et al.,
170	2016). The hindcasted wave time series (1994-2020) shows the typical seasonal and interannual
171	modulation of the incident wave climate at Truc Vert beach (Figure 2a).

172

2.2.2 Future wave climate (2020 - 2100)

Wave-driven shoreline change at cross-shore transport dominated sites is controlled by the 173 variability in incident wave energy including temporal clustering and chronology of storm wave 174 events (Splinter et al., 2014b; Dissanayake et al., 2015; Angnuureng et al., 2017). Thus, the 175 assessment of future shoreline evolution at Truc Vert requires a continuous wave time series with 176 high resolution (e.g. few hours). Bricheno and Wolf (2018) (hereafter BW18) provide state-of-the-177 art wave projections throughout the 21st century in the Northeast Atlantic region for the RCP8.5 178 179 and RCP4.5 scenarios. As part of the Coordinated Ocean Wave Climate Project (COWCLIP), 180 BW18 wave data belong to an ensemble of global and regional wave climate projections, forced with several Global Climate Models and using different wave models. Within COWCLIP, changes 181 were found to be robust in the North Atlantic region, suggesting a slight decrease of annual mean 182 183 H_s and a clockwise rotation of waves off the Aquitanian coast that is more pronounced for high 184 climate forcing (Morim et al., 2019). However, amongst the COWCLIP ensemble, to our knowledge, only BW18 produced uninterrupted time series of wave data with sufficient spatial 185

resolution to properly reproduce the wave climate offshore our study site. The continuous hourly 186 time series of wave conditions was produced by BW18 using a dynamical downscaling approach 187 and a nested setup of the WaveWatchIII® spectral wave model (Tolman, 2009). The wave model 188 covers the Northwest European coastal area with a grid resolution of 0.083° (<9 km) and was 189 forced with the downscaled EC-Earth global climate model (Hazeleger et al., 2012). For both RCP 190 191 scenarios, BW18 model is run from 2006 to 2100 in a regional atmospheric model configuration (~0.11° resolution), in the context of the EURO-CORDEX project. BW18 also provide the results 192 of a historic model run, forced with the EC-Earth model climate, for the period 1970-2004. Such 193 194 simulation is needed to estimate relative change between past and future wave climate or for the correction of the potential biases between the modelling results and reference wave data (e.g. wave 195 buoy data or modelled wave hindcast), which result from climate models bias (see e.g. Charles et 196 al., 2012). From the BW18 modelling, we extracted wave data (H_s , T_p , and D_m) over 2020-2100 197 (for shoreline projections) from the nearest grid point to the CANDHIS wave buoy (~3 km North-198 East; Figure 1a), in ~50 m depth, for both RCP8.5 and RCP4.5 scenarios. To reduce the bias in 199 modelled future waves, we analysed the seasonal quantiles of the 1994-2004 portion of BW18 200 historic wave time series (extracted at the same location as the 2020-2100 wave data) and the 201 seasonal quantiles of the NORGAS-UG hindcast, and set-up a seasonal quantile-quantile 202 correction that we applied to the 2020-2100 wave dataset (details in Text S1 of Supporting 203 Information). The corrected BW18 wave time series for RCP8.5 and RCP4.5 scenarios are shown 204 205 in Figure 2b and Figure 2c, respectively. Hereon, we refer to BW18 as the corrected wave time series. 206



Figure 2 Wave data offshore of Truc Vert, including: time series of H_s (black lines) and 3-month averaged $H_s^2 T_p$ (red lines) for (a) the 1994-2020 wave hindcast from NORGAS-UG model (44°39'9" N; -1°26'48" W), and (b) RCP8.5 and (c) RCP4.5 scenarios corrected 2020-2100 Bricheno and Wolf (2018) wave projections; linear trends (solid lines) of annual (d) summer and (e) winter mean H_s (dashed lines) of 2020-2100 corrected Bricheno and Wolf (2018) wave projections, for RCP4.5 (blue) and RCP8.5 (orange) scenarios. For RCP8.5 (RCP4.5), the trend of

summer and winter mean H_s are -2 mm/year (-1 mm/year) and -0.05 mm/year (-0.05 mm/year). These trends were tested to be statistically significant (more than 99% significance) using Student's t-tests. (f) Quantile-quantile comparison between RCP4.5 and RCP8.5's 3-month average of $H_s^2 T_p$ projections for the four seasons (black crosses) and for the full datasets (grey circles).

219

Here, we adopted $H_s^2 T_p$ (m²s) as a representative variable for deep-water wave energy. The 220 RCP8.5 and 4.5 2020-2100 wave series show a strong interannual modulation of incident wave 221 energy, which is in line with current wave climate characteristics offshore of Truc Vert. Both 222 scenarios of the BW18 wave projections show several peaks of the 3-month average $H_s^2 T_p$ that are 223 comparable to the 2013-2014 outstanding high-energy winter ($H_s^2 T_p = 178 \text{ m}^2 \text{s}$) experienced at 224 Truc Vert (Figure 2a-c). For the RCP8.5 (RCP4.5) scenario, the projected 3-month average $H_s^2 T_p$ 225 reaches at least 90% of the 2013-2014 peak in 2030, 2080, 2086, and 2099 (2060, 2068, 2073 and 226 2085) (Figure 2b,c). While characterized by similar integrated intensity, these winters are preceded 227 by different multi-annual energy trends, with the RCP8.5 (RCP4.5) 2080, 2086 and 2099 (2060 228 and 2068) winters following a positive trend of wave energy (similarly to the 2013-2014 winter), 229 and the 2030 (2060 and 2068) winter following a negative trend of winter energy. Although in 230 both RCP scenarios the incident wave energy fluctuates with a similar interannual period with 231 nearly the same average $H_s^2 T_p$ (52 and 54 m²s for RCP8.5 and RCP4.5, respectively), the RCP4.5 232 scenario associates slightly higher energy during Autumn, Summer and Spring (Figure 2f). The 233 2020-2100 summer mean wave height ($\overline{H_s}_{summer}$) fluctuates between 0.9 m and 1.7 m, with a 234 statistically significant decrease of 2 mm/year (1 mm/year) rates for the RCP8.5 (RCP4.5) (Figure 235 2d). Future winter mean wave height $(\overline{H_s}_{winter})$, which is a key driver of cross-shore wave-236 dominated shoreline evolution (Dodet et al., 2019), varies between 1.5 m and 3 m with a 237

statistically significant decreasing trend under 0.05 mm/year in both RCP scenarios (Figure 2e).
This is consistent with previous regional projections (Charles et al., 2012; Perez et al., 2015;
Morim et al., 2019).

241

2.3 Mean sea level and vertical land motion

242

2.3.1 Past mean sea level reconstruction

As SLR-driven shoreline retreat is explicitly accounted for in the calibration of the shoreline 243 models, past MSL information is required. We reconstructed the geocentric MSL change in the 244 Bay of Biscay over the period 2012-2020 using a Kalman filter approach assimilating available 245 tide gauge records in this region (Rohmer & Le Cozannet, 2019). The resulting SLR rates are 246 roughly constant at 2.1 \pm 0.1 mm/year (median $\pm \sigma$). Local relative MSL change at Truc Vert beach 247 was calculated by adding the effect of vertical land motion to the relative regional sea level 248 estimate. Vertical land motion in Truc Vert area was estimated using the near Cap-Ferret 249 250 permanent GNSS station from the SONEL database (Santamaria-Gomez et al., 2017), which provides data from 2005 to 2012, when the station was decommissioned. The GNSS station 251 measures the effects of Glacial Isostatic Adjustment and current gravitational, rotational and 252 deformation changes associated to ongoing glaciers and ice-sheets melting (Frederikse et al., 253 2020). We subtract their effects from the observed GNSS records over the observation period to 254 assess residual vertical ground motions obtaining a subsidence rate of 1.2 ±0.6 mm/yr. This results 255 in a roughly constant SLR rate of 3.3 ± 0.7 mm/yr over the past decade (see Figure S5 of Supporting 256

Information). The observed lowering ground might be due to slow subsidence of the former Leyre
riverbed (Klingebiel & Legigan, 1992).

The pointwise Cap-Ferret GNSS station information may not be exactly that of the surrounding area. This is part of the residual uncertainties of our study.

261

2.3.2 Future mean sea level projections

State-of-the-art GMSL projections until 2100 are available from the Special Report of Ocean and 262 Cryosphere in a Changing Climate (SROCC, Oppenheimer et al., 2019). SROCC estimates build 263 on the Fifth Assessment Report (AR5, Wong et al., 2014) with a revised assessment of the Antarctic 264 dynamics contribution based on new evidence on marine ice-sheets instabilities since the AR5. 265 SROCC provides median values of each sea level change contribution with associated *likely range* 266 for several RCP scenarios. Unlike other IPCC reports, the SROCC defines the likely range as the 267 17th-83rd percentiles of the distribution of sea-level rise (Oppenheimer et al., 2019). We reproduced 268 the SROCC global MSL projections to Truc Vert beach following Thiéblemont et al. (2019) and 269 considering the regional fingerprints of each mechanism contributing to sea-level changes, 270 including the effect of Glacial Isostatic Adjustment (Slangen et al., 2014). This results in regional 271 relative 2020-2100 SLR estimate (median and likely range) of 0.63 \pm 0.26 m and 0.37 \pm 0.16 m for 272 the RCP8.5 and RCP4.5 scenarios, respectively. 273

Residual vertical land motion, which is assumed to be due to slow-ongoing geological processes (see subsection 2.3.1 and Klingebiel & Legigan, 1992), is assumed to remain constant (1.2 ± 0.6 mm/yr) over the 21st century. Due to the large uncertainty (0.6 mm/yr) of the subsidence rate, the stability of the area is not excluded, but has a very low probability (2.1%). The inclusion of ground motion results in a local relative MSL rise of 0.73 ±0.27 m and 0.47 ±0.17 m from 2020 to 2100 for RCP8.5 and RCP4.5 scenarios, respectively (see Figure S5 in Supporting Information). Further
 detail on future SLR is provided in Section 3.1.

281 2.4 Shoreline change models

Here, we use two equilibrium-based models to assess wave-driven shoreline response; the Yates 282 et al. (2009) model, and an adaptation of the ShoreFor model (Davidson et al., 2013; Splinter et 283 al. 2014a). As the Truc Vert bathymetry iso-contours are essentially shore-parallel, breaking wave 284 conditions were computed directly from offshore wave conditions using the Larson et al. (2010) 285 formula. Chronic shoreline retreat induced by SLR was estimated using the Bruun (1962) model. 286 As shoreline change at Truc Vert is known to be dominated by cross-shore sediment transport with 287 negligible gradients in longshore transport (Castelle et al., 2014; Splinter et al., 2014a), we did not 288 compute longshore sediment transport. The following subsections describe the two wave-driven 289 290 shoreline models and the Bruun model.

291 2.4.1 Wave-driven shoreline models and free parameters

Equilibrium shoreline models are based on the principle that local wave climate drives the shoreline towards a time-varying equilibrium position at a rate that depends on the instantaneous wave thrust (e.g. wave power or energy) available to move the sediment, and the dynamic disequilibrium state of the beach (Wright & Short, 1984). The Yates et al. (2009) model and *ShoreFor* differ primarily in the formulation of the respective disequilibrium conditions.

297 2.4.1.1 *ShoreFor* model

The *ShoreFor* model (hereafter SF) adopts a disequilibrium condition based on the wave history, expressed as a disequilibrium of dimensionless fall velocity ($\Delta \Omega$) and its standard deviation ($\sigma_{\Delta \Omega}$). The governing equation for shoreline change rate reads:

301
$$\frac{dY}{dt} = k_s^{+/-} P^{0.5} \frac{\Delta\Omega}{\sigma_{\Delta\Omega}} + b \quad (1)$$

where, $k_s^{+/-}$ (m s⁻¹W^{-0.5}) is a response rate parameter, P(W) is the wave power at breaking, and 302 b(m/s) is a linear term trend. Following Robinet et al. (2018), the disequilibrium term $\Delta \Omega$ at a given 303 time is defined as the difference between the equilibrium dimensionless fall velocity ($\Omega_{eq}(\Phi)$) and 304 the offshore dimensionless fall velocity (Ω_0), where $\Omega_{eq}(\Phi)$ is a function of the sediment size, prior 305 wave conditions, and the free parameter Φ . The parameter Φ (days) is a site-specific 'beach 306 memory', and defines the time over which a given wave event has an impact over the equilibrium 307 state of the beach. The $k_s^{+/-}$ parameter is the shoreline response rate, and assumes different values 308 for accretion $(k_s^+, \Delta \Omega > 0)$ and erosion $(k_s^-, \Delta \Omega < 0)$ events, which are driven by different processes 309 associating different time scales. The values of the k_s ^{+/-} parameter for accretion and erosion 310 conditions are considered proportional through a coefficient $r(k_s^- = rk_s^+)$. The r coefficient is not 311 a model free parameter but is defined by the wave forcing, and is such that no trend in wave forcing 312 results in no trend in the modelled shoreline position over the simulated period: 313

314
$$r = \left| \frac{\sum_{i=1}^{N} \langle F^+ \rangle}{\sum_{i=1}^{N} \langle F^- \rangle} \right| \quad (2)$$

315
$$F = P^{0.5} \frac{\Delta \Omega(\Phi)}{\sigma_{\Delta \Omega}} \quad (3)$$

where *N* is the full length of the simulated period, F^+ and F^- are the forcing during accretion ($\Delta\Omega$ >0) and erosion ($\Delta\Omega$ <0) events, respectively, and $\langle . \rangle$ denotes an operation that removes the linear trend. Here, the sign of $\Delta\Omega$ does not change the absolute value of $F^{+/-}$. For an extended description of SF the reader is referred to Davidson et al. (2013) and Splinter et al. (2014a). In SF, the model free parameters to be calibrated at a given site are k_s^+ , Φ and *b*. Physically, the $k_s^{+/-}$ (m s⁻¹W^{-0.5}) is a measure of the efficiency of wave forcing to drive shoreline change (as described by Splinter et al., 2014a), which can also be interpreted as a time scale of shoreline response (Vitousek et al.,

2021). Indeed, a low efficiency corresponds to a slow shoreline response and a longer time scale, 323 and vice versa. $\Phi(days)$ is a time scale for the duration of the impact that past waves exerted on 324 the beach, and provides the ability for the model equilibrium condition to evolve along with long-325 term wave energy trends. The parameter b(m/s) is a linear term that encapsulates the effect of slow 326 processes, other than wave-driven equilibrium based, which may drive chronic shoreline change 327 (e.g. wind driven sediment transport) and that are not explicitly resolved in the model. We note 328 here that, while accounting for the effects of slow processes using a constant linear trend (i.e. b) 329 can improve the model skill for simulated periods within the decade, the application of such trend 330 over longer time scales (decades to centuries) becomes increasingly inaccurate (D'Anna et al., 331 2020). Therefore, given the long time scale of our application and the absence of secondary 332 processes (e.g. longshore gradients in sediment transport) that may drive long-term shoreline 333 trends at Truc Vert, we set b=0. 334

335 2.4.1.2 Yates model

In Yates' model (hereafter Y09) the disequilibrium condition is defined as a function of the current
 shoreline position, and the cross-shore rate of shoreline change is calculated as follows:

338
$$\frac{dY}{dt} = k_y^{+/-} E^{0.5} (E_{eq}(Y) - E) \quad (4)$$

where $E(m^2)$ is the wave energy, $k_y^{+/-}(m^2 \text{ s}^{-1}/\text{m})$ is the response rate parameter, Y(m) is the present shoreline position, and $E_{eq}(Y)$ is the wave energy in equilibrium with the current shoreline position *Y* through a linear relationship:

342

$$E_{eq}(Y) = a_1 Y + a_2$$
 (5)

where a_1 (m²/m) and a_2 (m²) are free model parameters. The $k_y^{+/-}$ parameter is analogous to $k_s^{+/-}$ of SF in that it represents the efficiency rate of the incident wave forcing to shoreline change, or a time scale parameter (see the analytical derivation of the Y09 time scale of shoreline response in

Vitousek et al., 2021). In the Y09 model no assumption is made on a possible relationship between 346 the k_v^+ and k_v^- , which are both considered model free parameters and, as well as a_1 and a_2 , require 347 specific calibration for each field site application. Contrarily to SF, here the equilibrium state 348 formulation (Equation 5) does not depend on recent wave conditions, making this model 349 insensitive to wave-climate variability on timescales longer than the calibration period. Instead, 350 351 Equation 5 depends on the current shoreline position (Y), introducing the potential for feedbacks between Y09 and shoreline change induced by other cross-shore processes (e.g. SLR). Herein, 352 such processes are resolved independently and linearly superposed, so that no feedback is enabled. 353 Physically, $k_v^{+/-}$, once again is a measure of the shoreline reactivity to the incident wave forcing, 354 and is expressed in (m s⁻¹/m). Although the dimensions of a_1 and a_2 are 'energy/meter' and 355 'energy', respectively, the role of these parameters in the model is purely empirical. A 356 rearrangement of the terms in Equations 2-3 results in combinations of model parameters that are 357 representative of equilibrium time and spatial scales (Vitousek et al., 2021). However, here we use 358 Y09 in its original form, where a_1 and a_2 are treated as empirical parameters. 359

360 2

2.4.2 Sea-level driven shoreline recession

We include SLR-driven shoreline recession using the Bruun (1962) model, which is based on the 361 equilibrium beach concept and cross-shore balance of sediment volume. While the reliability of 362 this model is highly debated for its oversimplification of the reality (Cooper & Pilkey, 2004; 363 Ranasinghe, 2012), its simple linear formulation has been extensively used worldwide. In addition, 364 365 Truc Vert beach is a relatively undisturbed beach-dune environment with large accommodation space, which makes this sites in line with most of the Bruun Rule underlying assumptions. The 366 Bruun model assumes that under rising sea level, on time scales larger than years, the average 367 368 beach profile translates upwards and landwards. The resulting shoreline retreat (dY_{SLR}/dt) depends

on SLR and the average slope of the active beach profile, here extending from the dune crest down
to the depth of closure (DoC), defined as the depth beyond which sediment exchange is considered
negligible (Bruun, 1988; Wolinsky & Murray, 2009):

$$\frac{dY_{SLR}}{dt} = \frac{SLR_{rate}}{tan\beta} \tag{6}$$

where SLR_{rate} is the rate of SLR (m/time), and $tan\beta$ is the average profile slope defined between the DoC and the dune crest. We estimated the DoC according to Hallermeier (1978), and the corresponding $tan\beta=0.023$ using the beach profile reported in Figure 1c.

376 2.5 Global Sensitivity Analysis

Numerical modelling of shoreline change inherits the uncertainties associated to input variables 377 and their complex interactions, affecting the robustness of the shoreline projections. While 378 numerical modelling provides a 'key-hole' to observe the explicit interactions among defined sets 379 of variables, sensitivity analysis provides a way to understand the role of input variables 380 uncertainties in shoreline predictions. Here, we use the framework proposed by D'Anna et al. 381 382 (2020), who used a variance-based Global Sensitivity Analysis (GSA) (Saltelli et al., 2008; Sobol', 2001) to investigate the relative contributions of the uncertainties affecting input variables to the 383 uncertainties of modelled shoreline predictions, and their evolution in time. The method consists 384 in propagating the input uncertainties through the model obtaining a probabilistic estimate of the 385 shoreline projections, and performing a GSA which decomposes the variance of model results into 386 several contributions, each one associated with an input variable. Each of these contributions is 387 used to estimate a measure of the model results sensitivity to the input uncertainties with a 388 sensitivity index known as *first-order Sobol' index* (S_i). The S_i (0-1) quantifies the ratio of output's 389

variance associated with the uncertainties of a given input X_i , i.e. the reduction in the output variance that would occur if the uncertain input X_i was set to its true value, and is defined as:

$$S_i = \frac{Var(E(Y|X_i))}{Var(Y)}$$
(7)

where *Var* is the variance operator, *E* is the expectation operator, *Y* is the modelled shoreline position, and X_i is the i-th uncertain input variable. Further details on GSA and S_i are provided in Text S3 of Supporting Information.

Here, we address the relative impact of uncertainties associated to SLR, DoC and of model free 396 397 parameters on shoreline projections (Y) and their evolution in time for the two different modelling approaches described in Section 2.4. Identifying the main source of model results uncertainties 398 through time is a fundamental step towards improving the reliability of long-term shoreline 399 projections. Following D'Anna et al. (2020), we computed the S_is using the modularized sample-400 based approach by Li and Mahadevan (2016), which allows accounting for the statistical 401 dependence between model free parameters, and we estimate S_i s for the purpose of "Factors" 402 Prioritization" (as defined by Saltelli et al., 2008). At a given time, the Factors' Prioritization 403 404 identifies the main driver of model results uncertainty (associating the largest S_i), that is, the uncertain input variable that would most reduce the output's variance when fixed to its true value. 405 The method can be summarized in three steps: 406



- 409 2) Generation of ensemble modelled shoreline projections, by means of a Monte-Carlo-based
 410 procedure (with accounts for dependence among the input parameters); and
- 411 3) Computation of first-order Sobol' index time series for each uncertain input variable.

The GSA results are interpreted as the repartition of the variance of shoreline projections into normalized portions (between 0 and 1) imputed to the uncertain input variables. For instance, at a given time, $S_{i,SLR} = 0.3$ means that uncertainties in future SLR alone are responsible for 30% of the variance in shoreline projections. However, the magnitude of a S_i alone is not sufficient to identify the main driver of the shoreline projections' variance, which is defined by comparing the values of S_i for all input variables and ranking them in terms of importance. Figure 3 synthesizes the generalized method and details for the Truc Vert probabilistic applications

419 (excluding the additional high-end SLR deterministic scenario).



420

Figure 3 Flowchart of the method applied herein, summarized for a general case (black box), and
for the Truc Vert application (red box) in the four application scenarios.

423 **3 Input probability distributions for future projections**

- 424 3.1 Probabilistic sea-level rise
- 425 Sea-level projections inherit uncertainties associated with physical unknowns and modelling of the
- 426 contributing processes. While many efforts were dedicated to assess such uncertainties, there is no

single approach to define MSL probability distributions yet (Jackson & Jevrejeva, 2016; Jevrejeva 427 et al., 2019; Kopp et al., 2014). We produced probabilistic relative MSL projections, conditional 428 to the RCP8.5 and 4.5 scenarios, defining time varying normal probability distributions 429 characterized by the yearly median and standard deviations obtained in Section 2.3.2 (Figure 4a,b), 430 following Hunter et al. (2013). In the high-emission scenario (RCP8.5), the large uncertainty 431 432 associated with Antarctic ice sheet dynamics generates a skewness of the distributions in the second half of the 21st century, enhancing the amount of possible extreme SLR (Grinsted et al., 433 2015; Jackson & Jevrejeva, 2016; Kopp et al., 2014). The upper tail of the skewed probability 434 distribution is very much debated (Jevrejeva et al., 2019) and is not represented by the Gaussian 435 distributions. Therefore, in addition to the Gaussian distribution reflecting the SROCC assessment 436 (Oppenheimer et al., 2019), we consider a high-impact, low probability high-end sea level scenario 437 that might take place for high greenhouse gas emissions (RCP8.5; black line in Figure 4b) 438 following the same assumptions as Thiéblemont et al. (2019) (see Text S2 in Supporting 439 Information for details). 440

The possibility that the subsidence rate revealed by the Cap-Ferret GPS station is not representative of the Truc Vert area (located at 8 km distance) constitutes a residual uncertainty that cannot be quantified, and is not accounted in this study due to the lack of quantitative information supporting an alternative scenario for residual vertical ground motions.

445

3.2 Depth of closure

The active beach profile slope is critical to SLR-driven erosion rate (Section 2.4), and strongly depends on the depth of closure (DoC). The DoC was calculated from the wave climate using the Hallermeier (1978) formula. Given that DoC depends on the period of time over which the Hallermeier formula is applied (Nicholls, 1998), we iteratively applied the Hallermeier formula

over a 1-year moving window of the future wave climate with a 30-days step. For both RCP8.5 and RCP4.5 scenarios, the latter procedure generated an ensemble of possible DoC values well fitted by a Gaussian distribution (Figure 4c). The DoC probability distribution shows higher median and standard deviation values in the RCP4.5 ($\mu = 17.2 \text{ m}$; $\sigma = 1.75 \text{ m}$) than in the RCP8.5 ($\mu = 16.3 \text{ m}$; $\sigma = 0.95 \text{ m}$). This results from the more frequent occurrence and larger wave heights associated to isolated extreme events in the RCP4.5 scenario, compared to the RCP8.5 scenario.

456

3.3 Model parameters

Numerical models are associated with uncertainties owing to the choice of modelling approach 457 and to the estimation of model free parameters. We accounted for the uncertainty conditional to 458 the choice of modelling approach assessing the shoreline projections using the Y09 and the SF 459 models described in Section 2.4.1, in two separated scenarios. Both models rely on shoreline 460 observations to calibrate the respective free parameters, and inherit uncertainties due to the quality 461 and amount of available data (Splinter et al., 2013), to possible non-stationarity of the parameters 462 in respect to the wave climate (Ibaceta et al., 2020), and to the optimization method. Uncertainties 463 affecting model free parameters of the Y09 model $(k_y^{+/-}, a_1, a_2)$ and the SF model (k_s^+, Φ) are 464 synthetized by their associated joined probability distribution. We follow the approach developed 465 in D'Anna et al. (2020), who calibrated the SF model free parameters using the Simulated 466 Annealing algorithm (Bertsimas & Tsitsiklis, 1993), and determined their joint probability 467 distribution by fitting an empirical multivariate distribution (multivariate kernel function) on an 468 ensemble of model parameters combinations. The authors built the latter ensemble selecting all 469 parameters combinations that produced a RMSE < 10 m against observed shoreline data during 470 the optimization process. Unlike D'Anna et al. (2020), here we calibrated the models between 471 January 2012 and December 2019, where no long-term trend in shoreline position is observed, in 472

line with the assumption of the SF parameter b=0 (see Section 2.4.1). In addition, we used the Nash-Sutcliffe (Nash & Sutcliffe, 1970) efficiency score (*NS*) instead of the RMSE to determine the models' performance (as for instance in Kroon et al., 2020). The *NS* measures the model skill in comparison to the 'mean model' (defined as the observed mean shoreline position), based on the error's variance, and it is calculated as follows:

478
$$NS = 1 - \frac{\sum_{n=1}^{N} (Y_m^n - Y_o^n)^2}{\sum_{n=1}^{N} (\overline{Y_o} - Y_o^n)^2}$$
(8)

where N is the number of observations, Y_m^n and Y_o^n are the n-th modelled and observed shoreline 479 positions, respectively, and \overline{Y}_{o} is the mean of the observed shoreline positions. The NS coefficient 480 can range between $-\infty$ and 1, where NS = 1 corresponds to a model perfectly reproducing the 481 observations, NS = 0 to a model with skill comparable to the 'mean model', and NS < 0 corresponds 482 to models less skilful than the 'mean model'. We obtained the probability distribution using 483 combinations of parameters that resulted in a $NS \ge 0.25$ (compared to the maximum NS = 0.63), 484 which corresponds to a max RMSE of ~10 m consistently with D'Anna et al. (2020). We defined 485 the latter threshold with the iterative procedure described in Text S4 of Supporting Information. 486 This procedure results in the probability distributions of $k_y^{+/-}$, a_1 , and a_2 for Y09, and k_s^+ and Φ for 487 SF shown in Figure 4d,e, with the range of possible parameters values reported in Table 1. 488





Figure 4 Probability distributions of: relative mean sea level over the period 2020-2100, including
the likely (dark shaded areas) and 5th to 95th percentile (light shaded areas) ranges, for (a) RCP4.5
and (b) RCP8.5 scenarios, with deterministic high-end sea-level projections based on 2100 high-

end 'highest-modelled' estimates following Thiéblemont et al. (2019) (black line); (c) Gaussian distributions of depth of closure values calculated over the 2020-2100 wave time series for RCP4.5 (blue curve) and RCP8.5 (red curve) scenarios; and empirical joint probability distributions of (d) *ShoreFor* $[k_{s}^{+}, \Phi]$ parameters, and (e) *Yates* $[k_{y}^{+/-}, a_{1}, a_{2}]$ parameters, obtained fitting a kernel density function (with bandwidths estimated from the marginal kernel density function for each variable) on 6000 combinations of model parameters producing *NS* > 0.25 against shoreline data.

- 501 **Table 1** Optimised combinations of cross-shore model free parameters, and respective range of
- 502 variation in the probability distributions.

Model	Model parameter	Optimised value	Distribution range
ShoreFor	k_s^{+} [m ^{1.5} s ⁻¹ W ^{0.5}]	4.4 x10 ⁻⁸	[2; 7.4] x10 ⁻⁸
Shoreron	arPhi [days]	1193	[400; 1423]
	k_{y}^{+} [m ² s ⁻¹ /m]	0.87	[0.24 ; 2]
Vatas	k_{y} [m ² s ⁻¹ /m]	0.5	[0.1 ;1.5]
Tutes	$a_{1} [{ m m}^{2}/{ m m}]$	-0.008	[-0.02 ; -0.004]
	$a_2 [{ m m}^2]$	0.49	[0.33 ; 1]

503

504

3.4 Model setup of shoreline projections

Four ensembles of 3000 possible shoreline trajectories from 2020 to 2100 were generated using the SF and Y09 shoreline change models, and the Bruun Rule, for the two RCP8.5 and RCP4.5 scenarios (Table 2). Wave-driven shoreline response (short-term) and SLR (long-term) were computed individually and then linearly combined, so that no feedback mechanisms occur between the models, in line with previous applications (D'Anna et al., 2020; Vitousek et al., 2017).

For each model and RCP scenario, 3000 simulations were run with different combinations of 510 model free parameters, DoC and SLR time series, sampled from the respective probability 511 distributions. Shoreline change was computed with a 3-hour time step from the 1st January 2020 512 to the 31st December 2099 starting from the same shoreline position ($Y_0 = 0$), and model outputs 513 were recorded with a 2-weeks resolution. As the characteristics of the MSL probability distribution 514 are time-dependent, we randomly sampled percentile values and extracted the corresponding MSL 515 at each year. The ensemble projections character was synthetized by the *likely range*, defined here 516 at each time step as the variance, and the envelope (min and max) of modelled shoreline positions, 517 acknowledging that the latter is dependent on the number of simulations and the tails of the 518 probability distributions. The impact of individual winters on shoreline projections is qualitatively 519 discussed observing the distributions of shoreline positions corresponding to the most seaward and 520 landward median shoreline position within each simulated annual cycle (1st September to 31th 521 August). We analysed the decadal shoreline trends by filtering the modelled shoreline time series 522 with a 5-year running mean. In addition, for RCP8.5 scenario, a deterministic high-end-SLR 523 simulation was run with both shoreline models using the optimized model parameters (Table 1) 524 and the median DoC. It is to be noted that the GSA results (i.e. S_i s) are calculated on the likely 525 range (variance) of the model results, regardless of the envelope of modelled shoreline positions. 526

527

Table 2 Probabilistic future scenarios for two Representative Concentration Pathways (RCP) and two different wave-driven modelling approaches, using the Bruun Rule and 3000 different combinations of model parameters, SLR percentile and DoC.

Future scenario	SLR-driven shoreline change	Wave-driven shoreline change	# Combinations of uncertain variables		
RCP 4.5	Bruun Rule	ShoreFor (SF)	3000		

		Yates (Y09)	3000
RCP 8.5	Bruun Rule	ShoreFor (SF)	3000
		Yates (Y09)	3000

531

532

533 **4 Results**

534 4.1 Shoreline projections

The four future scenarios in Table 2 resulted each one in 3000 shoreline evolution simulations 535 spanning 2020-2100 (Figure 5 and Figure 6). Figure 5c,d and Figure 6c,d represent the distribution 536 of 3000 modelled shoreline positions at each recorded output time. All scenarios show a net erosion 537 by 2100, mostly driven by SLR (Table 3). All model ensembles also show large interannual 538 variability that is essentially enforced by the interannual variability in incident winter-mean wave 539 height (Figure 5a,b and Figure 6a,b). In the RCP8.5 (RCP4.5) scenario we observe a long-term 540 shoreline change pattern responding to alternating sequences of high- and low-energy winters with 541 a period of ~20 years (~10 years) and even longer (Figure 5a,e,f and Figure 6a,e,f). 542

Figure 5c,d (Figure 6c,d) show several episodes of rapid erosion driven by isolated extreme energy winters, for instance for the RCP8.5 (RCP4.5) scenario in winter 2030, 2076, and 2086 (2068, 2073 and 2085). The two wave-driven shoreline models (Y09 and SF) produce consistent shortand long-term shoreline cycles, with larger tendency to accretion in SF than in Y09 during extended periods of low energy winters, for instance during 2050-2055 for RCP4.5 and 2060-2070 for RCP8.5 (Figure 5c,d and Figure 6c,d).

In the RCP4.5 emission scenario, the modelled 2020-2100 Truc Vert shoreline trend leads to a

likely (envelope) retreat of 15 to 33 m (4 to 75 m) with Y09, and 10 to 23 m (6 to 65 m) with SF.

551 On a yearly time scale, the shoreline position is likely (envelope) to be farther landward from the 552 initial position, by 76 m (123 m) with Y09, and 43 m (74 m) with SF (Figure 5c,d, Table 3). Indeed, 553 the occurrence of extreme winters can produce significant landward shifts of the envelope of 554 shoreline positions, as observed during the 2084-2085 winter (Figure 5c,d).



556

Figure 5 (a) Time series of winter mean wave height of the BW18 RCP4.5 projections (dashed line) with corresponding 5-year average (solid line); (b) BW18 RCP4.5 wave height time series (black line), and 3-month average $H_s^2T_p$ time series (red line); RCP4.5 scenario 2020-2100 shoreline projections at 14-days resolution obtained using (c) Y09 and (d) SF; and 5-year running mean shoreline projections modelled with (e) Y09, (f) SF, and the standalone Bruun Rule (green bars). Dark (light) blue shaded areas indicate the likely (envelope) range, i.e. variance (min-max), of shoreline position, and solid light line median shoreline position. The dashed vertical line

indicates the most landward shoreline position over the simulated period. Yellow shaded areasindicate examples of years including high-energy winters.

When forced with RCP8.5 scenario's wave and MSL projections, from 2020 to 2100 simulations indicate an average likely (envelope) erosion of 27 to 48 m (16 to 83 m) using Y09, and 14 to 33 m (2 to 67 m) using SF (Figure 6d,e). In this scenario, over the simulated period the likely (envelope) most landward shoreline position reaches up to 70 m (108 m) from the initial shoreline position with Y09 model, and 48 m (76 m) with SF (Figure 6c,d, Table 3). Similarly to the RCP4.5, here we observe for both models some important shifts in shoreline position distribution owing to extreme winters such as 2086's winter (Figure 6c,d).

In the high-end SLR scenario, both models predict a shoreline position within the envelope of probabilistic projections until 2090, before the shoreline moves further inland during the last decade (Figure 6d,e). The modelled 5-year averaged shoreline position in 2100 is of 88 and 74 m for Y09 and SF, respectively (Table 3). The most landward shoreline position observed throughout the simulation is 107 m with Y09, and 86 m with SF (black dashed line in Figure 6c,d).

The likely (envelope) ranges erosion produced by the combined Y09+Bruun models at the end of the simulated period are comparable (larger) to the standalone application of the Bruun Rule (Table 3, and in Figure 5,6,e,f with Bruun model predictions in green). With the combined SF+Bruun models, the likely (envelope) ranges of shoreline positions obtained show ~10 m (~15 m) less erosion than the Bruun Rule.





Figure 6 (a) Time series of winter mean wave height of the BW18 RCP8.5 projections (dashed line) with corresponding 5-year average (solid line); (b) BW18 RCP8.5 wave height time series (black line), and 3-month average $H_s^2T_p$ time series (red line); RCP8.5 scenario 2020-2100 shoreline projections at 14-days resolution obtained using (c) Y09 and (d) SF; and 5-year running mean shoreline projections modelled with (e) Y09, (f) SF, and the standalone Bruun Rule (green bars). Dark (light) shaded areas indicate the likely (envelope) range , i.e. variance (min-max), of

shoreline position. Black solid lines indicate shoreline projections in the RCP8.5 high-end SLR scenario. The dashed vertical line indicates the most landward shoreline position over the simulated period. Yellow shaded areas indicate examples of years including high-energy winters.

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Table 3 Likely (modelled shoreline variance) and envelope (min-max) values of the 5-year averaged projected shoreline position in 2100, and 2020-2100 most landward shoreline position, obtained using the standalone Bruun Rule (B), and the combined B with Y09 and SF equilibrium shoreline models, for the RCP4.5 and RCP8.5 probabilistic scenarios, and the deterministic highend SLR scenario.

Scenario		2100 5-year ave	eraged shoreline	Most landward		
		pos	ition	shoreline position		
		<i>likely</i> range	envelope	likely	envelope	
		(m)	(m)	(m)	(m)	
	Y09+B	-1533	-475	-76	-123	
RCP 4.5	SF+B	-1023	-652	-43	-74	
	В	-21 -33	-1760	-33	-60	
	Y09+B	-2748	-1683	-70	-108	
RCP 8.5	SF+B	-1433	-265	-48	-76	
	В	-2849	-2186	-49	-86	
		2100 5-year averaged shoreline		Most landward		
Determini	stic scenario	position		shoreline position		
		(m)		(m)		
Uigh and	Y09+B	-95		-111		
PCP 8 5	SF+B	-74		-84		
KCI 0.5	В	-81		-81		

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600

4.2 Global Sensitivity Analysis

In both RCP8.5 and 4.5 scenarios and for both shoreline model applications, the GSA shows that over the first 30 years of simulation the variance of modelled shoreline projections is driven primarily by the uncertainties in model free parameters, while the effects of SLR uncertainties on shoreline position become increasingly significant after 2050 (Figure 7 and Figure 8). The S_i s of the Y09 and SF response rate parameters ($k_y^{+/-}$ and k_s^+ , respectively) and the SF beach memory

parameter (Φ) show seasonal (6 months) and decadal modulation with a decreasing trend as 606 shoreline projections become more sensitive to SLR (Figure 7c,d and Figure 8c,d). Variations in 607 $k_v^{+/-}$ and k_s^+ are the primary source of shoreline projection uncertainties during accretion periods. 608 However, the response rate parameters' uncertainties have a stronger impact on seasonal scale 609 when using the Y09 model (Figure 7c), and a larger impact on interannual scale when using the 610 SF model (Figure 8c), due to the different response of the models to incident wave energy 611 variability. Seasonal modulation is also observed for the S_i s of the Y09 empirical parameters (a_1 612 and a_2), although the correlation between the variability in incident wave conditions and the 613 parameters' S_i s, (both filtered of their seasonal signal with a 1-year running mean) is negligible 614 (R²=~0.06 for a_1 , and R²=~0.03 for a_2). However, the estimated a_1 's and a_2 's S_i s remain below 615 20% during most of the simulated period with occasional peaks up to 45% (Figure 7e,f). The 616 primary effects of SLR uncertainties emerge at different times, which depend both on the RCP 617 scenario and on the shoreline model. When using Y09, a positive trend in SLR's S_i emerges in the 618 2050-2060 period, with SLR's S_i exceeding those of model parameters since approximately 2060-619 2070, for both RCP scenarios (Figure 7g). Instead, with SF in the RCP8.5 (RCP4.5) scenario, such 620 quasi-monotonic trend appears later, approximately during the 2070s' (2060s') and only exceeds 621 the model parameters' Sis after 2085 (2080) (Figure 8e). For all scenarios, DoC's Si slowly 622 increases, with similar trends as SLR's S_i, and reaches approximately 5% and 10%, in the RCP8.5 623 and 4.5 scenarios, respectively. This difference is probably due to the larger uncertainties of SLR 624 625 in the RCP8.5 scenario (Figure 4b), and to the larger variance of the DoC probability distribution obtained for the RCP4.5 scenario (Figure 4c). 626



627

Figure 7 Global Sensitivity Analysis results over the period 2020-2100 using the *Yates* model in the RCP4.5 (blue lines) and RCP8.5 (orange lines) scenarios. (a) RCP4.5 and (b) RCP8.5 Ensemble shoreline projections (shaded areas) over 2020-2100; First-order Sobol' index time

631 series for (c) k_y^+ , (d) k_y^- , (e) a_1 , (f) a_2 , (g) sea-level rise, and (h) depth of closure, with respective 632 linear fit (solid straight lines).



633

Figure 8 Global Sensitivity Analysis results over the period 2020-2100 using the *ShoreFor* model in the RCP4.5 (blue lines) and RCP8.5 (orange lines) scenarios. (a) RCP4.5 and (b) RCP8.5 Ensemble shoreline projections (shaded areas) over 2020-2100; First-order Sobol' index time series for (c) k_{s}^{+} , (d) Φ , (e) sea-level rise, and (f) depth of closure, with respective linear fit (solid straight lines).

639 **5 Discussion**

5.1 Sea-level rise

While observed shoreline erosion in Aquitaine is not yet attributed to SLR, sooner or later a SLR-641 driven signal will emerge from the current shoreline change variability, as sea levels are committed 642 643 to rise by meters over the coming centuries (Anderson et al., 2015; Oppenheimer et al., 2019). Our results suggest that these times of emergence of a SLR-driven erosive trend could be visible during 644 the 2nd half of the 21st century, possibly by 2070. This is consistent with the fact that uncertainty 645 (17th -83 th percentiles) in future sea level grows from roughly 15 cm by the mid 21st century to 30 646 647 cm (RCP4.5) and 50 cm (RCP8.5) in 2100. Yet, this result relies on our modelling assumptions, including the Bruun Rule and the Yates or ShoreFor models. 648

The GSA applications to four simulated scenarios indicate that uncertainties in the modelled 2020-2100 shoreline projections at Truc Vert are primarily caused by uncertainties in model free parameters between the present day and 2050. The effects SLR uncertainties always emerge as a significant contribution to the shoreline change uncertainties in the second half of the century. We also observed that the time evolution of S_i s and the onset of SLR uncertainties effects are conditional to the RCP scenario (in agreement with Le Cozannet et al., 2019), the choice of shoreline model, and the variability of forcing wave climate.

The shoreline trajectory obtained in the deterministic high-end SLR scenario exceeds the envelope of probabilistic projections in the last simulated decade. Truc Vert beach is remote and backed by a high (~20 m) and wide (~250 m) dune system, so that shoreline retreat is not limited by nonerodible geological outcrops or coastal structure. While such large erosion does not threaten any human assets close to Truc Vert beach, such scenario, though unlikely, questions adaptation planning in other eroding urbanised coastal areas with limited accommodation space in southwest France. 5.2 Shoreline models

664 While the SF and Y09 models are both based on the equilibrium beach concept, the respective 665 model structures and parameters associate different physical interpretations and shoreline 666 behaviours (Section 2.4.1). Therefore, the uncertainty associated with the choice of the equilibrium 667 modelling approach cannot be measured by direct confrontation of the S_i s obtained with the two 668 models, but requires consideration of the different model responses to the forcing conditions.

The results obtained for the two disequilibrium approaches (Y09 and SF) show similar seasonal 669 and interannual shoreline cycles, although with notably different amplitudes. Such behaviours are 670 rooted in the different expressions of the equilibrium physics adopted in the two wave-driven 671 models (i.e. the mechanism that would drive the shoreline to an equilibrium position under 672 constant wave conditions). Vitousek et al. (2021) analytically show that the type of equilibrium 673 674 condition is critical for the short- and long-term response of the shoreline model. On one hand, Y09's equilibrium condition depends on the current shoreline position, and is not influenced by 675 storm events that occurred prior to a given time scale that is implicitly defined by the model 676 calibration (see 'Appendix A' of Vitousek et al., 2021). On the other hand, SF's equilibrium state 677 is determined by the (time varying) past wave conditions with an explicit 'beach memory' 678 function, and evolves in time accordingly. This means that, in absence of other processes, the Y09 679 modelled shoreline oscillates persistently around the same position regardless of the temporal 680 variability of wave energy. Instead, SF can only achieve such a stable mean shoreline trend when 681 forced with a periodic long-term wave climate (Vitousek et al., 2021). Hence, in presence of long-682 term trends of wave energy, Y09 emphasizes the short-term shoreline erosion/accretion in order 683 to re-establish the equilibrium shoreline position, while SF adapts to the wave climate pattern. The 684 latter results in larger amplitudes of seasonal fluctuations and in attenuation of long-term 685 fluctuations, compared to SF. 686

The combined Y09 and Bruun models simulated shoreline ranges at 2100 are overall comparable 687 to the ranges of the standalone Bruun Rule, indicating that in this scenario the net erosion modelled 688 by 2100 is essentially driven by SLR. In fact, Y09 constrains the shoreline response to long-term 689 wave climate shifts to a limited range (as described above) while the linearly added contribution 690 of the Bruun model determines the shoreline trend. Instead, SF can produce wave-driven long-691 692 term shoreline trends that are combined with the Bruun retreat. This effect is observed in both RCP4.5 and 8.5 scenarios, where the decreasing wave energy trend (Figure 2d,e) is translated by 693 SF into shoreline accretion trends, resulting in less erosion than the Buun model alone (Table 3). 694 Such properties of the two model behaviours highlight the different model sensitivities to long-695 term variability of the wave climate, which can have implications on the uncertainties in shoreline 696 projections. Including the uncertainty of long-term wave climate variability in the ensemble 697 projections would allow investigating the uncertainties related to the different behaviours of the 698 shoreline models. 699

5.3 Model free parameters

Resolving process-based shoreline response to time-varying incident wave energy revealed that 701 uncertainties in model parameters have the largest impact over the first simulated 30 years, 702 regardless of the cross-shore shoreline model choice. Over this period, Y09 and SF uncertainties 703 in response rate parameters ($k_v^{+/-}$ and k_s^{+} , respectively) are responsible for most of the results 704 uncertainties, which increases during low energy winters (on seasonal scale), and is particularly 705 706 emphasized for SF in correspondence of extended low energy periods. This suggests that the assumption of a linear relationship between SF's response rate parameters $(k_s^- = r k_s^+)$ may not 707 708 hold in the context of long-term simulations, as it might depend on the evolution of waves 709 properties (Ibaceta et al., 2020). In fact, Ibaceta et al. (2020) found that, such relation is not necessarily linear, indicating that the value of r may vary dynamically with changes in wave regimes. While the S_i s of the remaining model parameters (Φ for SF; a_1 and a_2 for Y09) show a definite seasonality, their variability on longer time scales is unclear. However, Φ 's S_i , which exhibit relatively high values (up to 90%) at the beginning of the simulation, shows an overall decaying trend for both RCP scenarios applications. The a_1 and a_2 's S_i s remain weak, though not negligible, (<20%) over all the simulated period.

The behaviour of the model free parameters' S_i s highlights, once again, the importance of wave 716 energy variability in determining the impact of the parameters uncertainties on shoreline 717 projections. This was also observed in previous studies, which showed that changes in wave 718 regime can alter the model parameters and the functional relations between them (Ibaceta et al., 719 2020; Splinter et al., 2017). As a perspective of future work, one way to reduce the effects of model 720 free parameters' uncertainties on modelled shoreline may be to employ non-stationary parameters 721 that can adjust to changes in wave-climate regimes (Ibaceta et al., 2020). The use of non-stationary 722 parameters would also imply a dynamic value of the r parameter, reducing uncertainties associated 723 to the assumption of a linear relationship, between SF's response rate parameters. In addition, 724 rearranging the Y09 parameters so that the new parameters have a similar order of magnitudes 725 may increase the efficiency of model calibration, reducing model parameters uncertainties 726 (Vitousek et al., 2021). 727

728

5.4 The role of wave time series

Our results indicate that the shoreline erosion is not only associated with large winter energy, but also depends on the trends of past winter wave energy and the internal variability of high-energy events within the season. For instance, in the RCP4.5 scenario the winters 2084-2085 and 2059-2060 show similar 3-month averaged $H_s^2 T_p$ peak (164 m²s and 172 m²s, respectively), but they are

733 preceded by several years of negative and positive winter energy trend, respectively (Figure 2b). This results in the winter 2084-2085 producing a rapid landward shift of shoreline position 734 distribution, and the winter 2059-2060 driving more moderate annual changes while contributing 735 to a long-term erosive trend (Figure 5c,d). We also observe that the interannual patterns of 736 shoreline evolution are clearly correlated to those of winter wave energy. These behaviours 737 underline the critical role of high/low energy winters interannual cycles, as well as storms 738 sequencing, in wave-driven shoreline response, in line with previous studies (Dissanayake et al., 739 2015; Besio et al., 2017; Dodet et al., 2019). In addition, the temporal variability of wave climate 740 741 (e.g. seasonal distribution of storm events) has been observed to affect the frequency (or 'mode') of shoreline response (Splinter et al., 2017; Ibaceta et al., 2020). 742

Therefore, we further investigated the potential role of future waves uncertainties in shoreline 743 projections performing the GSA on an additional ensemble of 3000 simulations forcing the Y09 744 and SF models with 100 different wave time series. We generated 100 random synthetic wave 745 series using the method proposed by Davidson et al. (2017), which consists in building continuous 746 series of wave conditions by sampling 1-month portions from a reference dataset of existing wave 747 data (e.g. historic wave data) at a given location. The method generates synthetic wave time series 748 with random, though realistic, chronology of wave events, while maintaining the seasonal and 749 yearly character of the wave climate. However, this assumes a long-term stationarity of the 750 generated wave time series. We used the BW18 projections for the RCP8.5 scenario as reference 751 752 wave data. We individually applied the Davidson et al. (2017) method over 8 windows of 10 years from 2020 to 2100 in order to preserve the long-term (>10 years) characteristics of the reference 753 754 time series while providing enough sampling reference data (Figure 9a). For instance, all the synthetic events from 2030 to 2040 were generated using monthly samples from the 2030-2040
reference dataset.

757 When using the latter approach to generate ensemble waves the SF model shows some limitations.

Therefore, here we exploit only the test results obtained with Y09. The results of the SF test

application and the aforementioned limitations are illustrated in Text S5 and Figure S4 of

760 Supporting Information.



761

Figure 9 Ensemble of 3000 *Yates* simulations forced using (a) 3-month average energy $(H_s^2 T_p)$ of 100 random wave time series from 2020 to 2100 generated with the Davidson et al. (2017) method based on the BW18 wave projections for the RCP8.5 scenario; (b) Ensemble shoreline projections

over the analysed period (dark/light shaded areas indicate the likely/envelope range, i.e. variance (min-max), of shoreline position); First-order Sobol' index time series for (c) k_y^+ , (d) k_y^- , (e) a_1 , (f) a_2 , (g) sea-level rise, (h) depth of closure, and (i) wave energy, with respective time series calculated on the 1-year running average of model results (black lines).

The GSA shows that introducing uncertainties in the temporal distribution of wave events (Figure 769 9a) has a large impact on the variance of model results (Figure 9b) and, in turn, on the relative 770 contributions of the remaining uncertain input parameters (Figure 9c-h). In fact, accounting for 771 uncertainty in wave events chronology (though in a simplistic way) increases the overall model 772 variance throughout the entire simulated period (Figure 6c and Figure 9b), and associates a 773 dominating Si (up to 0.3) over the first half of the simulated period (Figure 9i). However, SLR's 774 S_i still emerges after 2060 and dominate shoreline projections uncertainties over the last two 775 simulated decades. We also observe that the inclusion of wave chronology uncertainty attenuates 776 the interannual variability of all S_is while preserving the seasonal and 10-year signals (Figure 9c-777 h). This is a natural consequence of the method used to generate the wave series ensemble. In fact, 778 779 the Davidson et al. (2017) method is designed to preserve the seasonal variability, while its application to fixed time windows of the reference time series constrains the ensemble members 780 to maintain the 10-year variability. The black lines in Figure 9c-i show the time evolution of Sis 781 obtained removing the seasonal signal from the model results with a 1-year running average. When 782 the seasonal variability of the results is removed, the SLR's S_i compensates the fluctuations of the 783 model parameter's S_is, resulting in an increased trend. 784

The test application illustrated above suggests that including uncertainties in short-term wave chronology can significantly impact the uncertainties of shoreline projections and the relative contributions of the remaining uncertain input variables. Further, introducing uncertainties on long-term non-stationarity of wave conditions would overcome the SF limitations occurring in this

789	specific application, and	may unveil new	^v implications	of the	different	Y09	and SF	equilibrium
790	approaches in the context	of probabilistic	long-term sho	reline	projection	IS.		

791

5.5 Assumptions and limitations

792 Wave projections are affected by uncertainties owing to the choice of the Global Climate Model (Morim et al., 2020) and random variability of wave events. Although our results are based on 793 deterministic BW18's wave projections, in the northeast Atlantic region the estimated future wave 794 795 statistics have been observed to be mostly sensitive to the RCP scenario (Morim et al., 2020). Yet, 796 the use of deterministic wave projections hides a potentially large impact of the uncertain waveclimate variability on both shoreline predictions uncertainty and behaviour of the shoreline models. 797 In addition, accounting for uncertainties in wave projections may also increase the uncertainties in 798 799 DoC, which were based on one deterministic wave time series in the present study. However, to 800 the authors' knowledge there is no other dataset of continuous 2020-2100 wave projections, over the north Atlantic area, with a sufficient spatial resolution to resolve the site-specific regional scale 801 processes. This underlines the need of continuous wave time series (obtained with different wave 802 models of fine enough spatial resolution, different climate models, for different RCP scenarios), 803 as well as tools allowing generating continuous realistic future wave time series, such as climate 804 based stochastic wave emulators (Anderson et al., 2019; Cagigal et al., 2020). 805

In the current work, we assumed that MSL 2020-2100 projections are normally distributed. However, the MSL distribution may be skewed towards higher values due to additional uncertainty related to Antarctic ice-sheet melting in the RCP8.5 scenario. We simulated a deterministic RCP8.5 high-end SLR scenario to define a low-probability/high-impact scenario for projected shoreline erosion. Yet, our high-end SLR scenario is based on a particular combination of highend contributions to sea-level rise, which makes no consensus in the scientific community (Bamber et al., 2019; Edwards et al., 2021; Stammer et al., 2019). While this is not included in the GSA, the use of a skewed probability distribution may lead to an earlier onset of SLR uncertainties in shoreline projections.

The Bruun Rule, used in our application to estimate SLR-driven shoreline recession, builds on several strong assumptions that reduce the applicability of this model to a limited range of beaches (Cooper et al., 2020). As the Truc Vert is an uninterrupted natural cross-shore transport dominated beach, with large sediment availability, most underlying assumption of the Bruun model are satisfied. However, alternative models to address beach response to SLR, such as *ShoreTrans* (McCarroll et al., 2020), can be implemented in this framework.

Coupling the Bruun Rule with Y09 and SF allows accounting for long-term effects of SLR while resolving short-term shoreline response to the wave climate. The Y09 and SF models do not explicitly resolve sediment sediment exchange between the different beach compartments (e.g. upper beach and dune), and may fail reproducing episodic shoreline changes such as short-term accretion following to dune erosion events. However, if such events occur during the model calibration period, as in our applications (i.e. winter 2013-2014), their influence on the bulk shoreline response is partially accounted.

Here, we investigated the main effect of the uncertainties in input variables (S_i s). While the estimated S_i of the DoC remains relatively low over the simulated period, in all simulated scenarios, the interaction of DoC and SLR uncertainties (i.e. *second-order Sobol' index*) may have a larger impact. However, estimating robust interaction terms would require a larger ensemble of simulations (several tens of thousands). Furthermore, in order to rigorously conclude on the negligible character of some uncertainties, GSA should be conducted within the factors' fixing setting (i.e., investigating the 'total effect' of uncertain variables, Saltelli et al., 2008). In the presence of dependence among the inputs, more advanced GSA indices should be used for this purpose. In particular, a method that employes the so-called *Shapley effects* has recently been proposed and showed very promising results (Iooss & Prieur, 2019). While the direct application of this method requires computational cost of several order of magnitudes larger than the Sobol' indices (see Iooss & Prieur, 2019), Broto et al. (2020) successfully implemented a more computationally efficient sampling-based method for GSA using Shapley indices. This may be an interesting perceptive for future works.

842 6 Conclusions

We performed a Global Sensitivity Analysis on probabilistic 2020-2100 shoreline projections at 843 the cross-shore transport dominated Truc Vert beach in southwest France. Time varying first-order 844 Sobol' indices were calculated for sea-level rise, depth of closure, and model free parameters for 845 two different cross-shore shoreline models (Yates and ShoreFor) and two RCP scenarios (RCP4.5 846 and RCP8.5). We show that uncertainties in shoreline projections are initially driven by 847 uncertainties in model free parameters, with the effects of SLR uncertainties only emerging in the 848 second half of the 21st century. However, the relative effects of SLR and model parameters 849 uncertainties on shoreline projections do not only depend on the shoreline modelling approach and 850 RCP scenarios, but their time evolution is also related to the forcing wave-climate variability. We 851 also emphasize the importance of accounting for uncertainties related to the temporal distribution 852 of wave energy, and therefore the need of ensembles of synthetic wave time series that account for 853 the inherent variability of the wave climate. 854

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870 Data availability statement

- All data used (wave, mean sea level and shoreline data) and produced (shoreline projections) in
- this work are available at <u>https://data.mendeley.com/datasets/gnvkx44t63/draft?a=a32c56ba-</u>
- 873 <u>f495-4652-9eda-964dea31cec6</u>.

874 **Conflicts of interest**

The authors declare that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research reported.

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