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Effects of Stochastic Wave Forcing on Equilibrium Shoreline Modelling Across the 21st Century Including Sea-Level Rise

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Abstract

Coastal communities are currently facing the challenge of climate change and coastal retreat. While scientists are moving towards ensemble-modelling approaches to address uncertainties on shoreline evolution predictions, they rarely account for the stochastic nature of wave conditions across a variety of temporal scales (e.g., daily, weekly, seasonal, and interannual). In this contribution, we investigate the effects of the inherent variability of wave conditions on past and future multi-decadal shoreline evolution at the, cross-shore transport dominated, beach of Truc Vert (France). Using a climate-based wave emulator and variance decomposition method, we address the relative impacts of uncertain wave chronology, sea-level rise and model free parameters on modelled shoreline change, while accounting for possible correlations and interactions among the input variables. This work is done for two different wave-driven equilibrium models. The results show that the equilibrium shoreline models respond differently to the ensemble wave forcing, with strong implications on the long-term variability of modelled shoreline. We find that the modelled shoreline variance is primarily driven by the uncertain wave chronology until mid-21st century, while the uncertainties on future sea-level rise become dominant after 2060 in all the simulated scenarios. We also found that interactions and correlations among the uncertain variables can affect the estimation of shoreline predictions uncertainties. Finally, we provide a perspective on the application of non-stationary wave-related model parameters as future research avenue for understanding uncertainties in modelled shoreline.

Keywords: Ensemble wave forcing; shoreline modelling; equilibrium shoreline models; sea-level rise; Truc Vert;

1. Introduction

Sandy beaches represent about one third of the Earth's ice-free coasts (Luijendijk et al., 2018), and provide an important natural (Schlacher et al., 2007) and socio-economical resource (Ghermandi and

34 Nunes, 2013) to coastal communities as well as a buffer zone during storm events. Open sandy coasts
35 are ubiquitous worldwide, with shorelines continuously adapting to climate drivers over multiple time
36 scales (Montaño et al., 2021; Stive et al., 2002), so that temporal shifts in sea level and wave climate
37 can strongly affect the dynamics of sandy shorelines (Ranasinghe, 2016). On this type of coasts,
38 shoreline change is often dominated by wave energy variations on the time scales of storms to seasons
39 and years due to interannual variability of winter wave energy (Dodet et al., 2019), while sea-level rise
40 (SLR) affects shoreline trends over longer time scales (decades to centuries) (Ranasinghe, 2020). The
41 complex dynamics of sandy beaches together with the limited predictability of the future climate make
42 shoreline predictions challenging, forcing coastal scientists, managers and engineers to embrace
43 uncertainties (Ranasinghe, 2020; Toimil et al., 2020). Indeed, the input parameters and variables of
44 (statistical or numerical) shoreline models include uncertainties, which derive from simplifications and
45 limited knowledge of some physical processes (model assumptions) or from the inherent variability of
46 a model forcing (climate unpredictability), which cascade through the model and result in uncertain
47 model predictions (Toimil et al., 2021). Thus, current practices for coastal impact assessments are
48 moving towards probabilistic frameworks for a robust risk-informed decision-making (Hinkel et al.,
49 2019; Wainwright et al., 2015).

50 Probabilistic, mostly ensemble-based, approaches have become increasingly popular to study the impact
51 several sources of uncertainties on shoreline predictions. However, most studies focused on the impact
52 of uncertainties in future SLR on shoreline predictions while accounting for probabilistic extrapolated
53 trends of wave-driven shoreline change (Athanasiou et al., 2020; Le Cozannet et al., 2016; Thiéblemont
54 et al., 2021, 2019; Vousdoukas et al., 2020), or resolving ~hourly shoreline response to deterministic
55 realizations of future wave climate (D'Anna et al., 2021a, 2020), and did not include the inherent
56 variability of wave climate.

57 The natural variability of the wave conditions introduces an unavoidable component of uncertainty to
58 wave projections, which makes the intra-seasonal and intra-storm chronology of wave events hardly
59 predictable (Mankin et al., 2020). Even when associating a comparable cumulative wave energy,
60 different storm sequences can result in very different shoreline responses (Baldock et al., 2021; Coco et
61 al., 2014; Eichertopf et al., 2020; Splinter et al., 2014a). Thus, the intrinsic uncertainty associated with
62 the variability of wave conditions can have a significant impact on the confidence in modelled shoreline
63 projections (Toimil et al., 2021; Vitousek et al., 2021).

64 As the limited predictability of the future climate (and waves) introduces a certain uncertainty (Deser,
65 2020) to shoreline predictions, the use of large ensembles is advocated to quantify its contribution to the
66 uncertainty in model results (Mankin et al., 2020). Davidson et al. (2017) developed a method to
67 generate ensembles of annual wave time series by sampling and shuffling monthly wave sequences from
68 a pool of historical wave data. Although this method preserves the seasonal variability of the wave

69 climate, it does not ensure a realistic variability on longer time scales. The recent development of
70 stochastic climate-based wave emulators enabled the efficient generation of large ensembles of
71 indefinitely long wave series that are characterized by different chronologies of events while obeying to
72 realistic climate patterns (Anderson et al., 2019; Antolínez et al., 2016; Cagigal et al., 2020; Pringle and
73 Stretch, 2019; Rueda et al., 2016).

74 Resolving long-term wave-driven shoreline change in ensemble settings requires high computational
75 efficiency. In this context, equilibrium shoreline models are particularly convenient tools (Montaño et
76 al., 2020) as they simulate cross-shore shoreline response to wave-driven sediment transport processes
77 on time scales from hours to decades with low computational effort (Alvarez-Cuesta et al., 2021a;
78 Davidson, 2021; Davidson et al., 2013; Jaramillo et al., 2020; Lemos et al., 2018; Robinet et al., 2018;
79 Splinter et al., 2014b; Toimil et al., 2017; Yates et al., 2009). These models are based on the concept
80 that changes in incident wave energy drive the shoreline towards a time-varying equilibrium position
81 (Wright and Short, 1984) that is typically formulated as a function of either the current shoreline position
82 (Miller and Dean, 2004; Yates et al., 2009) or the past wave conditions (Davidson et al., 2013; Splinter
83 et al., 2014b). Although both equilibrium approaches have shown good skill in simulating multi-year
84 shoreline change (Castelle et al., 2014; Montaño et al., 2020), their different responses to wave energy
85 variability (D'Anna et al., 2021a; Vitousek et al., 2021) motivate further considerations on the respective
86 skills in reproducing shoreline change under different wave forcing scenarios, particularly on multi-
87 decadal timescales. Further, equilibrium shoreline models rely on the parametrization of some physical
88 processes that require site-specific calibration against shoreline observations, of which the quality and
89 availability introduce uncertainties in the model parameters (Splinter et al., 2013) that can significantly
90 affect model predictions (D'Anna et al., 2020).

91 To date, few studies investigated the influence of uncertainties associated with short- and long-term
92 variability of wave conditions on shoreline modelling. Cagigal et al. (2020) applied a stochastic wave
93 emulator to force ensemble long-term shoreline predictions to several sites dominated by cross-shore
94 sediment transport processes to replicate shoreline return periods observed in the past. Kroon et al.
95 (2020) and Vitousek et al. (2021) quantified the relative contributions of the uncertainties associated
96 with the inherent wave variability and model parameters to longshore (1 year) and cross-shore (8 years)
97 shoreline projections, respectively. Alvarez-Cuesta et al. (2021b) examined short- and long-term drivers
98 of the mean shoreline change at two longshore transport dominated sites using a wave ensemble and
99 three percentiles of future SLR for two RCP scenarios. Toimil et al. (2021) produced multi-ensemble
100 2081-2100 projections to quantify the uncertainties associated with the individual steps of the modelling
101 process, including uncertainties on SLR, waves, storm surges, and future climate scenario for two
102 shoreline models. The works mentioned above resolved cross-shore wave-driven shoreline change using
103 disequilibrium approach of the same kind, that is, where the beach equilibrium state is defined by the
104 current shoreline position (Miller and Dean, 2004; Yates et al., 2009).

105 Many efforts have been dedicated to quantify the impact of intrinsic uncertainty on shoreline predictions.
106 However, the role of the inherent wave conditions variability on ensemble shoreline predictions in
107 relation to uncertain SLR and model free parameters, and how substantially different modelling
108 approaches respond to this type of uncertainties, has not been investigated. In addition, the wave-driven
109 model free parameters uncertainties are strongly connected to the wave forcing variability (D'Anna et
110 al., 2021a, 2020; Davidson et al., 2017; Ibaceta et al., 2020; Montañó et al., 2021; Splinter et al., 2017,
111 2014b; Vitousek et al., 2021), and the effects of possible interactions and correlations between the
112 stochastic wave forcing and other uncertain model inputs have not yet been investigated.

113 In this contribution, we investigate the response of two different wave-driven equilibrium shoreline
114 models to wave-forcing ensembles, and investigate how stochastic wave forcing affects the respective
115 long-term shoreline predictions in relation to other uncertain factors (e.g. SLR) while accounting for
116 possible interactions among them. A Global Sensitivity Analysis (GSA, Saltelli et al., 2008) is
117 performed to quantify the contributions of uncertain variables to the total uncertainties on shoreline
118 trajectories modelled with two equilibrium modelling approaches. The GSA estimates the model
119 sensitivity 'globally' by exploring all the range of plausible values for the uncertain inputs while
120 accounting for all possible interactions and statistical dependence between them. The analysis is carried
121 out on the cross-shore transport dominated Truc Vert beach (France) accounting for uncertainties in free
122 model parameters, future wave climate variability and SLR projections for two future representative
123 greenhouse-gas concentration pathway (RCP) scenarios. We investigate an additional scenario over the
124 past 23.5 years, where only wave chronology and model free parameters are considered as uncertain
125 input variables.

126 The remainder of the paper provides a description of Truc Vert beach, the data, the shoreline models
127 and the method used herein (Section 2); the assessment of the probability distributions associated to the
128 uncertain model inputs, required for the GSA, and the ensemble modelling setup (Section 3). The results
129 are presented and discussed in Section 4 and 5, respectively, followed by the conclusions (Section 6).

130 **2. Study Site, Material and Method**

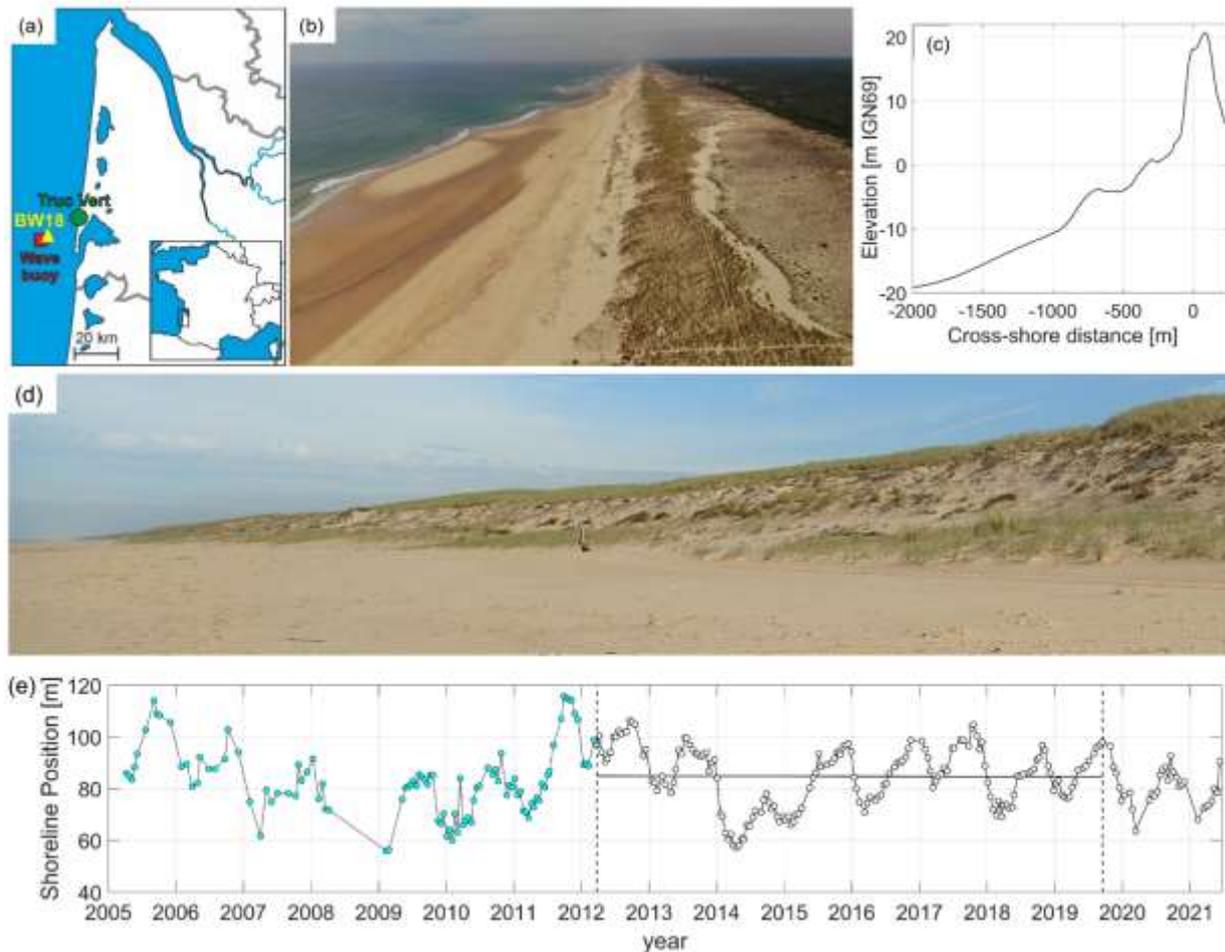
131 **2.1. Truc Vert beach**

132 Truc Vert is a sandy beach located within the ~130 km long straight Gironde coast, southwest France.
133 It is backed by a high (~20 m) and large (~250 m) aeolian dune (Robin et al., 2021) separating the beach
134 from a large area of state-owned forest (Figure 1a-d). The beach is exposed to a highly energetic wave
135 climate generated in the North Atlantic Ocean. Incident wave energy mostly comes from the west-
136 northwest direction with a strong seasonal modulation of significant wave height (H_s) and peak wave
137 period (T_p) (Castelle et al., 2018a; Charles et al., 2012; Robinet et al., 2016) reaching monthly mean
138 values of 1.1 m and 9 s in August, and 2.4 m and 12.8 s in January, respectively. The local winter wave
139 energy also shows interannual variations driven by natural large-scale patterns of atmospheric variability

140 such as the West Europe Pressure Anomaly (Castelle et al., 2017), which affects the spatio-temporal
141 distribution of storm events and clustering winters (Castelle et al., 2015; Masselink et al., 2016). Cross-
142 shore processes driven by the temporal variability of incident wave energy have been recognized to be
143 the main driver of shoreline changes at Truc Vert (Castelle et al., 2014; Robinet et al., 2018, 2016), in
144 line with the negligible longshore drift gradients in this area (Idier et al., 2013). Truc Vert is a meso-
145 macro tidal beach with a ~3.7 m annual mean spring tidal range and a maximum astronomical tide range
146 reaching up to 5 m (Castelle et al., 2018a), with negligible tidal currents compared to wave-driven
147 currents in the nearshore zone.

148 Starting from the early 2000s, Truc Vert beach has been monitored monthly to bi-monthly with
149 topographic DGPS surveys from 2003 (with 1-year gap in 2008) (Figure 1e), with additional field
150 campaigns including a 5-weeks campaign of daily bathymetric surveys in 2008 (Parisot et al., 2009;
151 Sénéchal et al., 2011), and seasonal high-resolution digital elevation models from photogrammetry of
152 UAV images covering 4 km of beach-dune since 2017 (Laporte-Fauret et al., 2019). Here, following
153 Castelle et al. (2014) and Robinet et al. (2016), the shoreline position is defined as the intersection of
154 the beach profile with the 1.5 m level contour above mean sea level, which approximately corresponds
155 to the mean high water level at Truc Vert beach and best correlates to variations in total beach-dune
156 volume. For more details on the topo-bathymetric datasets, see Castelle et al. (2020).

157 Over the past few decades, the Truc Vert coastline as well as the dune foot have been observed to be
158 approximately stable (Castelle et al., 2018b), with some exceptions such as the extreme winter of 2013-
159 2014, characterized by rapid successions of severe storms that caused large erosion and dune scarping
160 (Castelle et al., 2015; Masselink et al., 2016). The absence of coastal or inland structures nearby, together
161 with the wealth of available data, make this site a worthy benchmark for modelling and interpreting
162 shoreline response to natural processes.



163

164 **Figure 1.** (a) Map of the southwest coast of France with the location of Truc Vert beach (green), and wave hindcast
 165 grid point co-located with the CANDHIS in situ wave buoy (red); Photographs of Truc Vert beach and dune
 166 landscape from (b) UAV aerial view (photo by B. Castelle), and (d) foredune view (photo by S. Bujan); (c) 4 km
 167 alongshore-averaged beach-dune profile from merged 2008 topo-bathymetry (submerged beach) and 2018 UAV-
 168 photogrammetry digital elevation model (emerged beach and dune); (e) Time series of alongshore-averaged
 169 shoreline (1.5-m elevation proxy) position from April-2005 to June-2021 derived from the topographic surveys.
 170 Vertical dashed lines divide the data prior to March-2012 (cyan circles) from data used for model calibration (2012-
 171 2019) with the respective linear trend and validation (2019-2021) (white circles) (see Section 3.1).

172 2.2. Sea level and wave data

173 Historical wave data was required for calibration of the shoreline models and for generating the wave
 174 ensemble used in this work to force the probabilistic past and future shoreline projections. Information
 175 on past and future relative mean sea level (MSL) at Truc Vert beach was needed to account for SLR-
 176 driven shoreline erosion during model calibration and simulations. Herein we used the same datasets of
 177 past wave conditions, past MSL, and future SLR projections adopted in D'Anna et al. (2021a). In this
 178 Section, we briefly describe these datasets, which are all extended here to June 2021.

179 Historical incident wave conditions at Truc Vert beach were obtained from the NORGAS-UG regional
 180 wave model (Michaud et al., 2016). The NORGAS-UG model provides hourly hindcast wave conditions
 181 over the French Atlantic coastal area, and has been extensively validated against data from a number of
 182 wave buoys (Michaud et al., 2016). We extracted the time series of significant wave height (H_s), peak

183 period (T_p) and mean direction (D_m) from January 1994 to June 2021, at the model grid point co-located
184 with the in situ CANDHIS directional wave buoy (44°39'9"N; -1°26'48"W) moored in 54-m depth
185 (Figure 1a). Figure 2a shows the characteristic strong seasonality of the incident wave energy
186 (synthesized here by $H^2_s T_p$) at Truc Vert, with also prominent winter wave energy interannual variability.

187 We adopted a constant rate of historical relative SLR of 3.3 ± 0.7 mm/year (median $\pm \sigma$), obtained by
188 D'Anna et al. (2021a) from the combination of geocentric MSL change and vertical land motion at Truc
189 Vert beach. Future relative MSL at Truc Vert beach was estimated using global SLR projections until
190 2100 and the respective likely ranges (17th – 83rd percentiles) from the Special Report on Oceanic and
191 Cryosphere in a Climate Change (SROCC; Oppenheimer et al. 2019), for the RCP4.5 and RCP8.5
192 scenarios. The global MSL estimates are projected to Truc Vert beach accounting for the regional
193 fingerprint of each process contributing to SLR, including Glacial Isostatic Adjustment (Slangen et al.,
194 2014), in line with Thiéblemont et al. (2019). Finally, the contribution of vertical land motion was added
195 assuming that this process will maintain the past observed rate of 1.2 ± 0.6 mm/yr over the 21st century
196 (as in D'Anna et al., 2021a).

197 **2.3. Shoreline change models**

198 As Truc Vert shoreline change is mostly driven by cross-shore sediment transport processes (Castelle et
199 al., 2014; Robinet et al., 2018, 2016), we resolved cross-shore shoreline response to the incident wave
200 climate using the *ShoreFor* (Davidson et al., 2013; Splinter et al., 2014b) and the Yates et al. (2009)
201 equilibrium shoreline models. Given that the Truc Vert offshore bathymetric iso-contours are mostly
202 shore-parallel, breaking wave conditions, which are required to force the above models, were estimated
203 with the Larson et al. (2010) empirical formula. Long-term shoreline retreat induced by SLR was
204 modelled using the Bruun (1962) Rule. The wave-driven models and the Bruun Rule were run separately
205 and then linearly combined in order to avoid spurious feedback mechanisms between the models
206 (D'Anna et al., 2021b), in line with previous works (Vitousek et al., 2017).

207 **2.3.1. Wave-driven shoreline models, disequilibrium conditions and free** 208 **parameters**

209 The *ShoreFor* and Yates et al. (2009) models are both rooted in the equilibrium beach concept, which
210 assumes the existence of a time-dependent equilibrium state between the beach and the incident wave
211 conditions. Based on this concept, the rate and direction of shoreline change depends on the combination
212 of the incident wave force and the disequilibrium state of the beach (Wright and Short, 1984). The main
213 difference between *ShoreFor* and the Yates et al. (2009) models lies in the approach adopted to quantify
214 the (dis)equilibrium state and how this responds to the time-variability of wave conditions.

215 **2.3.1.1. *ShoreFor***

216 The *ShoreFor* model (herein SF) disequilibrium approach is based on the present and past dimensionless
217 fall velocities (Ω), and the concept of *beach memory*. The rate of shoreline change is estimated as:

218
$$\frac{dY}{dt} = k_s^{+/-} P^{0.5} \frac{\Delta\Omega}{\sigma_{\Delta\Omega}} \quad (1)$$

219 where, $k_s^{+/-}$ ($\text{m s}^{-1}\text{W}^{-0.5}$) is a response rate parameter, $P(W)$ is the wave power at breaking, $\Delta\Omega/\sigma_{\Delta\Omega}$ is the
 220 disequilibrium term, and b (m/s) is a linear trend term. The disequilibrium state at a given time is defined
 221 as the normalized difference between the equilibrium and current dimensionless fall velocities ($\Delta\Omega =$
 222 $\Omega_{eq} - \Omega$), here calculated from offshore wave conditions (Robinet et al., 2018):

223
$$\Omega = \frac{H_{s,o}}{T_p w} \quad (2)$$

224
$$\Omega_{eq} = \sum_{i=1}^{2\varphi} \Omega_i 10^{-i/\varphi} \left[\sum_{i=1}^{2\varphi} 10^{-i/\varphi} \right]^{-1} \quad (3)$$

225 where w (m/s) is the sediment fall velocity, and φ (days) is a beach memory parameter. The equilibrium
 226 term (Ω_{eq} , Equation 3) is defined by the weighted average of Ω over the past 2φ days, attributing to φ
 227 the role of ‘memory’ of the beach. As w is generally assumed constant over time and φ is a stationary
 228 model parameter, the dynamic equilibrium state fully relies on the variability of wave conditions,
 229 providing SF with the ability to respond to long-term variations of wave regime.

230 The response rate parameter $k_s^{+/-}$ represents an efficiency rate, which determines the rate of shoreline
 231 change in response to the wave forcing. This parameter associates different values for accretion ($\Delta\Omega > 0$,
 232 k_s^+) and erosion ($\Delta\Omega < 0$, k_s^-) events to account for the different time scales related to the respective
 233 driving processes. In SF, the k_s values for accretion and erosion are assumed to be linearly related by a
 234 so-called ‘erosion rate’ parameter r ($k_s^- = r k_s^+$). The r parameter is such that an increasing (decreasing)
 235 trend the wave forcing over the simulated period produces an erosive (accreting) trend of shoreline
 236 change, and is estimated as follows:

237
$$r = \left| \frac{\sum_{i=1}^N \langle F^+ \rangle}{\sum_{i=1}^N \langle F^- \rangle} \right| \quad (4)$$

238
$$F = P^{0.5} \frac{\Delta\Omega}{\sigma_{\Delta\Omega}} \quad (5)$$

239 where F^+ and F^- refer to accretion ($\Delta\Omega > 0$) and erosion ($\Delta\Omega < 0$) events, respectively, $\langle \cdot \rangle$ indicates an
 240 operation that removes the linear trend, and N is the number of time-steps over the simulated period.
 241 The parameter b represents a residual, steady, shoreline trend due to any unresolved long-term processes
 242 over the simulated period (e.g. SLR, longshore sediment transport gradients, etc.). φ , k_s^+ and b are site-
 243 specific free parameters that require calibration against observed wave and shoreline data. Given the
 244 negligible contribution of long-term processes such as longshore drift gradients in the Truc Vert area

245 (Idier et al., 2013), and that uncertainties on the linear trend explode over the long time scales (D'Anna
246 et al., 2020) simulated here (decades to centuries), we set $b=0$.

247 **2.3.1.2. Yates Model**

248 In the Yates et al. (2009) model (herein Y09) the disequilibrium condition is expressed in terms of
249 incident wave energy ($\Delta E = E_{eq} - E$), where the equilibrium state E_{eq} is defined as a function of the
250 current shoreline position Y . In Y09, the rate of shoreline change is calculated as follows:

$$251 \quad \frac{dY}{dt} = k_y^{+/-} E^{0.5} (E_{eq}(Y) - E) \quad (6)$$

252 where $k_y^{+/-}$ ($m^2 \text{ s}^{-1}/m$) is the response rate parameter, $E(m^2)$ is the wave energy, $Y(m)$ is the current
253 shoreline position, and $E_{eq}(Y)$ is the wave energy that would cause no change to the current shoreline
254 position Y . Similarly to SF, the response rate parameter $k_y^{+/-}$ indicates the rate (or efficiency) of shoreline
255 response to the wave forcing, and associates different values for accretion (k_y^+ , $\Delta E > 0$) and erosion (k_y^- ,
256 $\Delta E < 0$). However, contrary to SF, in Y09 k_y^+ , and k_y^- are independent free parameters. The equilibrium
257 wave energy E_{eq} is related to the shoreline position through the empirical *equilibrium energy function*:

$$258 \quad E_{eq}(Y) = a_1 Y + a_2 \quad (7)$$

259 where $a_1(m^2/m)$ and $a_2(m^2)$ are empirical coefficients. While a_1 and a_2 associate the dimensions of
260 'energy per meter' and 'energy', respectively, these are to be interpreted as empirical parameters. In
261 Y09, the values for a_1 , a_2 , k_y^+ , and k_y^- are specific to the site of application, and need calibration against
262 available wave and shoreline observations. Y09 does not include an explicit 'beach memory' term, but
263 implicitly accounts for recent past events through Equation 7. In fact, this relationship allows damping
264 the efficiency of wave-driven shoreline change as the shoreline approaches its equilibrium position
265 (Vitousek et al., 2021; Yates et al., 2009). However, as the coefficients of Equation 7 (a_1 , a_2) are
266 estimated based on the wave conditions observed during the calibration period and remain stationary
267 over time, Equation 7 does not respond to shifts in wave climate. Recently, Vitousek et al. (2021) showed
268 that a rearrangement of Y09 free parameters results in combined terms that can be interpreted as local
269 equilibrium time and spatial scale factors. However, in this application we retained the original form of
270 Y09, interpreting a_1 and a_2 as empirical parameters.

271 **2.3.2. Sea-level induced shoreline erosion**

272 The chronic shoreline recession driven by SLR was estimated here with the Bruun (1962) model. This
273 model is based on cross-shore sediment balance conservation under the assumption that the equilibrium
274 beach profile shape remains unchanged over time. According to the Bruun model, over time scales larger
275 than years, the beach profile adapts to the slow-rising sea level with an upward and landward shift
276 resulting in a mean shoreline retreat (dY_{SLR}) given by:

277

$$\frac{dY_{SLR}}{dt} = \frac{SLR_{rate}}{\tan\beta} \quad (8)$$

278 where SLR_{rate} is the rate of SLR(m/time) and $\tan\beta$ is the mean slope of the active beach profile. Here,
 279 the latter profile was defined between the dune crest and the ‘depth of closure’, beyond which no
 280 significant sediment exchange is assumed to occur (Bruun, 1988; Wolinsky and Murray, 2009). We
 281 estimated $\tan\beta = 0.023$ using the beach profile reported in Figure 1c and the depth of closure calculated
 282 according to Hallermeier (1978). Although the generalized applicability of the Bruun model has been
 283 questioned due to its restricting assumptions (Cooper et al., 2020; Cooper and Pilkey, 2004; Ranasinghe
 284 et al., 2012), Truc Vert beach settings are in line with most of Bruun’s underlying assumptions (D’Anna
 285 et al., 2021b).

286

2.4. Method

287

2.4.1. Multivariate stochastic climate-based wave emulator

288 Equilibrium shoreline models require continuous time series of incident wave conditions with a time
 289 resolution of the order of hours. In this study, we produced an ensemble of synthetic wave forcing
 290 conditions using the climate-based stochastic wave emulator developed by Cagigal et al. (2020). For a
 291 given location, the emulator exploits broad spatial scale sea level pressure fields and synoptic patterns,
 292 together with local historical wave data, to generate ensembles of unique continuous realistic wave time
 293 series. The wave series are generated through: (i) a statistical downscaling of climate forcing relying on
 294 annual and daily synoptic patterns; (ii) an intra-seasonal chronology model based on autoregressive
 295 logistic regression (Anderson et al., 2019); and (iii) a ‘stretching and shuffling’ of intra-storm historical
 296 wave properties using Gaussian copulas. This method ensures that the modelled wave time series present
 297 different chronologies of events while preserving intra-storm to interannual statistical properties
 298 consistent with the historical data. The latter means that the generated time series are also characterized
 299 by the same long-term trend observed over the historical wave data. The wave emulator has already
 300 been applied to produce ensembles of wave time series for probabilistic shoreline modelling at several
 301 sites based on the respective records of historical wave conditions, and showed good skill in reproducing
 302 observed shoreline erosion statistics (Cagigal et al., 2020; Vitousek et al., 2021). For a more detailed
 303 outline of the underlying methodology see Cagigal et al. (2020).

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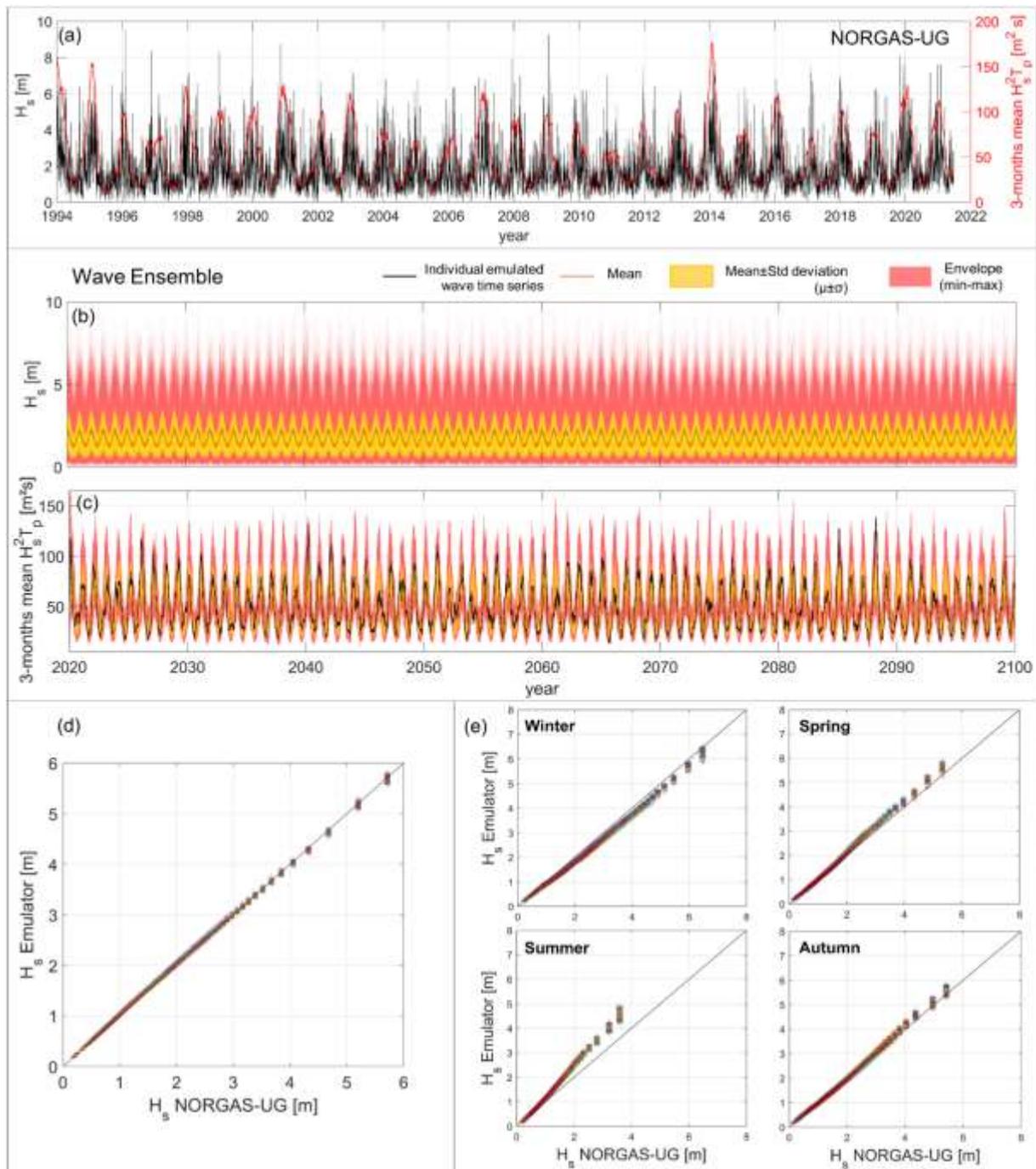
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310

We used the wave emulator to model 200 hourly time series of wave conditions (H_s , T_p , D_m) from
 January 1994 to December 2009, based on 27 years (1994-2020) of wave hindcast data offshore Truc
 Vert beach (Section 2.2) and sea level pressure fields from the Climate Forecast System Reanalysis
 (Saha et al., 2010). Figure 2b shows the mean (orange line), standard deviation (yellow area), and the
 min-max envelope (red area) of the emulated H_s series, which attained extreme values of same order of
 magnitude as observed during the hindcast period ($H_s \sim 8-10$ m). Figure 2c illustrates the standard
 deviation (yellow area) and envelope (red area) of the 3-month averaged $H_s^2 T_p$ ensemble, along with an

311 example of individual time series (black line). The statistical properties of the generated ensemble
312 showed good agreement with the historical wave data. Figure 2d,e show a *quantile-quantile* comparison
313 of H_s between the reference hindcast data (1994-2020) and each member of the wave ensemble (1994-
314 2099) for the full time series and their seasonal repartition, respectively. Here, seasons were defined as
315 follows: Winter (December-January-February), Spring (March-April-May), Summer (June-July-
316 August) and Autumn (September-October-November). The comparisons of T_p and D_m are shown in the
317 Supplementary Material (Figure S1). While the H_s quantiles estimated on the entire time series show a
318 near-perfect consistency (Figure 2c), the seasonal plots show some discrepancies (Figure 2d). However,
319 these differences are not expected to affect the analyses carried out in this work (as discussed in Section
320 5.4). Consistently with the historical wave series, the winter mean wave heights of the emulated time
321 series show no significant trend between present day (2021) and the end of the 21st century (Figure S2).



322

323 **Figure 2.** (a) Time series of H_s (black line) and 3-month averaged $H_s^2 T_p$ (red line) from 1994 to 2021 from
 324 NORGAS-UG hindcast model; Envelope (min. and max.) (red area) and mean \pm σ interval (yellow area) of the
 325 200 (b) H_s and (c) 3-month averaged $H_s^2 T_p$ time series from 2021 to 2100, generated using the wave emulator,
 326 with mean H_s (orange line) and the 3-month averaged $H_s^2 T_p$ of an individual time series; quantile-quantile
 327 comparison between the H_s of hindcast data and each member of the wave ensemble for (d) the full time series,
 328 and (e) their seasonal repartition.

329

2.4.2. Global Sensitivity Analysis

330

The uncertainties associated to model assumptions and climate unpredictability propagate through the
 331 model resulting in uncertain model predictions. Regardless of their nature, the uncertainties affecting
 332 the inputs can have a different influence on the model outcome. In variance-based approaches, the

333 uncertainties associated with a variable are represented by its variance. We quantified the different
334 contributions to the uncertainties on modelled shoreline change at Truc Vert beach by performing a
335 variance-based GSA (Saltelli et al., 2008). The variance-based GSA explores the full range of realistic
336 combinations of uncertain model inputs with the aim to divide the uncertainties (i.e. variance) of
337 probabilistic model results into several portions, each one attributed to an uncertain model input (or a
338 set of inputs). The resulting contribution that an uncertain input X_i provides to the uncertainties in model
339 predictions is given by the main effect (first-order sensitivity), and by interactions terms (higher-order
340 sensitivity). The main effect measures the sensitivity of model results to variations of the X_i value alone,
341 while the higher-order components measure the additional effects that simultaneous variations of X_i with
342 other uncertain inputs have on the results' variance. The latter accounts for the fact that simultaneous
343 variation of multiple X_i 's may drive a larger contribution to the results variance than the cumulated main
344 effects (individual variations) of X_i 's. For each uncertain input X_i , the normalized main effect of X_i
345 uncertainties on the model results can be synthesized by a sensitivity measure (S'_i), also known as first-
346 order *Sobol' indices* (Sobol', 2001), expressed as:

$$347 \quad S'_i = \frac{\text{Var}(E(Y|X_i))}{\text{Var}(Y)} \quad (9)$$

348 where Y is the model prediction, X_i is the i -th uncertain input variable, $E(Y|X_i)$ is the expected value of
349 Y conditional to X_i , and $\text{Var}(E(Y|X_i))$ is the variance of the $E(Y|X_i)$ s obtained for all the possible values
350 of X_i . S'_i quantifies the percentage of the model results variance that can be attributed to the uncertainties
351 on the variable X_i alone. When X_i interacts with other uncertain inputs (e.g. X_j) within the model, the
352 uncertainties associated with X_j may amplify the impact of X_i on the results uncertainties (and those of
353 X_i may amplify the impact of X_j) compared to the first-order effects. In this case, the contribution of X_i
354 and X_j to the variance of model results is larger than $S'_i + S'_j$. The latter contribution as well as higher-
355 order effects can be estimated by calculating higher-order *Sobol' indices* with formulations analogous
356 to Equation 9 (see Text S2 of Supplementary Material).

357 The GSA described above builds on the assumption that all the uncertain input variables are statistically
358 independent from one to another. If two or more uncertain inputs are statistically dependent, say X_i and
359 X_j , such correlations can significantly influence the uncertainties of model results, and the S'_i includes
360 some information that is also included in S'_j , regardless of the possible interactions between the two
361 variables (Do and Razavi, 2020; Iooss and Prieur, 2019). This is the case, for instance, of the calibrated
362 shoreline model parameters, which can associate up to more than 70% correlation coefficient (see
363 Section 3.1).

364 The *Shapley Effects* (Sh 's) have been proposed based on the *Shapley values* (Shapley, 1953) to
365 overcome the difficulties in the interpretation and use of the *Sobol' indices* in presence of statistical
366 dependence and interaction among inputs (Iooss and Prieur, 2019; Owen, 2014; Song et al., 2016). The

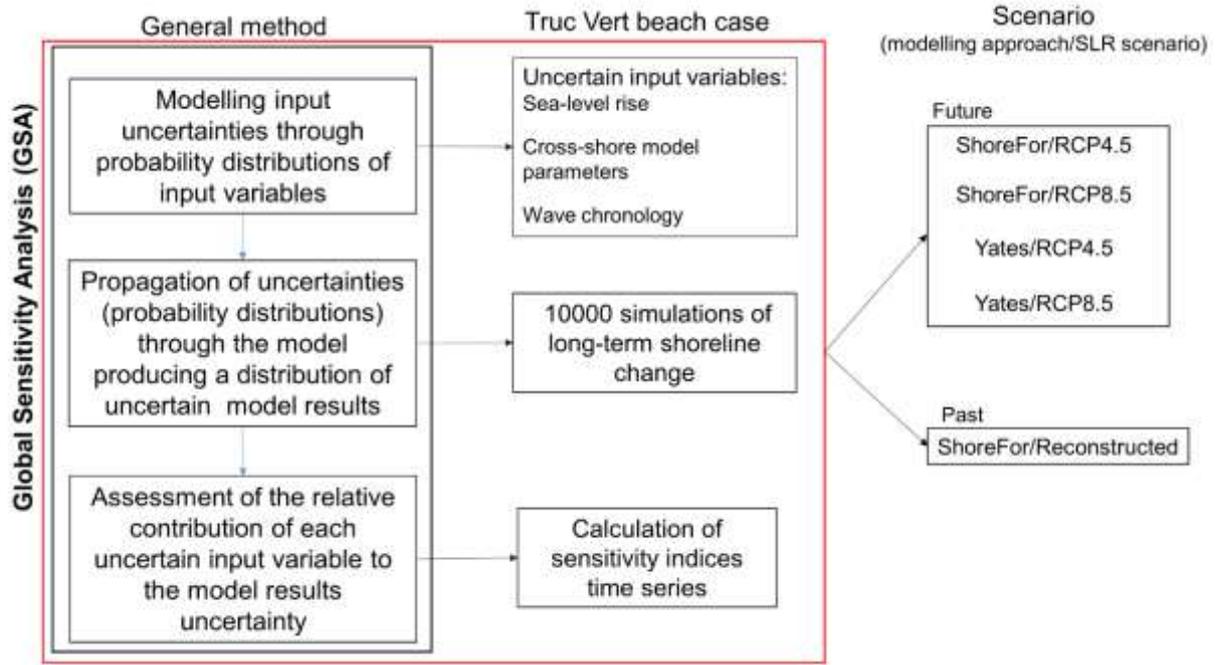
367 *Shapley values* were originally introduced in game theory to evaluate the “fair share” of team players
 368 after a game based on their individual contributions and their interactions with other players. In the
 369 context of the GSA the ‘players’ are the uncertain model inputs, and the model results variance is the
 370 ‘value’ to share. The Sh_i quantifies the percentage of output variance ($0 \leq Sh_i \leq 1$) associated to the input
 371 variable X_i , including the main effect, an equitable share of all its interaction terms with other variables,
 372 and the contributions of possible statistical dependence (correlation) among the uncertain inputs, and is
 373 expressed as follows:

$$374 \quad Sh_i = \frac{1}{k} \sum_{A \subseteq K \setminus \{i\}} \binom{k-1}{|A|}^{-1} (S_{A \cup \{i\}} - S_A^{clos}) \quad (10)$$

$$375 \quad S_A^{clos} = \frac{\text{Var}(E(Y|X_A))}{\text{Var}(Y)} \quad (11)$$

376 where S_A^{clos} indicates “closed Sobol’ indices” defined by Owen (2014), k is the number of uncertain
 377 input variables, $K \setminus \{i\}$ is the set of input indices $(1, \dots, k)$ excluding i , A is a subset of $K \setminus \{i\}$, and $|A|$ is the
 378 cardinality number of the subset A (see Text S2 of Supplementary Material for details). For a given input
 379 X_i , $Sh_i=1$ indicates that the uncertainties on X_i are accountable for the entirety of the results uncertainties,
 380 while for $Sh_i=0$ the model results are essentially insensitive to X_i , and the sum of all Sh ’s equals 1. While
 381 Sh ’s include the first- and higher-order terms and the shared effects of inputs correlations to the model
 382 results, they do not provide these contributions separately.

383 Here, we analysed the time-varying effects of uncertainties associated to model free parameters, SLR,
 384 and wave chronology on the modelled Truc Vert shoreline change using the Shapley Effects, while first-
 385 order Sobol’ indices were computed to support the discussion in Section 5.2. In addition, we assessed
 386 the impact of the shoreline modelling approach choice by repeating the application for each of the two
 387 wave-driven models (SF and Y09). The framework described above requires the definition of a
 388 probability distribution for each uncertain input variable, a large number of realizations based on a
 389 Monte-Carlo procedure (accounting for statistical dependence among the variables), and the
 390 computation of Shapley effects at each analysed time step (Figure 3).



391

392 **Figure 3.** Method outline of a generalized case (black box) and the Truc Vert beach applications (red box) for past
 393 and future different sea-level rise and shoreline modelling scenarios. Figure modified from D’Anna et al. (2020).

394 **3. Input Uncertainties**

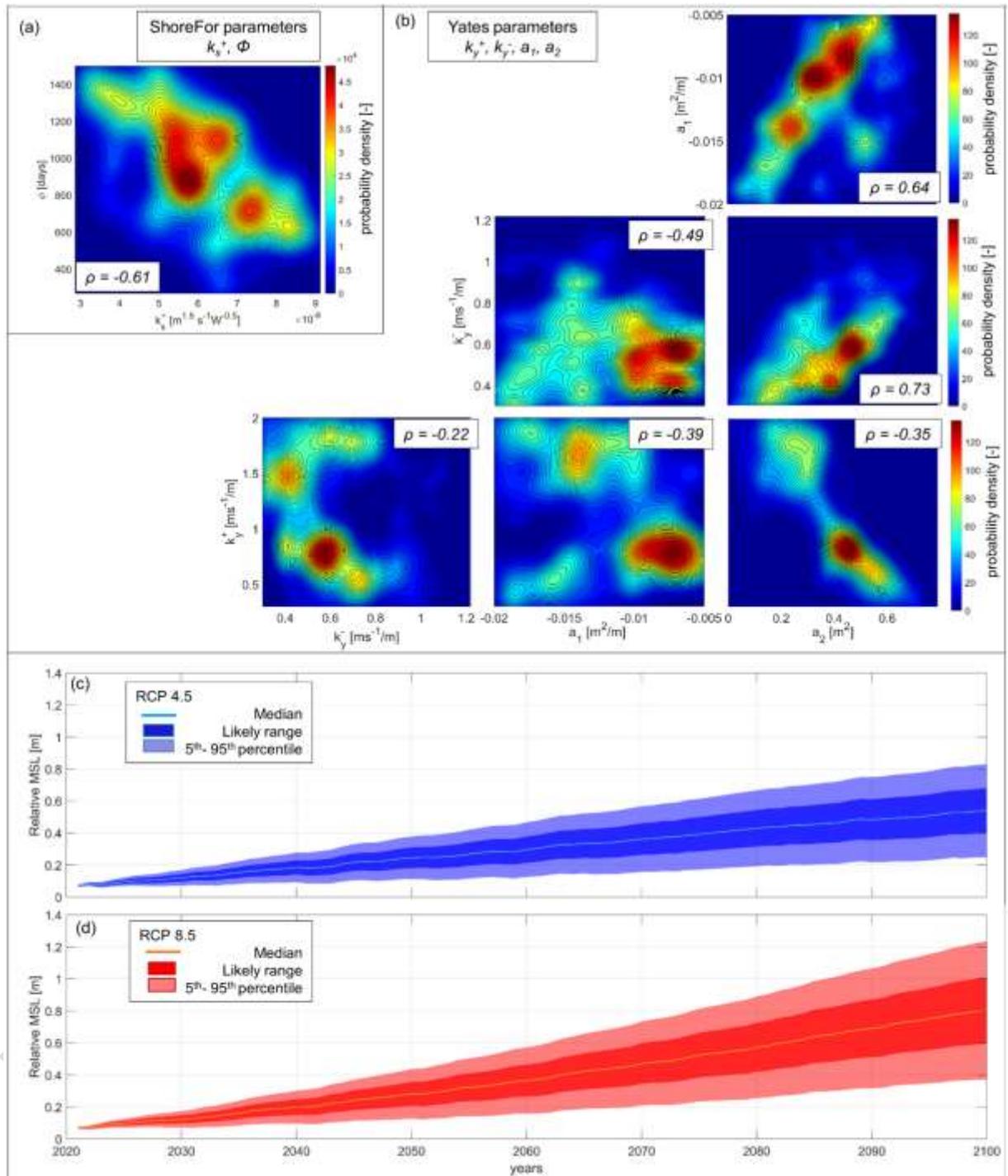
395 **3.1. Model free parameters**

396 Equilibrium shoreline models are affected by uncertainties related to the underlying physical
 397 assumptions as well as their data-driven nature. We accounted for the former by running and comparing
 398 the GSA for different scenarios using the disequilibrium approaches of the SF and Y09 models (Section
 399 2.3.1). These models require the calibration of free parameters that associate uncertainties depending on
 400 the extent, density and quality of the available shoreline datasets (Splinter et al., 2013). The uncertainties
 401 on the calibration of SF (k_s^+ , φ) and Y09 ($k_y^{+/-}$, a_1 , a_2) model free parameters were represented by the
 402 respective joined probability distributions, defined using the approach adopted by D’Anna et al. (2021a).
 403 In this approach, the shoreline models were calibrated using the Simulated Annealing algorithm
 404 (Bertsimas and Tsitsiklis, 1993), which generates a large number of model parameters combinations
 405 before converging to a set of best-fit parameters. The parameters combinations that produce a model
 406 performance higher than a predefined threshold were selected and used to fit an empirical multivariate
 407 probability distribution (multivariate kernel function). The model performance was measured in terms
 408 of Nash-Sutcliffe score (NS) (Nash and Sutcliffe, 1970), which quantifies the model skill compared to
 409 the skill associated with the mean of the observed shoreline position (\bar{Y}_o).

$$410 \quad NS = 1 - \frac{\sum_{n=1}^N (Y_m^n - Y_o^n)^2}{\sum_{n=1}^N (\bar{Y}_o - Y_o^n)^2} \quad (12)$$

411 where N is the number of observations, Y_m^n and Y_o^n are the n -th modelled and observed shoreline
 412 positions, respectively. An NS value of 1 indicates that the model perfectly reproduces the observed

413 shoreline positions, while $NS=0$ corresponds to a model as skilful as the straight mean (\bar{Y}_0). The
414 minimum threshold used to fit the free parameters probability distribution is set to $NS \geq 0.25$, which is
415 an appropriate value for SF and Y09 applications at Truc Vert beach (D'Anna et al., 2021a). Here, we
416 calibrated the models over the period March 2012 – September 2019, which show no long-term shoreline
417 trend supporting the assumption that $b=0$ in the SF model. Further available shoreline observations up
418 to June 2021 (Figure 1e) were exploited for the validation of the ensemble simulations. Shoreline data
419 prior to 2012 is discarded from the calibration procedure due to the lower confidence deriving from the
420 limited alongshore coverage of their associated topographic survey (Castelle et al., 2020; D'Anna et al.,
421 2020). Over the calibration period, the Y09 and SF models produce a Root-Mean-Square-Error (RMSE)
422 of 5.1 m and 7.2 m, respectively, and a coefficient of determination R^2 of 0.80 and 0.65, respectively.
423 The resulting probability distributions of Y09 and SF model free parameters are shown in Figure 4a,b
424 together with the respective Pearson correlation coefficients (denoted ρ) indicating several levels of
425 correlation among the model parameters. The ranges of possible parameters values are reported in Table
426 1.



427

428 **Figure 4.** Joint distributions of (a) the ShoreFor (k_s^+ , ϕ) and (b) Yates ($k_y^{+/-}$, a_1 , a_2) free parameters with the
 429 corresponding Pearson correlation coefficients ρ ; and probability distributions of 2021-2100 sea-level rise
 430 projections for (c) the RCP4.5 and (d) RCP8.5 scenarios, with the respective 66% confidence interval (dark-shaded
 431 areas) and 5th-95th percentile range (light-shaded area).

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

Model	Model parameter	Optimised value	Distribution range
ShoreFor (SF)	$k_s^+ [m^{1.5} s^{-1} W^{-0.5}]$	5.0×10^{-8}	$[1.6; 9.8] \times 10^{-8}$

	φ [days]	1127	[106; 1729]
Yates (Y09)	k_y^+ [$\text{m}^2\text{s}^{-1}/\text{m}$]	0.71	[0.15 ; 2.41]
	k_y^- [$\text{m}^2\text{s}^{-1}/\text{m}$]	0.56	[0.10 ; 1.32]
	a_1 [m^2/m]	-0.01	[-0.02 ; -0.003]
	a_2 [m^2]	0.46	[0.01 ; 0.79]

434 **3.2. Sea-Level Rise**

435 Information on past relative MSL associates uncertainties related with measurement errors of the
 436 geocentric MSL and the vertical land motion. This kind of uncertainties are very small compared to the
 437 uncertainties on the free parameters of shoreline models, and have been shown to have a negligible
 438 impact on the uncertainties of shoreline change at Truc Vert over the past 20 years (D'Anna et al., 2020).
 439 Therefore, here the uncertainties on past SLR were not included in the GSA.

440 Uncertainties on future SLR estimates essentially derive from unknowns on the future climate scenario
 441 and modelling of the different contributing processes. These sources of uncertainty were accounted
 442 through the likely range of the SROCC projections. Following D'Anna et al. (2021a), we produced
 443 probabilistic MSL projections assuming a Gaussian distribution (in line with Hunter et al., 2013), with
 444 median and standard deviation corresponding to the yearly median and likely range SROCC estimates
 445 for the RCP4.5 and RCP8.5 scenarios (Figure 4c,d). As the SROCC projections refer to the year 2007,
 446 we re-fitted the projections between 2021 and 2100, conditioning the MSL median and likely range to
 447 the corresponding values observed in 2021. See Text S1 and Figure S3 of Supplementary Material for
 448 more details on this correction. As the characteristics of the future MSL probability distribution are time-
 449 dependent, in the following applications MSL time series were defined for a given percentile (p) by
 450 extracting the sea level corresponding to p at each year.

451 **3.3. Waves chronology**

452 The stochastic nature of wave conditions provides a portion of uncertainties to the modelled shoreline
 453 change, which responds differently to different chronologies of wave events. In order to account for the
 454 uncertainties on wave chronology, we define an indicator variable (i.e. categorical variable) that takes
 455 up discrete values between 1 and 200, each value being associated to a given time series described in
 456 Section 2.4.1 (index 1 for time series N°1, index 2 for time series N°2, etc.). Then, we randomly and
 457 uniformly sample the values of the indicator variable to select the time series used to force the shoreline
 458 modelling realizations within the GSA. In the following, the influence of the wave chronology is
 459 analysed by assessing the Shapley Effect of the defined indicator variable. This differs from the analysis
 460 of uncertain model free parameters and future SLR percentiles in that the indicator variable is not a
 461 quantitative value but a categorical number. This approach, has been applied by Rohmer (2014) for
 462 spatially varying uncertain inputs, allows accounting for the bulk effect of stochastic time-varying wave
 463 forcing on the uncertainties of modelled shoreline positions.

464 3.4. Models setup

465 Ensembles of simulated shoreline time series were generated for one ‘past scenario’ and four ‘future
466 scenarios’ at Truc Vert beach. All scenarios covered the calibration period (March 2012 – September
467 2019) and a validation period (September 2019 – June 2021). In the ‘past scenario’, shoreline evolution
468 was simulated from January 1998 to June 2021 using SF and the Bruun model. As the Y09 computation
469 of shoreline change at a given time is dependent on the previous shoreline position, the model does not
470 allow propagating the uncertainties on modelled shoreline towards the past. Therefore, the Y09 model
471 application to the ‘past scenario’ was not included in the main analysis, as discussed in Section 5.1.
472 Although wave data is available on the ‘past scenario’ simulated period, here we considered random
473 wave conditions characterized by the same statistical properties as the hindcast wave data, i.e. wave data
474 generated with the stochastic climate-based wave emulator (Section 2.4.1). In the ‘future scenarios’, the
475 shoreline position was projected over March 2012 – December 2099 using Y09 and SF with the Bruun
476 model for the RCP4.5 and 8.5 SLR scenarios. The models were forced using MSL time series
477 corresponding to percentiles randomly sampled between the 5th and 95th, and the randomly selected wave
478 time series characterized by the same properties as the past wave climate (Section 3.3).

479 For each ensemble, several thousands of shoreline trajectories were simulated using different
480 combinations of model free parameters, sea level percentiles and wave time series sampled from the
481 respective probability distributions. One exception is the ‘past scenario’, where local SLR is considered
482 deterministic with a constant rate of 3.31 mm/year, while only the model free parameters and forcing
483 wave series were sampled for each model run. Over the calibration and validation periods, the models
484 were forced using the observed (deterministic) wave and sea-level time series. The starting time of both
485 past and future shoreline simulations was set to the starting date of the models calibration (23rd May
486 2012), so that the modelled shoreline trajectories fit the shoreline data as observed during the calibration
487 and the uncertainties on simulated past shoreline change propagate towards the past. All simulations are
488 run with a 3-hour time step and outputs were stored with a 2-weeks frequency. The ensembles of model
489 results were analysed through the *envelope* (min-max) and the *likely range*, defined here as the standard
490 deviation interval ($\mu \pm \sigma$), of the simulated shoreline positions. The former is an indicator of the shoreline
491 response to extreme wave events, while the latter is proportional to the results variance (σ^2) used to
492 perform the GSA. Herein, positive (negative) variations of the shoreline position $dY/dt > 0$ ($dY/dt < 0$)
493 indicate shoreline accretion (erosion).

494 The *Shapley Effects* (Section 2.4.2) were computed for each stored model output excluding the
495 calibration and validation periods (i.e. excluding March 2012 – June 2021) by post-processing the inputs
496 and the results of the ensemble model realizations with a nearest-neighbour search technique (Broto et
497 al., 2020), using the 15 nearest neighbours. Before the *Sh*’s computation, the uncertain input values were
498 rescaled with a whitening procedure in order to achieve a homogeneous scale, and the wave time series
499 were treated as a categorical input, i.e. they are identified as the i -th, \dots , j -th, time series. For each GSA

500 application, we estimated 90% confidence bounds applying a 100-iteration bootstrapping at three
 501 different times of the simulated period for the ‘future scenarios’ (1st Jan. 2030, 2060 and 2090) and two
 502 for the ‘past scenario’ (1st Jan. 2000 and 2010). Confidence intervals were estimated by sampling without
 503 replacement with a proportion of the total sample size of 0.80, drawn uniformly (following the
 504 implementation in R *sensitivity* package).

505 **Table 2.** Past and future simulated ensembles based on 10000 different combinations of model parameters, SLR
 506 percentile and wave time series, for two future Representative Concentration Pathways (RCP) and two different
 507 wave-driven modelling approaches with the Bruun Rule.

Scenario	SLR scenario	SLR-driven shoreline model	Wave-driven shoreline model	Dataset name	Combinations	Simulated period
Past	Reconstructed	Bruun Rule	<i>ShoreFor</i> (SF)	SF+B/Past	10000	1998-2021
Future	RCP 4.5	Bruun Rule	<i>ShoreFor</i> (SF)	SF+B/RCP4.5	10000	2012-2100
			<i>Yates</i> (Y09)	Y09+B/RCP4.5	10000	
	RCP 8.5	Bruun Rule	<i>ShoreFor</i> (SF)	SF+B/RCP8.5	10000	
			<i>Yates</i> (Y09)	Y09+B/RCP8.5	10000	

508

509 4. Results

510 4.1. Past and future shoreline ensembles

511 The modelling setup described in Section 3.4 (Table 2) produced five ensembles of simulated shoreline
 512 position time series: one covering the past 23.5 years (Figure 5a), and four spanning from present day
 513 to 2100 (Figure 5b-e). Figure 5a-c and Figure 5d,e show the envelopes (min-max) and likely ranges
 514 ($\mu \pm \sigma$) of shoreline trajectories obtained using the SF and Y09 approaches, respectively, for the different
 515 scenarios. All modelled ensembles consistently fit the shoreline data over the calibration period (2012-
 516 2019) and well reproduce the large erosion associated with the particularly energetic winter of 2013-
 517 2014. The models also reproduce the shoreline variations observed during the validation period (2019-
 518 2021), with a mean determination coefficient $R^2=0.73$ and a mean RMSE=10.65 m. Over the validation
 519 period, the modelled shoreline ensembles capture the erosive trend associated with the increasing
 520 interannual winter wave energy in 2019-2021 (Figure 2a), with shoreline data falling within the range
 521 of the modelled ensembles (Figure 5). Compared to the ‘future scenarios’, the SF+B application to the
 522 past scenario shows slightly larger ranges of modelled shoreline over the calibration and validation
 523 periods (Figure 5a). This is due to the influence of the ensemble forcing wave conditions prior to 2012
 524 on the SF shoreline change computed over the following period.

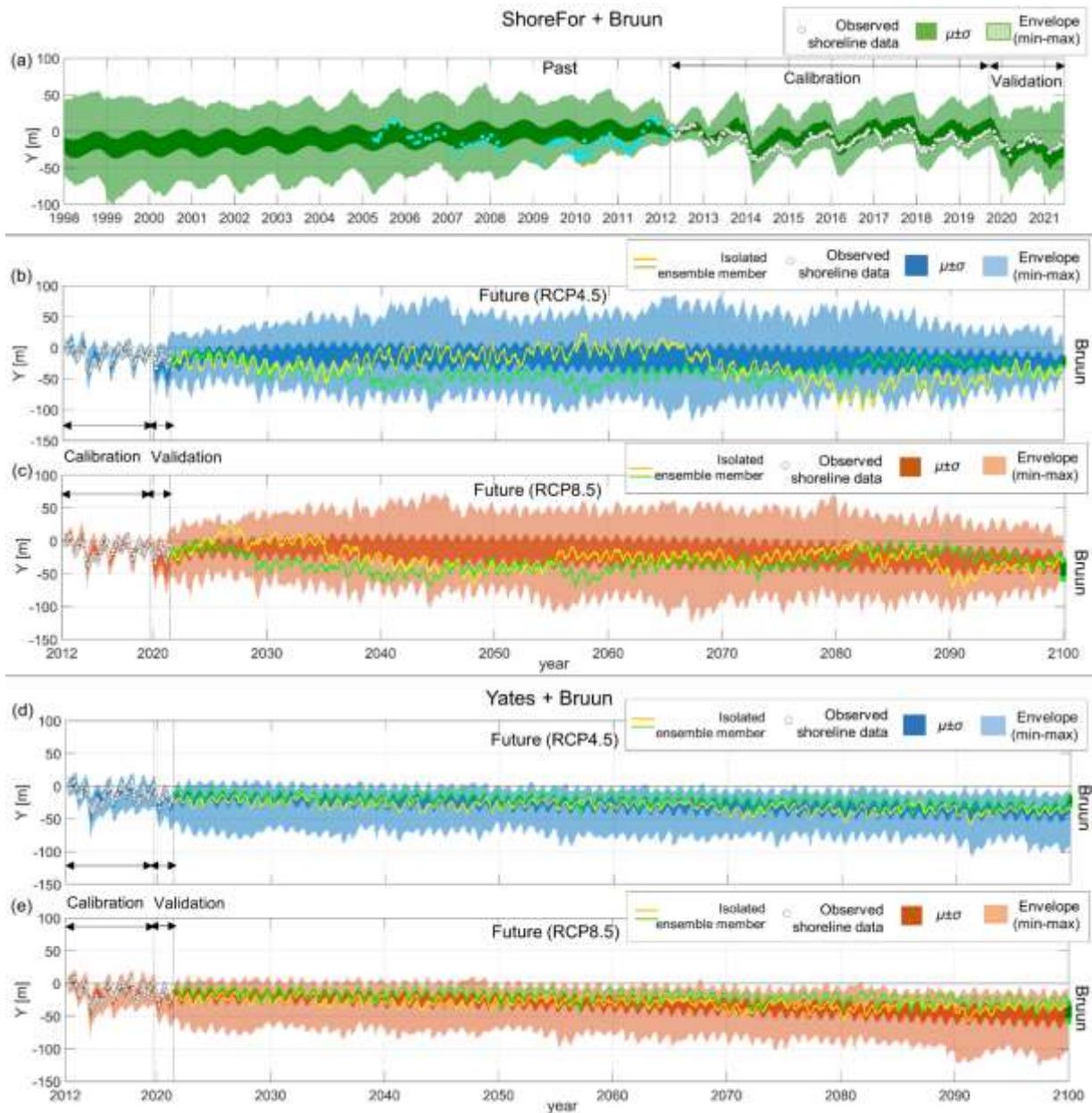
525 In the ‘past scenario’ (Figure 5a), the likely range (envelope) of shoreline position varies from [-29 m;
 526 -7.6 m] ([-59.2 m; 46.9 m]) in 1998 to [-8.3 m; -1 m] ([-15.1 m; 6.3 m]) in 2012. The application of
 527 ensemble wave forcing (1998-2012) results in a ‘richer’ envelope of possible shoreline trajectories and
 528 visibly larger prediction variance compared to the calibration and validation period (2012-2021) where
 529 a deterministic wave time series was applied (Figure 5a). The ensemble results also envelope the

530 shoreline data prior to 2012, which was discarded from the model calibration but provides a realistic
531 reference of shoreline variability.

532 Figure 5b-e show the ‘future scenarios’ of ensemble shoreline projections modelled combining the
533 Bruun model with SF and Y09, respectively, for two SLR scenarios (RCP4.5 and 8.5). All models were
534 forced with the same random selection of wave time series, and no feedbacks were allowed between the
535 wave- and SLR-driven models. Therefore, any long-term shoreline trend induced by each wave series
536 of the ensemble is reproduced identically for the RCP4.5 and 8.5. Hence, the results obtained for the
537 different RCP scenarios only differ in the magnitudes of the SLR-driven erosional trends. Indeed, using
538 either SF or Y09, the RCP8.5 scenario produces a more eroded shoreline position in 2100 and a larger
539 variance compared to the RCP4.5 scenario. Likely ranges and envelope values of the 2100 simulated
540 shoreline position are summarized in Table 3 for each ‘future scenario’, including the corresponding
541 ranges resulting from the application of the Bruun Rule alone.

542 The application of ensemble wave forcing series (from 2021 to 2100) results in different interannual and
543 multiannual shoreline patterns for the two wave-driven shoreline models (SF and Y09). In the two SF
544 future scenarios (Figure 5b,c), the ensemble projections show an initial period of overall accretion of
545 (2021-2030). Over the remaining part of the projection period (2030-2100), the likely range of shoreline
546 position maintains a seasonal character with a stable long-term erosive trend. Instead, the envelopes of
547 simulated shoreline trajectories show inter- and multi-annual fluctuations of both the most accreted
548 (max) and eroded (min) modelled shoreline position, highlighting the SF ability to respond to long-term
549 variability of the wave conditions. This is also illustrated by the two individual modelled shoreline
550 trajectories extracted from the ensembles (yellow and green lines in Figure 5,c). The width of both likely
551 range and envelope of shoreline position increases progressively from 2021 to ~2030 as the memory of
552 (deterministic) wave conditions prior to 2021 decays. After 2030, the likely ranges gradually grow until
553 ~2070 before narrowing until 2100 (as discussed in Section 5.1), while the envelope range follows the
554 same trends with superposed interannual variations, once again, associated to the temporal patterns of
555 the forcing wave series (Figure 5b,c).

556 When wave-driven shoreline change is modelled with the Y09 model (Figure 5d,e), both likely range
557 and envelope of simulated shoreline positions show a clear seasonal signal with a regular erosive trend
558 throughout the entire projection period (2021-2100), regardless of the RCP scenario. Here, the individual
559 shoreline trajectories (yellow and green lines in Figure 5d,e), forced with the same wave series as the
560 individual realization selected for the SF model, evolve with no long-term variations. In these two
561 scenarios, the width of likely ranges and envelopes grows gradually, and the lower bound of the envelope
562 exhibits some interannual variability.



563

564 **Figure 5.** Ensemble shoreline evolution simulated using the (a-c) *ShoreFor* and (d,e) *Yates*, combined with Bruun
 565 models, including the envelope (light-shaded areas) and the standard deviation intervals ($\mu \pm \sigma$) (dark-shaded areas)
 566 of the 10000 simulated shoreline trajectories, respectively, over (a) the 1998-2021 period ('past scenario'), and
 567 from 2012 to 2100 ('future scenarios') for the (b,d) RCP4.5 and (c,e) RCP8.5 future sea-level rise scenarios.
 568 Yellow and green lines (b-e) are individual model realizations within the ensemble. Black dashed lines delimit the
 569 calibration and validation periods, including shoreline observations (white circles). Cyan-coloured circles (a)
 570 indicate shoreline data prior to March 2012.

571 **Table 3.** Model results at 2090 and 2100 obtained for the four 'future scenarios' and the applications of the
 572 Bruun Rule alone, including the likely range ($\mu \pm \sigma$) and envelope (min-max) of simulated shoreline position, and
 573 the mean of 1-year averaged shoreline trajectories.

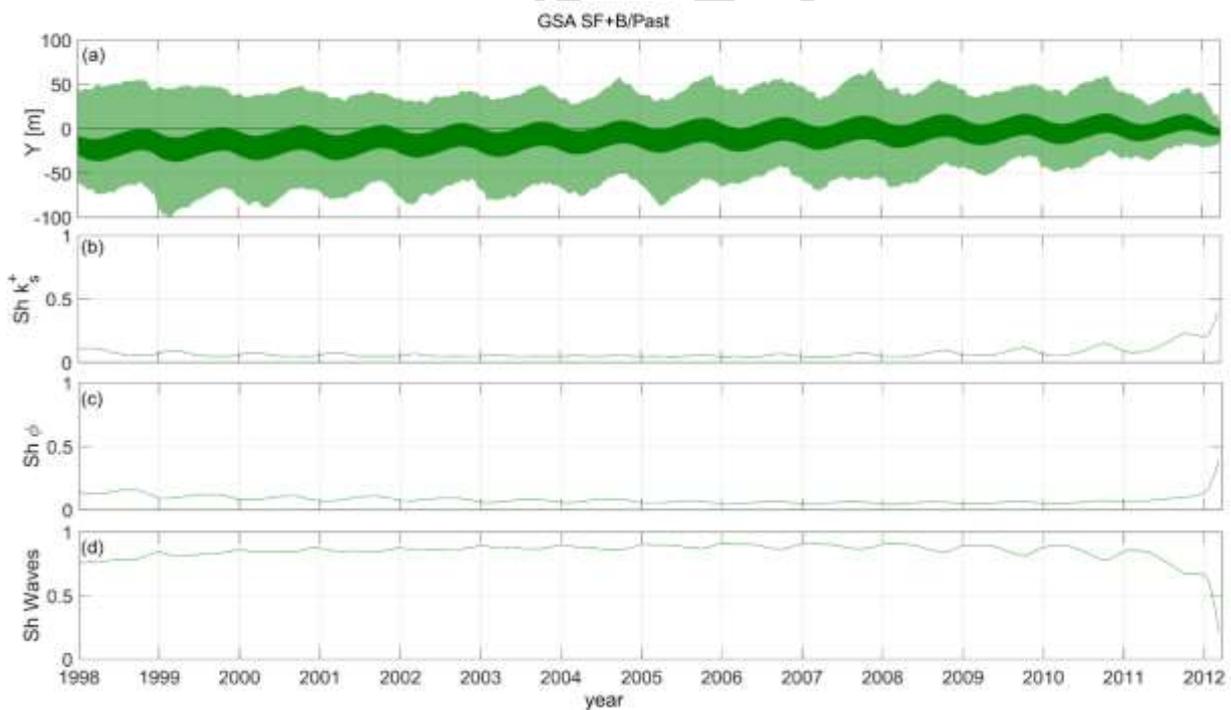
Future scenario	2090 modelled shoreline position		2100 modelled shoreline position	
	Likely range ($\mu \pm \sigma$)	Envelope (min-max)	Likely range ($\mu \pm \sigma$)	Envelope (min-max)
(SF+B)/RCP4.5	[-39 m; -7 m]	[-88 m; 44 m]	[-27 m; -12 m]	[-40.5 m; -0.7 m]

(SF+B)/RCP8.5	[-47 m; -12 m]	[-96 m; 40 m]	[-41 m; -19 m]	[-57 m; -3 m]
(Y09+B)/RCP4.5	[-47 m; -29 m]	[-79 m; -10 m]	[-48 m; -29 m]	[-93 m; -13 m]
(Y09+B)/RCP8.5	[-58 m; -35 m]	[-105 m; -15 m]	[-61 m; -36 m]	[-101 m; -15 m]
Bruun/RCP4.5	[-25 m; -15 m]	[-31 m; -11 m]	[-37 m; -28 m]	[-43 m; -22 m]
Bruun/RCP8.5	[-37 m; -21 m]	[-45 m; -13 m]	[-53 m; -33 m]	[-62 m; -25 m]

574

575 4.2. Global Sensitivity Analysis

576 For each stored model output time-step (2 weeks), the GSA decomposed the variances (i.e. uncertainties)
577 of the simulated shoreline ensembles into a set of *Shapley Effects* corresponding to the uncertain model
578 inputs. The GSA for the ‘past scenario’ results in roughly stable *Sh*’s of the model free parameters and
579 the wave chronology over time, with mild long-term trends. As the model variance reduces from 1998
580 to 2012, the *Sh* values of the SF parameters k_s^+ and ϕ first decrease from 15% to 5% and 13% to 5%
581 (~2006), respectively, then increase to 40% and to 39%, respectively by 2012. The wave chronology’s
582 *Sh* gradually increases from 78% to 85% (~2006) before decaying to 21% (Figure 6b-d). The 90%
583 confidence bounds were estimated to be within $\pm 1\%$ for all the variables. All *Sh*’s show a mild seasonal
584 signal, where the *Sh*’s of free parameters increase during accretion (low wave energy) periods, with a
585 similar but out-of-phase signal for wave chronology’s *Sh*.



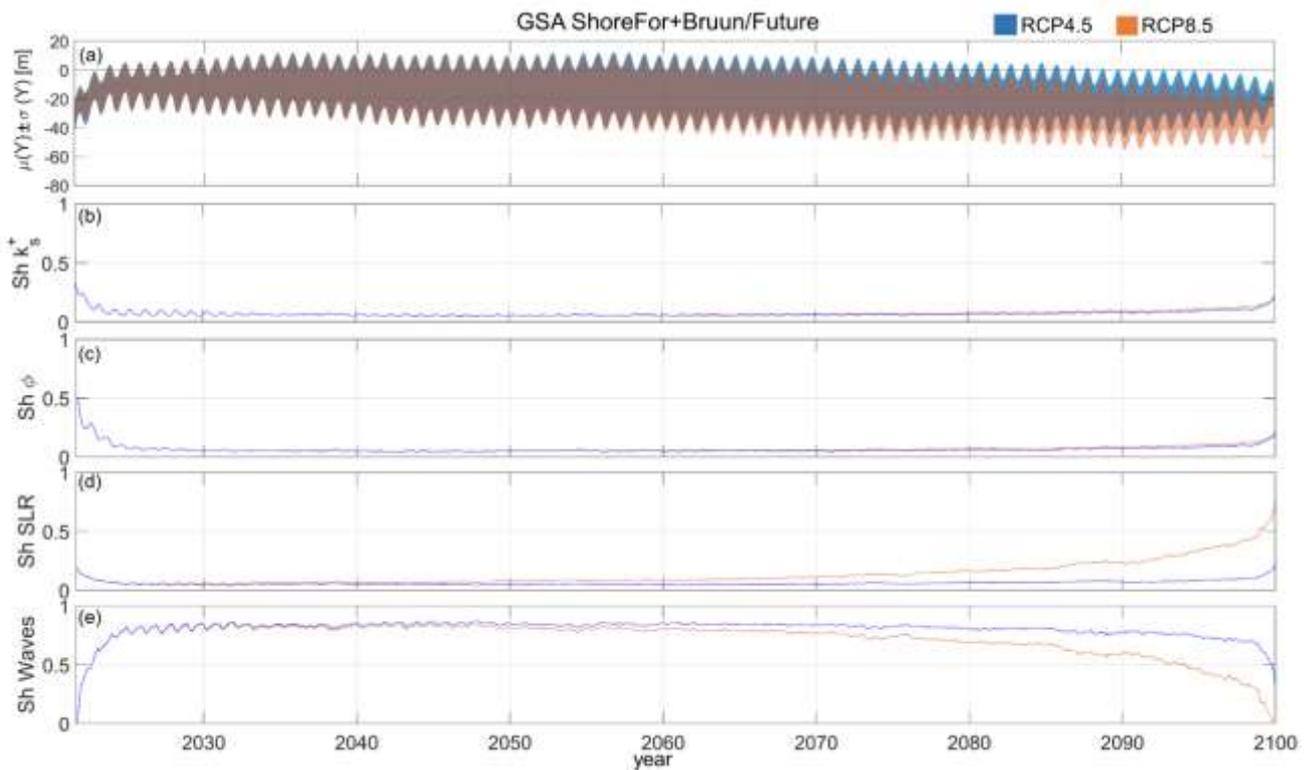
586

587 **Figure 6.** Global Sensitivity Analysis results for the ‘past scenario’, including time series of: (a) the ensemble
588 simulated shoreline positions from 1998 to 2012; and *Shapley Effects* of the *ShoreFor* parameters (b) k_s^+ and (c)
589 ϕ , and (d) wave chronology, with the respective linear fit (black lines).

590 Figure 7 and Figure 8 show the GSA results for the ‘future scenarios’ where wave-driven shoreline
591 change is simulated using the SF and Y09 models, respectively. For both modelling approaches, the

592 Sh 's show a similar behaviour between the RCP4.5 and RCP8.5 scenarios, with notable differences only
 593 in the second half of the 21st century, where the two SLR uncertainties diverge significantly.

594 In the SF scenarios, the model free parameters k_s^+ and ϕ control the initial model variance of the
 595 projection period, with Sh 's attaining 32% and 48%, respectively, before exponentially decaying to 6%
 596 and 5% by 2030 (Figure 7b,c). Starting from 2030, both Sh 's of k_s^+ and ϕ gradually increase up to 10%
 597 by 2095, and further up to ~18% by 2100. The SLR Sh rapidly drops from 20% to 5% between 2021
 598 and 2025, then grows gently back to ~20% by 2080 and dramatically up to 80% by 2100 in the RCP8.5
 599 scenario (Figure 7d). In the RCP4.5 scenario, the model sensitivity to SLR remains below 10% until
 600 2097 before increasing up to 23% by 2100 (Figure 7d). The impact of the uncertain wave chronology
 601 raises up to ~83% from 2021 to 2025, and then decreases progressively mirroring the behaviour of SLR
 602 Sh (Figure 7). In the RCP8.5 (RCP4.5) scenario, the wave chronology Sh decays down to ~70% (~80%)
 603 by 2080, and accelerates down to 0% (~30%) at the end of the simulated period.

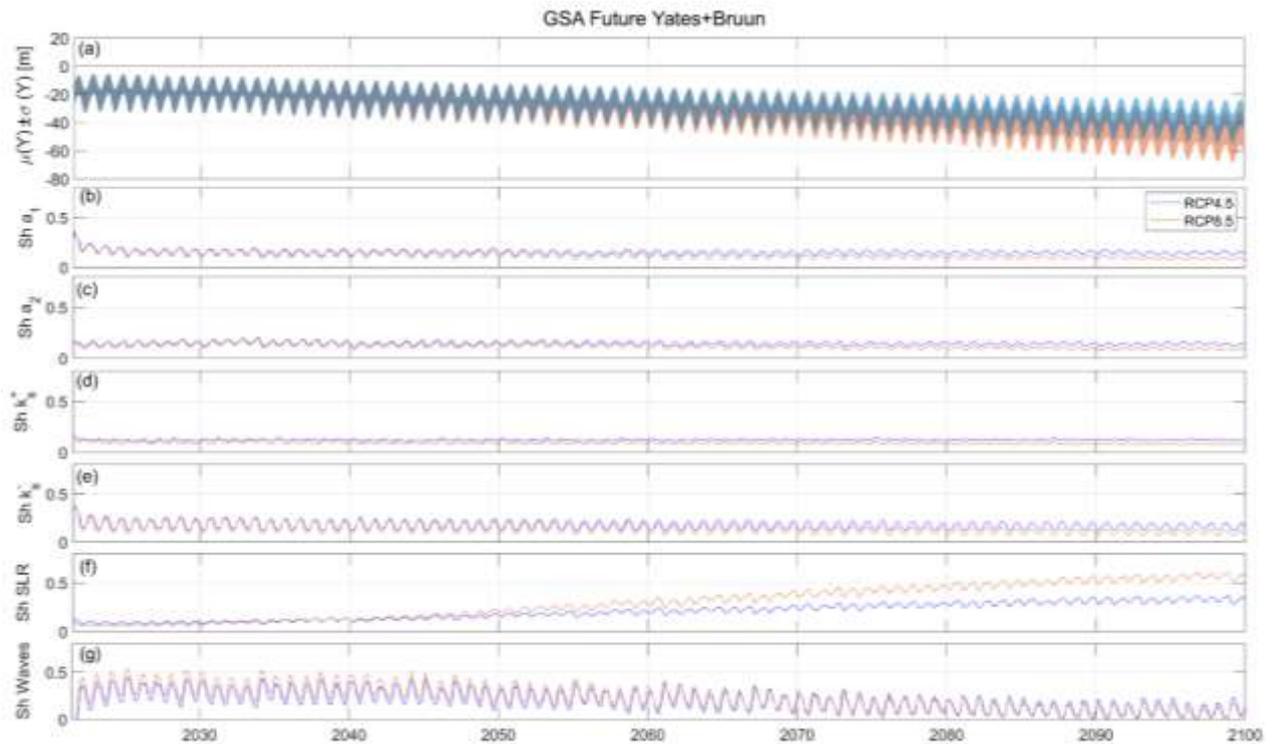


604

605 **Figure 7.** Global Sensitivity Analysis results for 'future scenarios' simulated using *ShoreFor* for the RCP4.5
 606 (blue) and RCP8.5 (orange) SLR scenario. Time series of (a) standard deviation of simulated 2021-2100
 607 shoreline positions, and *Shapley Effects* of model parameters (b) k_s^+ and (c) ϕ , (d) sea-level rise rate, and (e)
 608 wave chronology.

609 When using the Y09 approach, the GSA produces the series Sh shown in Figure 8. The Sh 's of the
 610 empirical Y09 parameters a_1 and a_2 decrease regularly from the initial values of 23% and 14%,
 611 respectively, to 10% by 2100 (Figure 8b,c). Over the projection period, the Sh of k_y^+ (k_y^-) decreases from
 612 23% to 10% (10% to 8%), and associates a well-defined (weak) seasonal signal with higher values
 613 during the summer (winter) (Figure 8d,e). SLR's Sh increases regularly from ~5% in 2021 to 20% in

614 2050, and up to 58% and 32% in the RCP8.5 and RCP4.5 scenarios, respectively (Figure 8f). The wave
 615 chronology's Sh shows a decreasing long-term trend mirroring the behaviour of SLR's Sh and a marked
 616 seasonality. In both RCP scenarios, the waves' Sh ranges between 45% and 18% over the first decade
 617 (2021- 2030), and between 17% and 1% (23% and 1%) over 2090-2100 for the RCP8.5 (RCP4.5)
 618 scenario (Figure 8e).



619

620 **Figure 8.** Global Sensitivity Analysis results for 'future scenarios' simulated using Yates' model for the RCP4.5
 621 (blue) and RCP8.5 (orange) SLR scenario. Time series of (a) standard deviation of simulated 2021-2100 shoreline
 622 positions, and *Shapley Effects* of model parameters (b) a_1 (c) a_2 , (d) k_y^+ , (e) k_y^- , (f) sea-level rise rate, and (g) wave
 623 chronology.

624 5. Discussion

625 5.1. Effects of stochastic wave chronology

626 *Past scenario*

627 Despite the availability of wave hindcast data, we forced the 'past scenario' simulations using ensemble
 628 (stochastic) wave conditions. This choice is motivated by two reasons: (i) including stochastic wave
 629 chronologies in the 'past scenario' allows to analyse the relative impact of the intrinsic uncertainties of
 630 waves and the epistemic uncertainties of model free parameters on simulated shoreline; and (ii) since
 631 the wave forcing ensemble is based on the aforementioned hindcast data, existing shoreline hindcasts
 632 and observations can provide a qualitative validation for the emulated wave time series.

633 In the 'past scenario', where shoreline change is simulated using SF and the Bruun model and
 634 uncertainties on SLR are omitted, the modelled shoreline shows an overall accreting trend from 1998 to

635 2012. This is consistent with previous ensemble shoreline reconstructions over the same period at Truc
636 Vert beach (D'Anna et al., 2020), which produced similar shoreline trends and 1998 envelope of
637 shoreline positions, providing a qualitative validation of the wave ensemble used here.

638 Using the SF model in the 'future scenario', the GSA identified the inherent wave forcing variability as
639 the dominant driver of the modelled shoreline variance, with the estimated Sh 's value of the wave
640 chronology roughly doubling the cumulated effects of the k_s^+ and φ parameters over the simulated period
641 (Figure 7b,c,e). All Sh 's time series exhibit a very mild seasonal signal between 2005 and 2012,
642 associated with higher model sensitivity to the k_s^+ and φ parameters during low-energy periods
643 (summers), and stabilize over time as the model variance increases (Figure 7b,c). Compared to previous
644 GSAs where only model free parameters governed the modelled shoreline variance (D'Anna et al.,
645 2020), the effects of uncertainties in wave forcing variability override and buffer the complex seasonal
646 patterns of the model sensitivity to model free parameters. Our findings are also in line with the
647 analytical results of Vitousek et al. (2021), who showed that the intrinsic uncertainties on wave
648 chronology can more than double the contribution of the epistemic uncertainty on calibrated model
649 parameters to the shoreline ensemble variance.

650 Although the Y09 model does not allow to propagate the uncertainties on modelled shoreline towards
651 the past, for the sake of completeness of this analysis, we repeated the 'past scenario' GSA using the
652 Y09 model instead of SF, where the initial condition was set to the mean shoreline position obtained
653 during the model calibration (2012-2019) (Text S3 of Supplementary Material). Unlike the SF 'past
654 scenario' application, the use of Y09 results in no long-term trend of the shoreline ensemble, with
655 seasonal fluctuations around a stable position equal to the mean shoreline position observed during the
656 calibration (2012-2019) (Figure S4). The GSA results show that, on average, the uncertainties in
657 modelled shoreline trajectories are driven by the stochastic wave chronology for 44% while the
658 remaining 56% of shoreline uncertainty is partitioned among the model free parameters (Figure S5).

659 *Future scenarios*

660 The differences in ranges of shoreline projections observed for the Y09+B and SF+B applications reflect
661 the different representations of the physical mechanisms and assumptions underlying the respective
662 disequilibrium formulations. These behaviours were also observed and analysed in previous studies that
663 described the different model responses to short- and long-term variations in the wave forcing (D'Anna
664 et al., 2021a; Vitousek et al., 2021). The SF equilibrium condition is defined by past wave conditions
665 over a fixed time proportional to the beach memory (φ), so that the equilibrium state of the beach adapts
666 dynamically to the wave climate and its temporal variations. Instead, the Y09 equilibrium condition is
667 defined by the previous shoreline position and the fixed equilibrium energy function ($E_{eq}=a_1Y+a_2$),
668 which does not respond to past wave forcing variations beyond a time scale implicitly determined by
669 the fixed value of the a_1 and a_2 parameters. The different responses to multiannual variations in wave

670 conditions are clearly illustrated by the individual model realizations reported in Figure 5b-e (yellow
671 and green lines). First, the variance of modelled shoreline trajectories is constrained within a limited
672 bound when using the Y09 model, while this is not necessarily the case for SF, consistently with the
673 analysis of Vitousek et al.'s (2021). However, while characterized by different chronologies, the
674 members of the wave ensemble used here preserve consistent seasonal to multiannual statistics, which
675 somehow constrain the SF envelope of shoreline ensemble to a fixed possible range. The Y09+B and
676 SF+B ensemble shoreline projections also show notable differences in the trends and the ranges of
677 modelled shoreline positions over the initial projection period. In fact, SF equilibrium state over the
678 initial projection period is influenced by the deterministic wave conditions prior to 2021 and the current
679 (random) wave conditions, until the deterministic conditions are 'forgotten'. Given that the two years
680 prior to 2021 are characterized by high-energy winters, the equilibrium condition over the initial
681 projection period is more likely to result in a constructive (accretive) disequilibrium. Over this same
682 period, the Y09 equilibrium condition is only affected by the current (random) wave energy, resulting
683 in an immediate spread of model results and possible trajectories. The narrowing of ensemble ranges
684 observed over the last years of the SF+B projections derives from the assumption that the SF parameter
685 r (Section 2.3.1/Equation 4), which defines the ratio between k_s^+ and k_s^- , is such that the trend in
686 modelled shoreline is conditioned to the trend of the wave forcing (Splinter et al., 2014b). Therefore,
687 given that all the wave time series are constrained to the same long-term trend, SF will tend to reproduce
688 the same trend by the end of the simulated period for any selected wave time series. The latter model
689 limitation suggests that the assumption of a fixed linear relationship between erosion/accretion response
690 rates may not valid on such long time scales where, instead, the values of model free parameters are
691 likely to be non-stationary (Ibaceta et al., 2020). The SF assumption on the r parameter has also
692 implications on the GSA, as it drives the SLR's and waves' Sh 's to diverge rapidly towards high and
693 low values, respectively (Figure 7d,e), once again, questioning the validity of r 's formulation in the
694 context of long-term simulations.

695 The GSAs for the 'future scenarios' suggest that the uncertainties on wave chronology steadily dominate
696 the variance of shoreline projections until the effects of SLR start concurring to shoreline uncertainties.
697 The estimated Sh 's show that for the simulated scenarios the uncertain future SLR always becomes the
698 primary driver of modelled shoreline variance after 2060. Compared to previous GSA applications on
699 the same study site, but based on deterministic wave time series (D'Anna et al., 2021a), the inclusion of
700 ensemble wave forcing in future shoreline projections postponed the onset of the SLR dominance on the
701 uncertainties of the model results by ~10 years.

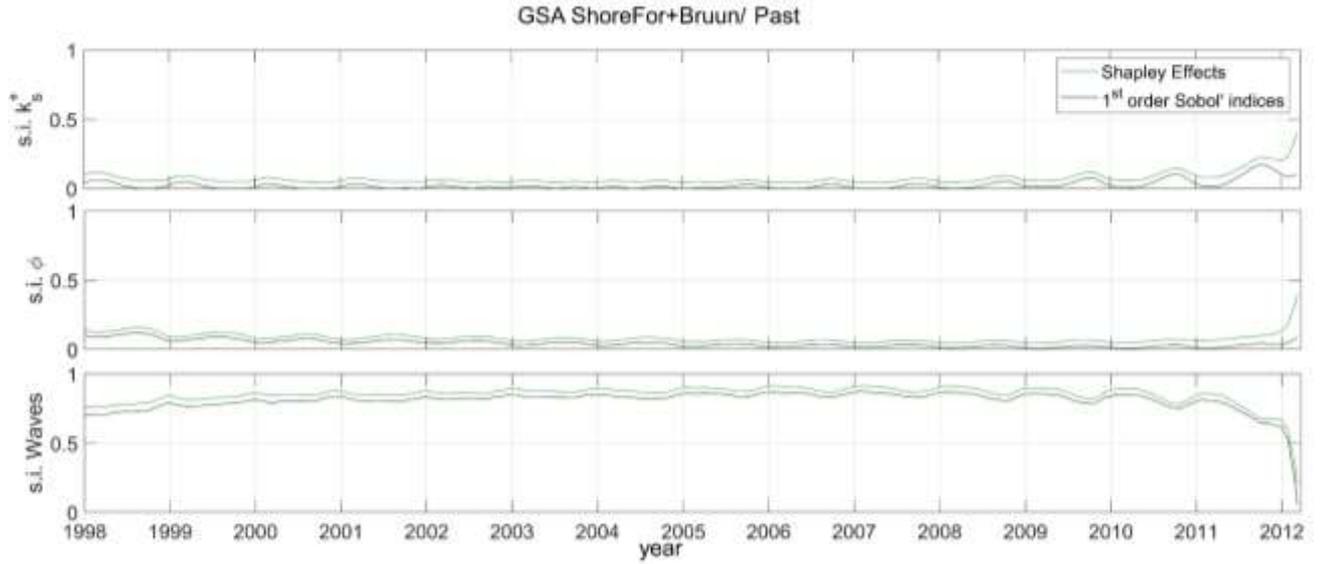
702 **5.2. Waves uncertainties, interactions and correlation effects**

703 Given the connection between model free parameters and wave forcing in the Y09 and SF models
704 formulations (Splinter et al., 2014b; Vitousek et al., 2021), the interaction of these variables and the
705 respective uncertainties within the model may drive higher-order effects contributing to the results

706 uncertainties. Moreover, the correlations among the model parameters of both shoreline models (Figure
707 4a,b) may further influence the decomposition of the results variance. While a full decomposition of the
708 model results variance that allow discriminating main and interaction terms, and correlation effects is
709 still a matter of ongoing research (Mara and Becker, 2021), here we investigate the presence of
710 interaction and correlation effects by comparing the Sh 's with the corresponding individual main effects
711 estimated with first-order Sobol' indices (S_i 's) (Equation 9, Section 2.4.2).

712 The difference between Sh_i and S'_i associated to the variable X_i provides an indication of the presence
713 of the cumulated effects of the cumulated terms of correlations and interactions between X_i with the
714 other uncertain inputs. The comparison between Sh 's and S_i 's for the 'past scenario' (Figure 9) suggests
715 the presence of such correlation and interaction effects, between the free model parameters and the wave
716 conditions, on modelled shoreline uncertainties when using the SF model. Indeed, for this scenario the
717 cumulated differences between Sh 's and S_i 's of all the uncertain variables make up $\sim 15\%$ of the total
718 results variance on average, and up to $\sim 75\%$ (near 2012). The latter highlights the risk of underestimating
719 the influence of the model inputs uncertainties on the results uncertainties, and suggests the potential
720 occurrence of contributing waves-parameters interactions. Interestingly, we observe that the seasonal
721 signal of the model sensitivity to the free parameters (higher sensitivity during low-energy periods) is
722 associated to the first-order effects (Figure 9), which is in line with previous assessments of main effects
723 on the modelled shoreline (D'Anna et al., 2020).

724 We acknowledge however that the afore-described comparison analysis should only be considered a
725 qualitative indication of the joint impact of interactions and correlations, which might be larger than the
726 differences observed here. This is related to the effects of correlation among uncertain inputs that are
727 partitioned among the correlated variables in the Shapley effects (by construction), but may be
728 accounted redundantly in the Sobol' indices of the correlated variables (Section 2.4.2), causing a
729 possible overestimation of first-order Sobol' indices, hence introducing some biases in the differences
730 $Sh_i - S_i$.



731

732 **Figure 9.** Comparison of *Shapley Effects* (green lines) and *1st order Sobol'* (black lines) sensitivity indices (s.i.)
 733 of the *ShoreFor* free parameters (a) k_s^+ , (b) ϕ , and (c) wave chronology, for the 'past scenario' ensemble.

734 5.3. Dynamic model free parameters

735 The analysis in Section 5.1 highlighted some shortcomings of both the SF and Y09 approaches: the
 736 Y09's limits in reproducing large interannual shoreline patterns, and the SF long-term trend imposed by
 737 the fixed r parameter. The respective limitations can be attributed, at least partially, to the assumption
 738 of stationary model parameters. Indeed, the SF's free parameters values have been observed to be
 739 dependent on time variations of the wave forcing (Ibaceta et al., 2020; Splinter et al., 2017), while Y09's
 740 parameters prevent the equilibrium condition from adapting to shifts in the wave forcing (Vitousek et
 741 al., 2021), as discussed in Section 5.1. Therefore, we make a further step to explore the potential impact
 742 of the assumption of stationary model free parameters on long-term shoreline projections and run two
 743 more sets of 10000 simulations using dynamic values for some of the Y09 and SF parameters for the
 744 'future scenario' RCP8.5.

745 Vitousek et al. (2021) proposed a physical interpretation of the Y09 free parameters, where the a_2
 746 parameter in Equation 7 is identified as fixed background wave energy ($a_2 = \hat{E}$) that contributes to define
 747 the site-specific equilibrium time scale and range of shoreline excursion. Based on site-specific
 748 calibration of the model, the optimized value of $\sqrt{a_2}$ was found to approximate that of the average
 749 significant wave height (\overline{H}_s) over the observed period, so that Equation 7 becomes:

$$750 E_{eq}(Y) = a_1 Y + a_2 \approx a_1 Y + \overline{H}_s^2 \quad (13)$$

751 We run an ensemble of simulations using a modified and calibrated Y09 model (hereon Y09*) based on
 752 Equation 13, and we define the background wave energy at a given time as the average significant wave
 753 height over the past n years ($\overline{H}_s = \overline{H}_s(t)$). This assumption not only provides a dynamic character to
 754 Y09's equilibrium condition, but also brings Y09 conceptually closer to SF in that the time-window ' n '

755 is analogue to SF's 'beach memory' ϕ . For this application, we set $n=5$ years, which correspond roughly
 756 to the upper limit of SF's ϕ values (Table 1). The Y09* model achieves slightly improved skill than Y09
 757 (Section 3.1), with RMSE=4.95 m and $R^2=0.82$ on over the calibration. Over the validation period the
 758 Y09* model produces an ensemble mean (minimum) RMSE of 8.1 m (3.2 m) and a mean (max) R^2 of
 759 0.89 (0.92), showing a net improvement compared to the Y09 ensemble (Section 4.1). The individual
 760 shoreline trajectories (yellow and green lines in Figure 10a) show how Y09* produces interannual
 761 fluctuations that were not visible in the Y09 results (Figure 5e). The use of a time-varying a_2 parameter
 762 produces a more irregular envelope of simulated shoreline positions compared to the results obtained
 763 with stationary parameters, with larger amplitudes of the shoreline positions envelope (Figure 10a). It
 764 is to be noted that since a_2 is fully defined as a function of H_s and the n value is fixed, a_2 is no longer an
 765 uncertain model parameter and Y09* has less uncertain inputs than Y09.

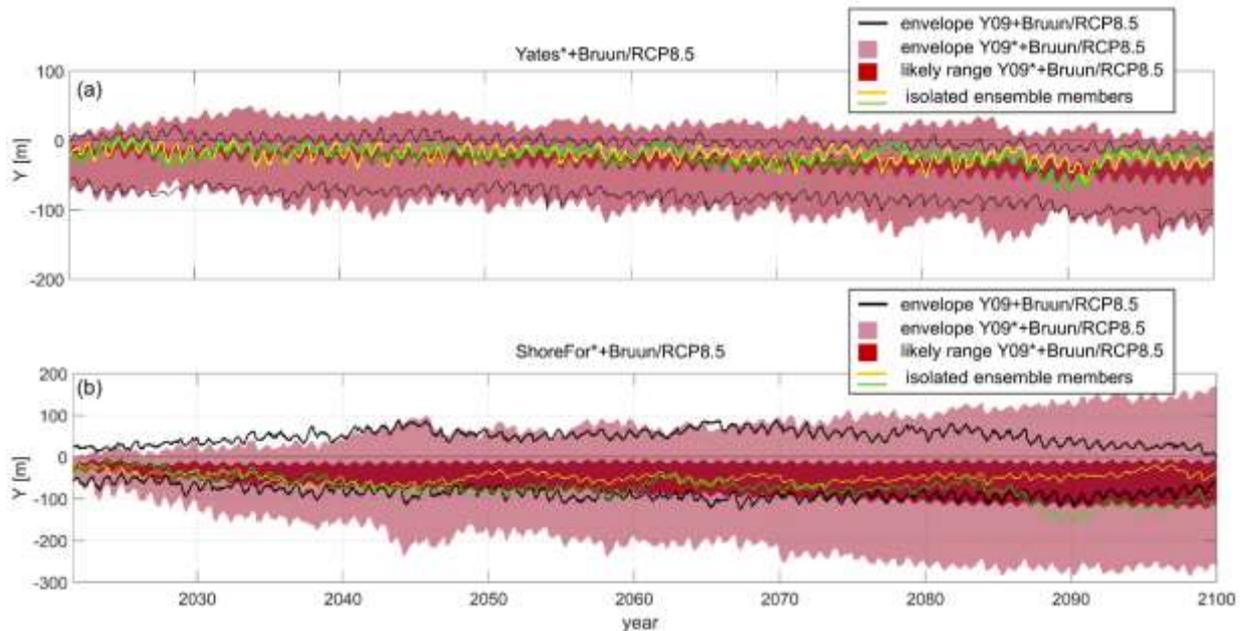
766 In the SF model, the ratio of erosion/accretion shoreline response rate (r) is calculated as a function of
 767 the trend in wave forcing over the full extent of the simulated period (Equation 4). Here, we relate r to
 768 the forcing wave climate dynamically and generate a time series of r values by applying Equation 4 over
 769 a progressive time window instead of the full simulation period. At a given time step (t), $r(t)$ is calculated
 770 based on the previous n years ($n < \text{simulation period}$) of wave forcing, as follows:

$$771 \quad r(t) = \left| \frac{\sum_{t-n}^t \langle F^+ \rangle}{\sum_{t-n}^t \langle F^- \rangle} \right| \quad (14)$$

772 Such formulation preserves the original SF concept that links the trends of shoreline change and wave
 773 climate but allows different multi-decadal wave climate patterns to result in different shoreline positions
 774 by the end of the simulated period. We calibrated a modified SF (hereon SF*) model based on Equation
 775 14 with $n=5$ years and used it to run a new ensemble of simulations. The SF* model produces an
 776 RMSE=6.8 m and a $R^2=0.71$ on the simulated period, showing some improvement compared to SF
 777 (Section 3.1). The model skill also improved over the validation period, with a mean (min) RMSE of
 778 8.62 m (3.05 m) and a mean (max) R^2 of 0.85 (0.93). The use of non-stationary values for the r parameter
 779 results in a progressive increase of the modelled shoreline variance, due to the increasing number of
 780 possible sequences of high- and low- energy winters (Figure 10b). The values of erosion/accretion rate
 781 r computed with Equation 14 occasionally attains values above 10 and near 0. This is likely to cause the
 782 σ (envelope) ranges of the modelled shoreline to spread over time up to roughly [-10 m; -110 m] ([150
 783 m; -250 m]). However, while the SF* tested here is based on some arbitrary assumptions (i.e. $n=5$, no
 784 limits in the range of r variability), the model produces different long-term trends in response to the
 785 different wave forcing time series, and do not converge to the same final shoreline position at the end
 786 of the simulated period.

787 The latter applications show that introducing non-stationarity in the Y09 and SF parameters can
 788 significantly affect the modelled shoreline response to the wave climate variability and potentially

789 improve the models performances. This encourages future research efforts towards unravelling the
790 inherent relationship between the temporal variability of free parameters and wave climate, and move
791 towards more comprehensive shoreline models. However, these simulations are based on some arbitrary
792 assumptions and are not to be interpreted as an improved assessment of shoreline projections.



793

794 **Figure 10.** Ensemble of simulated shoreline trajectories from 2021 to 2100 for the RCP8.5 future sea-level rise
795 scenario using the Bruun Rule with the modified (a) Yates et al. (2009) and (b) ShoreFor models, including: the
796 envelope (light-shaded areas) and the standard deviation intervals ($\mu \pm \sigma$) (dark-shaded areas); two individual model
797 realizations (yellow and green lines). Black solid lines indicate the limits of the envelope of the corresponding
798 simulations obtained using the original Yates et al. (2009) and ShoreFor models.

799 5.4. Assumptions and limitations

800 One of the main assumptions of this work is that the current wave climate remains unchanged in the
801 future. In fact, the wave ensemble used here assumes that all the simulated wave time series maintain
802 the same seasonal to multiannual statistics observed in the past wave data, and accounts only for the
803 intrinsic uncertainty associated with the short-term variability of wave conditions. However, climate
804 change could alter the future wave climate in some regions of the world (Morim et al., 2020), potentially
805 affecting the evolution of sandy shorelines. On one hand, the wave climate over the northeast Atlantic
806 region is not expected to change significantly over the 21st century (Bricheno and Wolf, 2018; Morim
807 et al., 2019), with dynamically downscaled projections estimating a ~ 2 mm/year decrease of winter
808 mean H_s in the Truc Vert area (Charles et al., 2012; D'Anna et al., 2021a). On the other hand, the limited
809 extent of the hindcast wave data used to generate the wave ensemble (26 years) hinders the inclusion of
810 uncertainties on wave forcing variability on time scales longer than a few decades. In addition, changes
811 in the temporal distribution of extreme events may affect the long-term wave climate cycles (Lobeto et
812 al., 2021), and in turn the multi-annual shoreline variability. The inclusion of uncertain future waves in
813 shoreline projections requires wave ensembles accounting for different realistic climate-driven wave

814 climate patterns, such as multi-model ensembles or emulated ensembles based on future climate. To the
815 Author's knowledge, such ensembles do not exist.

816 While the ensemble of wave time series generated with the wave emulator capture the overall
817 characteristics of the reference past 26-year wave series, the comparison of seasonal wave energy
818 distribution shows some differences (Section 2.4.1). Indeed, the emulator slightly underestimates
819 extreme H_s in the winter, and overestimates them in the remaining seasons. These differences are likely
820 due to a smoothing effect of the seasonality produced by the emulator, together with the strong seasonal
821 variability of the wave climate observed at Truc Vert. However, these differences tend to compensate
822 throughout the different seasons, preserving the overall yearly properties of the wave climate (Figure
823 2d), so that the simulations are only expected to underestimate seasonal excursions of the modelled
824 shoreline.

825 In this work, we estimated the future local relative MSL based on SROCC projections. Recently, the
826 *IPCC 6th Assessment Report (AR6)* provided updated SLR projections to 2150 (Magnan et al., 2019),
827 including new considerations on the Antarctic Ice-sheet dynamic contribution to SLR, and based on
828 combined Shared Socio-economic Pathways (SSP) (Riahi et al., 2017) and RCP scenarios. However,
829 our sea level projections (2021-2100) remain close to the medium confidence projections published in
830 *AR6 Working Group I - Chapter 9* (within the order of 1 cm difference).

831 Finally, we modelled SLR-driven shoreline recession using the Bruun model, which builds on a number
832 of assumptions that limit its applicability to a reduced selection of beaches (Cooper et al., 2020). As
833 Truc Vert beach is a cross-shore transport dominated, uninterrupted beach with large accommodation
834 space most of the Bruun model assumptions are satisfied. However, alternative rule-based approaches
835 (McCarroll et al., 2021), or dynamically coupled wave-driven and sea-level equilibrium approaches
836 (D'Anna et al., 2021b) could be implemented for applications of this framework to a wider range of
837 sites. In addition, here the Bruun Rule combined linearly with Y09 and SF with no feedbacks between
838 wave- and SLR-driven modelled processes, preventing any interaction between wave forcing and SLR
839 uncertainties. Approaches that combine wave- and sea-level-driven processes in a coupled fashion (i.e.
840 with feedback between the models), may reveal further contributions of the wave forcing uncertainties
841 to modelled shoreline change.

842 **6. Conclusions**

843 We applied a Global Sensitivity Analysis to long-term shoreline evolution modelling at the cross-shore
844 transport dominated Truc Vert beach (France) including the intrinsic uncertainties associated with
845 unknown wave chronology and using two different equilibrium shoreline models. Our results suggest
846 that uncertainties in wave chronology play an exceedingly important role in probabilistic shoreline
847 modelling. When modelling shoreline change with no uncertainties on SLR (e.g. 'past scenario' and
848 near-future projections), the uncertain wave chronology is responsible for up to 83% of the modelled

849 shoreline variance. We also find that the interactions between the uncertain wave chronology and model
850 parameters within the models and the correlation among the model parameters can significantly
851 influence shoreline predictions uncertainties, highlighting the interplay between intrinsic and epistemic
852 uncertainties. The future shoreline projections suggest that the onset of the SLR dominance on the
853 uncertainties of the model results can be expected to start from 2060, with strong implications for future
854 research priorities and decision-making in climate change adaptation planning where coastal settings
855 are similar to Truc Vert beach. While the two equilibrium modelling approaches compared in our
856 applications (*ShoreFor* and *Yates*) show different responses to wave climate variability and its
857 uncertainties, the main conclusions drawn above are valid for both approaches. We also found that
858 applying non-stationary model free parameters by linking them to the wave climate variability can
859 significantly alter the model behaviour, and further research efforts in this direction could improve the
860 understanding of model uncertainties.

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874 **Data Availability Statement**

875 All data used and produced within the current work is available at the following Mendeley data online
876 repository:

877 DOI: 10.17632/cnwyhh475s.1

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