



HAL
open science

Satellite-derived equilibrium shoreline modelling at a high-energy meso-macrotidal beach

Georgios Azorakos, Bruno Castelle, Vincent Marieu, Déborah Idier

► **To cite this version:**

Georgios Azorakos, Bruno Castelle, Vincent Marieu, Déborah Idier. Satellite-derived equilibrium shoreline modelling at a high-energy meso-macrotidal beach. *Coastal Engineering*, 2024, pp.104536. 10.1016/j.coastaleng.2024.104536 . hal-04573878

HAL Id: hal-04573878

<https://brgm.hal.science/hal-04573878>

Submitted on 13 May 2024

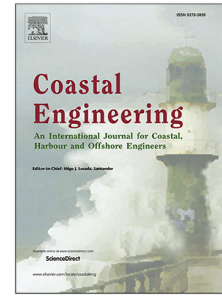
HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Journal Pre-proof

Satellite-derived equilibrium shoreline modelling at a high-energy meso-macrotidal beach

Georgios Azorakos, Bruno Castelle, Vincent Marieu, Déborah Idier



PII: S0378-3839(24)00084-X
DOI: <https://doi.org/10.1016/j.coastaleng.2024.104536>
Reference: CENG 104536

To appear in: *Coastal Engineering*

Received date: 19 September 2023
Revised date: 29 April 2024
Accepted date: 5 May 2024

Please cite this article as: G. Azorakos, B. Castelle, V. Marieu et al., Satellite-derived equilibrium shoreline modelling at a high-energy meso-macrotidal beach. *Coastal Engineering* (2024), doi: <https://doi.org/10.1016/j.coastaleng.2024.104536>.

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

© 2024 Published by Elsevier B.V.

Satellite-derived equilibrium shoreline modelling at a high-energy meso-macrotidal beach

Georgios Azorakos^a, Bruno Castelle^a, Vincent Marieu^a, Déborah Idier^b

^a*Univ. Bordeaux, CNRS, Bordeaux INP, EPOC, UMR 5805, Allée Geoffroy Saint-Hilaire, Pessac, 33615, Nouvelle Aquitaine, France*

^b*BRGM, (French Geological Survey), 3 Av. Claude Guillemin, Orléans, 45100, Centre, Val de Loire, France*

Abstract

Modelling and predicting the future of sandy shorelines is a key challenge in coastal research and is critical for sustainable coastal management. However, currently the most skillful shoreline models strongly rely on data to calibrate the free parameters, and are thus restricted to a few well monitored sites in the world. Here we address the challenges and opportunities offered by optical satellite imagery to provide useful information for equilibrium shoreline model calibration on cross-shore transport dominated sites. We focus on Truc Vert beach, southwest France, where previous work showed good equilibrium model skill to reproduce shoreline change from the time scales of hours (storms) to decades. Satellite derived waterlines are extracted over 11 years (2009-2020) and further transformed into satellite derived shorelines (SDS) with different water level corrections (e.g. tide and/or run up) and varying alongshore averaging lengths, and thus different uncertainties, in order to test model performance. Successively the timeseries duration and sampling frequency required for model calibration were also investigated. The model calibrated using the SDS data showed similar skill as the model

calibrated using in-situ alongshore averaged shoreline positions, even for the uncorrected SDS dataset which Root Mean Square Error (RMSE) are approximately 30 m. Alongshore averaging was found to be the only necessary processing of the SDS data while any other site-specific corrections did not significantly improve model skill. Finally to further investigate the effect of sampling frequency and noise in the dataset we performed an analysis using a synthetic shoreline. Our results suggest that the effect of noise is negligible as long as the sampling frequency remains high ($dt \leq 30$ days). Pending further validation, results show the strong potential of using uncorrected SDS dataset for shoreline model calibration at cross-shore transport dominated sandy coasts.

Keywords:

Shoreline, Satellite data, Numerical modelling, Calibration

1. Introduction

Coastal areas constitute some of the most populated and developed land zones in the world (Small and Nichols, 2003) with high natural and socio-economical significance (Ghermandi and Nunes, 2013). Luijendijk et al. (2018) found that $\sim 24\%$ of the global ice free sandy shorelines are eroding at rates exceeding 0.5 m/year, while Vousdoukas et al. (2020) suggested that these numbers are projected to increase under the influence of climate change. Although more in depth analysis is needed (Cooper et al., 2020), these findings highlight the importance of monitoring, understanding and predicting sandy shoreline evolution.

Sandy coasts can be highly dynamic environments constantly adjusting

12 their position in response to a variety of processes spread over a wide spatio-
13 temporal range. Changes in sediment availability and mean sea level influ-
14 ence shoreline response on the timescales ranging from decades to millenia
15 (Larson and Kraus, 1995; Murray, 2007). On shorter timescales and on cross-
16 shore transport dominated sites, shoreline response is often dictated by vari-
17 ations in incident wave conditions from the time scale of single storms to
18 seasonal and interannual variability in the incident wave climate (Castelle
19 and Masselink, 2023). Anthropogenic factors can also have a significant and
20 potentially irreversible impact on the shoreline position (Aagaard et al., 2004;
21 Ranasinghe and Turner, 2006; Ojeda et al., 2008).

22 Reduced complexity shoreline models, such as Yates et al. (2009); David-
23 son et al. (2013); Splinter et al. (2014); Vitousek et al. (2017); Robinet et al.
24 (2018); Antolínez et al. (2019); Tran and Barthélemy (2020) to name a few,
25 have enabled the scientific coastal community to successfully simulate sandy
26 shoreline evolution from timescales of days (single storms) to years (seasonal
27 and interannual variability) and even to decades (long term shoreline trends)
28 (Splinter et al., 2013; Castelle et al., 2014; Robinet et al., 2020). Not resolving
29 all the complex processes explicitly reduces the computational cost of these
30 models. While process based models need more data like complete topogra-
31 phy and bathymetry of an area, reduced complexity models require mainly
32 shoreline position datasets spanning over several years for their calibration
33 (Montaño et al., 2020). Of particular relevance are equilibrium shoreline
34 models that show very good skill on cross-shore transport dominated sites
35 (Splinter et al., 2014). Splinter et al. (2013) showed that due to the empirical
36 and data driven nature of these equilibrium models, high-quality observa-

37 tional datasets spanning more than 5 years are needed for the calibration of
38 the free parameters. High-quality observational datasets however are limited
39 to a few surveyed sites (Turner et al., 2016; Ludka et al., 2019; Castelle et al.,
40 2020; Bertin et al., 2022; McCarroll et al., 2023), or video-monitored beaches
41 (Splinter et al., 2014; Pianca et al., 2015; Ibaceta et al., 2020) in the world,
42 thus limiting the application of equilibrium data driven models.

43 Publicly available satellite imagery, cradled a new approach in remote
44 sensing and provided long term (more than 30 years) high temporal reso-
45 lution (approximately bi-weekly) shoreline data covering the entire planet
46 (Vos et al., 2019a). However, Vos et al. (2019a, 2023) recognized issues with
47 shoreline detection on satellite images at gently sloping and meso-macrotidal
48 environments, where low tide images must also be discarded due to the pres-
49 ence of complex bar/rip systems. Castelle et al. (2021) showed that satellite
50 derived shorelines (SDS) at a high energy meso-macrotidal coast can deviate
51 by more than 30 m from the surveyed shoreline position and proposed ways
52 to address the issue. While astronomical tide and runup adjustment pro-
53 vides the best correction at Truc Vert in southwest France (Castelle et al.,
54 2021), Konstantinou et al. (2023) showed that optimal water level correction
55 (astronomical tide and/or set-up and/or runup) strongly depends on beach
56 state. Konstantinou et al. (2023) also showed that low image availability due
57 to e.g. areas with high cloud cover can dramatically restrict temporally the
58 type of phenomenon that can be detected (e.g., seasonal/interannual variabil-
59 ity). Finally, open SDS datasets are often extracted along single transects,
60 which are spaced by hundreds of metres, and may not be representative of
61 the true shoreline variability on intermediate beaches due to the presence of

62 alongshore variable features like migrating megacusp embayments. Transect
63 spacing and alongshore averaging are therefore important processing param-
64 eters affecting SDS accuracy. These observations question the reliability of
65 uncorrected SDS data in gently sloping, high-energy and meso-macrotidal
66 environments, especially when lacking in-situ derived shoreline data to com-
67 pare with. To which extent such SDS data can be used to calibrate data
68 driven equilibrium shoreline models is virtually unknown.

69 Most studies using SDS observations to date, focused on interannual
70 shoreline variability (e.g. Castelle et al., 2022) or long term trends (e.g. Lui-
71 jendijk et al., 2018), rather than their potential for modelling applications. A
72 handful of studies integrating SDS observations in dynamic shoreline models
73 have emerged recently. Alvarez-Cuesta et al. (2021a,b, 2024) incorporated 30
74 years of SDS data into a dynamic shoreline modelling system to simulate 40
75 km of the Mediterranean Spanish coast. Ibaceta et al. (2022) assimilated SDS
76 data into their model in order to track variability in model free parameters
77 while simulating 14 years of shoreline evolution at a microtidal beach on the
78 east coast of Australia. Vitousek et al. (2023) integrated SDS observations
79 into their shoreline model to hindcast 20 years of coastal change over the
80 entire coast of California. Vitousek et al. (2023) demonstrated that model
81 calibration with water level corrected SDS yielded similar skill to model cal-
82 ibration with in- situ observations at a meso tidal beach. However, the
83 influence of the type of water level correction was not addressed, and the un-
84 corrected SDS were not tested in model calibration. Crucially, uncorrected
85 SDS datasets does not require local beach slope, astronomical tide data and
86 breaking wave parameters for further correction, and can be thus generated

87 at any site globally.

88 In the present work we investigate the possibility of using SDS datasets to
89 calibrate the state-of-the-art equilibrium shoreline model proposed in David-
90 son et al. (2013), by testing different water level corrections at the high
91 energy meso-macrotidal beach of Truc Vert, southwest France. 11 years of
92 SDS data were used and a simulated annealing non-linear optimization algo-
93 rithm (Bertsimas and Tsitsiklis, 1993) was systematically applied to various
94 SDS datasets (different water level corrections, alongshore averaging lengths,
95 duration and sampling frequency) in order to find the best fit model param-
96 eters and further address model skill by comparing with field data. The study
97 site, data used and methodology adopted in the present work are detailed
98 in sections 2 and 3. The results are presented and briefly discussed in sec-
99 tion 4 while a detailed discussion and the conclusions follow in sections 5
100 and 6. Pending further validation, the findings of the present study suggest
101 that uncorrected SDS data can potentially be used to calibrate data driven
102 equilibrium shoreline models in high energy meso-macrotidal environments
103 without a priori knowledge of the site.

104 **2. Field site and data**

105 *2.1. Truc Vert beach*

106 The coast of Nouvelle Aquitaine in southwest France (Figure 1b) stretches
107 approximately 250 km along a straight, low-lying shoreline backed by high
108 vegetated coastal dunes (Laporte-Fauret et al., 2020) excluding a few small
109 stretches interrupted by coastal resorts (Castelle et al., 2018b). The off-
110 shore wave climate is generated in the north Atlantic ocean predominantly

111 by eastward tracking extra tropical cyclones (Castelle et al., 2020). In the
112 present work the remote beach of Truc Vert (panel a in Figure 1), located
113 approximately 2 km away from the nearest inland car park beach entry, is
114 chosen as a case study. Besides a mechanical profiling of the coastal dune
115 backing the beach that took place in the early 1980s (Robin et al., 2021), the
116 beach has never been nourished, affected by hard structures or by any direct
117 anthropogenic activity.

118 Truc Vert is a high energy meso-macrotidal double barred open beach
119 backed by tall ($\sim 20\text{-}25$ m above Mean Sea Level) and wide (~ 250 m) coastal
120 dunes (see Figure 1). Tide is semi-diurnal with an annual mean spring tidal
121 range of ~ 3.7 m and largest tidal range of ~ 5 m. The wave climate is
122 seasonally modulated with monthly average significant wave height $\overline{H_s}$ and
123 peak wave period $\overline{T_p}$ ranging from 1.11 m and 9 s in July, with a dominant
124 west-northwest direction, to 2.4 m and 12.8 s in January with a dominant
125 west direction (Castelle et al., 2017).

126 The sediment composition primarily consists of medium quartz sand, with
127 a median diameter of $d_{50} \approx 350 \mu\text{m}$. The beach sediment displays substantial
128 variability ranging from $200 \mu\text{m}$ to $700 \mu\text{m}$, associated with a wide range
129 of bedforms such as bar/rip channels, megacusps, cusps, and megaripples
130 (Gallagher et al., 2011). The outer bar is subtidal and modally crescentic,
131 while the inner bar, situated in the intertidal zone, is mostly classified as a
132 transverse bar and rip and during the summer months tends to transition
133 into a low tide terrace (see Figure 1). The average spacing between rips is
134 approximately 400 m for the inner bar and 700 m for the outer bar, although
135 these values can vary considerably over space and time. The presence of rip

136 channels incising the inner bar leads to significant alongshore variations in
137 beach morphology, with pronounced megacusp embayments (Figure 1 a) in
138 the alignment of the rip channels typically evolving on seasonal timescales.
139 The outer bar on the other hand, can drive larger scale beach variability
140 during severe storms which can persist for several years (Castelle et al., 2020).

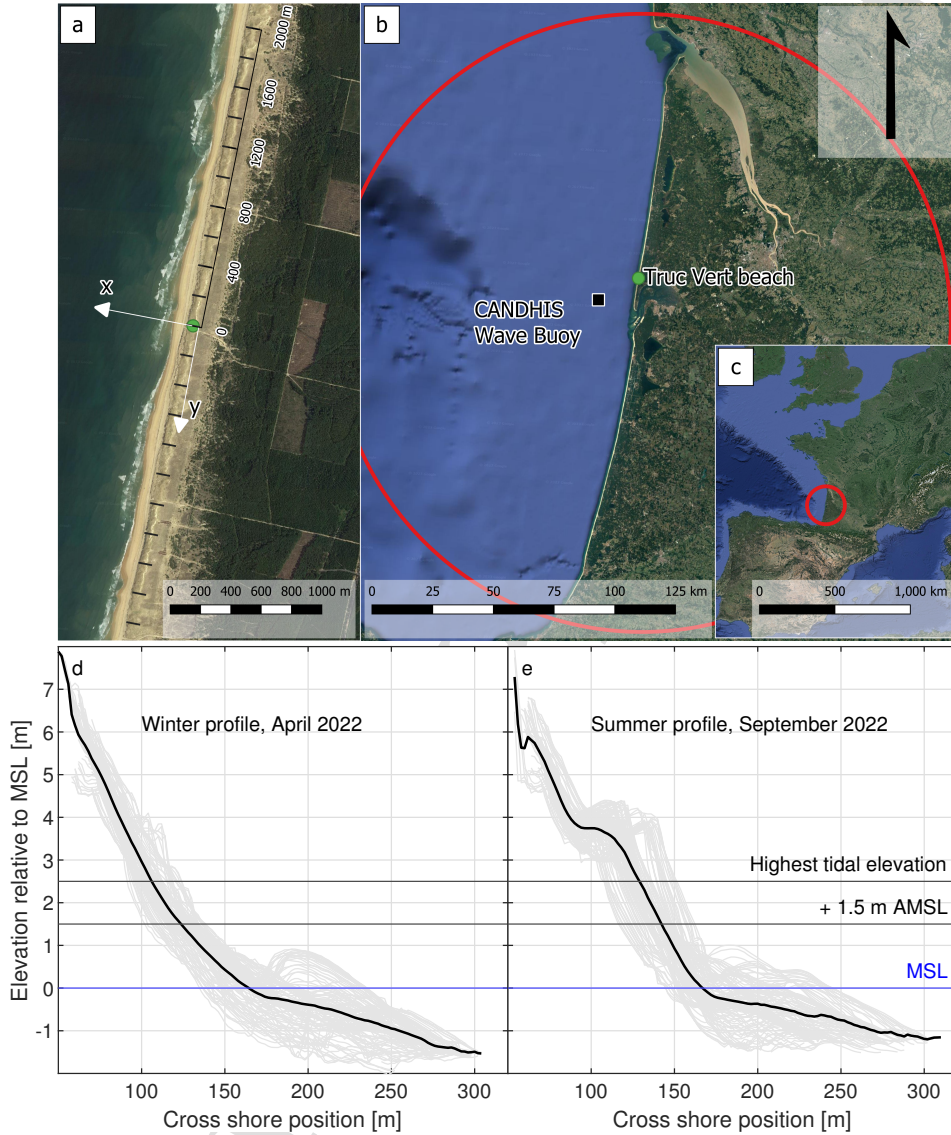


Figure 1: (a) Survey zone and reference frame at Truc Vert beach. (b) Location map of Truc Vert beach, southwest France indicating the position of the CANDHIS wave buoy (Cap Ferret wave buoy 03302). (c) Overview of the area. Winter (d) and summer (e) profiles measured in 2022. The thick black line indicates the alongshore average profile, while the gray lines are the individual profiles extracted every ~ 20 m from the alongshore window considered.

141 In the long term Truc Vert beach can be considered stable (Castelle et al.,
142 2018a), despite the fact that the highly interannually variable winter wave
143 energy can result in severe beach and dune erosion (Castelle et al., 2015;
144 Masselink et al., 2016). The shoreline evolution is mainly dominated by cross
145 shore processes showing strong seasonal and interannual variability, with
146 moderate and extreme winters alternating (Robinet et al., 2016; Masselink
147 et al., 2016).

148 2.2. Wave Data

149 Due to lack of continuous wave measurements from the CANDHIS di-
150 rectionnal wave buoy, which is moored in ~ 50 m depth offshore of Truc
151 Vert beach (see Figure 1), hourly wave timeseries were extracted from the
152 NORGAS-UG regional wave hindcast (Boudière et al., 2013), at the grid
153 point coinciding with the location of the buoy. The NORGAS-UG regional
154 model covers the Atlantic coast of France on an unstructured mesh. The
155 nearshore is resolved with mesh elements of ~ 200 m while the model resolu-
156 tion becomes coarser further offshore with mesh elements of ~ 10 km in the
157 deepest parts of the domain.

158 The wave model results have been validated against several measured
159 data and yielded correlation coefficients of 0.96-0.99, RMSE of 0.15-0.21 m
160 and a bias of -0.02-0.04 m (Michaud et al., 2016). The significant wave height
161 H_s , peak wave period T_p and mean wave direction (MWD) extracted from
162 the aforementioned wave hindcast are depicted in Figure 2. The timeseries
163 shows the typical seasonal and interannual variability of the incident wave
164 climate at Truc Vert beach with a prevailing W-NW wave incidence. The
165 surveyed shoreline is depicted in panel a of Figure 2 together with H_s .

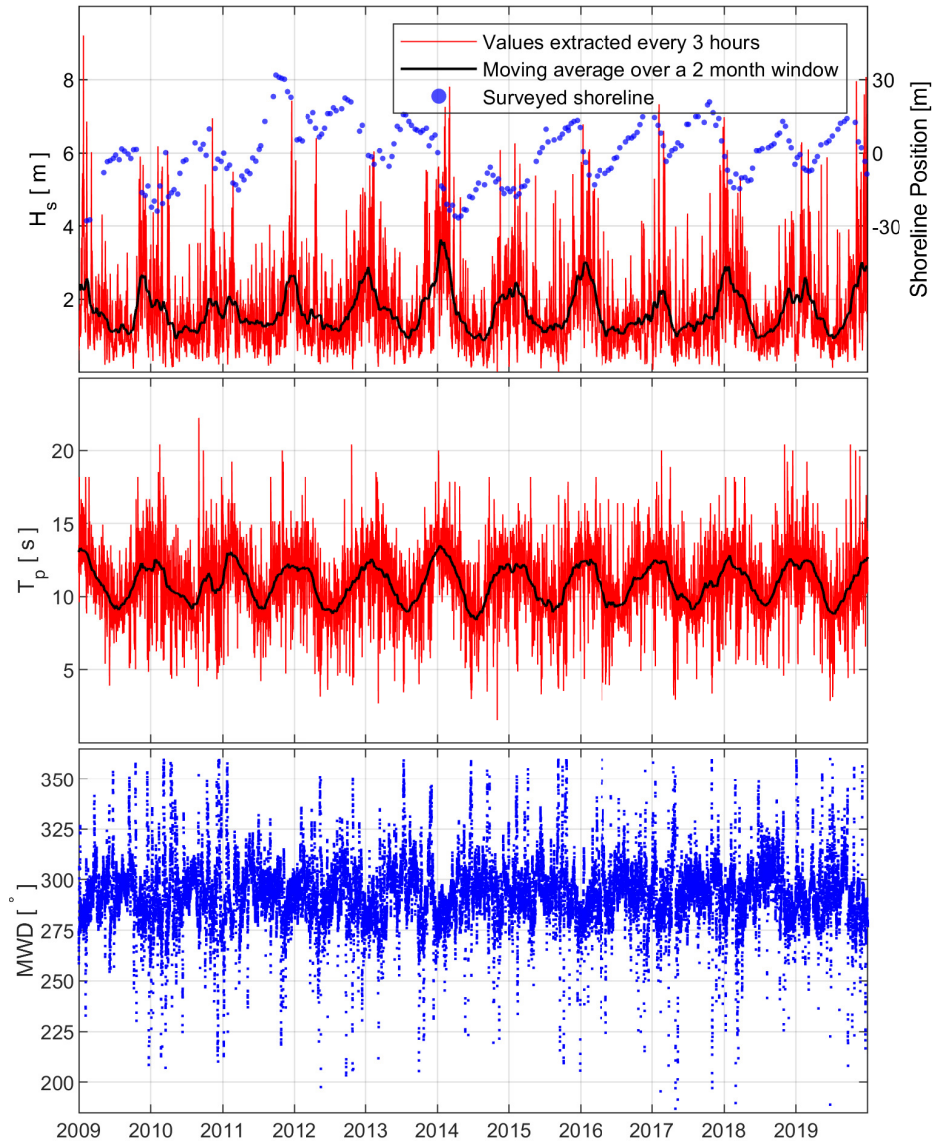


Figure 2: Offshore wave conditions during the period considered in the present work extracted at the location of the buoy (see Figure 1). The significant wave height H_s , peak wave period T_p and mean wave direction (MWD) are depicted in the upper, middle and lower panel of the figure. The alongshore averaged surveyed shoreline positions are plotted on the right axis of the upper panel.

166 *2.3. Shoreline Data*

167 Five different shoreline / waterline datasets extending from January 2009
 168 to December 2019 have been considered in the present work, summarized and
 169 depicted in Figure 3. The single transect (S_{IS}) extracted at $y = 0$ (see Figure
 170 1, a) as well as the alongshore averaged in-situ shoreline timeseries ($\overline{S_{IS}}$),
 171 have been derived from monthly to bimonthly sampled topographic GNSS
 172 surveys, performed during spring low tide at Truc Vert beach (see Figure 1)
 173 in the frame of a long-term monitoring program established in 2003 (Castelle
 174 et al., 2020). S_{IS} and $\overline{S_{IS}}$ correspond to the 1.5 m elevation Above Mean Sea
 175 Level (AMSL) shoreline proxy (see Figure 1), as this has been found to best
 176 correlate with the beach-dune volume (Robinet et al., 2016). The overbar
 177 denotes alongshore averaging over the survey domain, which increased from
 178 approximately 600 m in 2009 to slightly over 2300 m in 2016. In the present
 179 work, the alongshore-averaged in situ shoreline $\overline{S_{IS}}$ is considered as the true
 180 shoreline to which both satellite-derived and simulated shoreline data will be
 181 further compared. Unless stated otherwise the alongshore domain considered
 182 in the present work is the largest available at each point in time which after
 183 2016 is stabilized to ~ 2.4 km.

184 The satellite-derived, alongshore-averaged, uncorrected waterline $\overline{W_S}$, tide-
 185 corrected shoreline $\overline{S_{ST}}$ and tide and runup corrected shoreline $\overline{S_{STR}}$ depicted
 186 in Figure 3 were generated by Castelle et al. (2021). These datasets were com-
 187 puted from the waterlines W derived from optical satellite imagery along 4
 188 km of coastline at Truc Vert (see panel a in Figure 1). The extraction of
 189 the instantaneous waterline position W , was performed using the python
 190 toolkit CoastSat (Vos et al., 2019b) which is freely available on GitHub

191 (<https://github.com/kvos/CoastSat>). CoastSat is a Google Earth Engine
192 enabled open-source Python toolkit that allows the user to obtain waterline
193 position time-series at any sandy coastline worldwide from publicly available
194 satellite imagery. Landsat 5, 7 & 8 (L5, L7 & L8) images with a spatial
195 resolution of 30 m and Sentinel-2 (S2) images with a spatial resolution of
196 10 m can be retrieved to a user defined window. In succession the images
197 are being processed to remove cloudy pixels and enhance spatial resolution.
198 The methodology for the extraction of the instantaneous waterline position
199 is described in detail in Vos et al. (2019a).

200 Castelle et al. (2021) applied water level corrections by translating hori-
201 zontally the waterline W using a constant beach slope of 0.05 and the water
202 level at the coast at the satellite flyover time. The water level at the coast
203 was estimated using a coastal model hindcast of water level (Pineau-Guillou,
204 2013) validated at Truc Vert by Castelle et al. (2020). To estimate the wave
205 run up component of the instantaneous water level at the satellite flyover
206 time Castelle et al. (2021) used the run up formulations proposed by Senechal
207 et al. (2011) that has been calibrated at Truc Vert and can be scaled using
208 offshore wave height alone at Truc Vert. The two waterline datasets, namely
209 W_S and $\overline{W_S}$ include all usable satellite images since 2009. The two water
210 level corrected datasets $\overline{S_{ST}}$ and $\overline{S_{STR}}$, include all images extracted when
211 total water level η_t exceeds 0.5 & 0.2 m respectively. Although disregarding
212 low tide images improved the quality of the timeseries, it significantly reduces
213 the amount of observations. For a detailed and in depth description of the
214 methodology and analysis resulting to the three satellite derived datasets,
215 the reader is referred to Castelle et al. (2021).

216 The raw waterline data extracted from the satellite images W_S as well as
217 its 4-km alongshore averaged dataset $\overline{W_S}$ can deviate from the shoreline po-
218 sition significantly, especially in a high energy meso-macrotidal environment
219 like Truc Vert. The computed root mean square error for the $\overline{W_S}$ dataset
220 reported in Castelle et al. (2021) is in the order of 30 m and the correlation
221 is poor with $R^2 < 0.5$ (see panel c in Figure 3). The single transect satellite
222 derived waterline W_S shows similar agreement when compared against the in
223 situ derived shoreline position S_{IS} considering the same transect (see panel d
224 in Figure 3) with a slightly smaller error. Alongshore averaging and applying
225 tide and/or wave runup correction on the satellite derived waterline positions
226 can largely improve the agreement with in situ shoreline $\overline{S_{IS}}$ (Castelle et al.,
227 2021; Konstantinou et al., 2023). It is important to note that the comparison
228 ($RMSE$, R^2 & $bias$) consider satellite images and beach surveys separated
229 by up to 10 days.

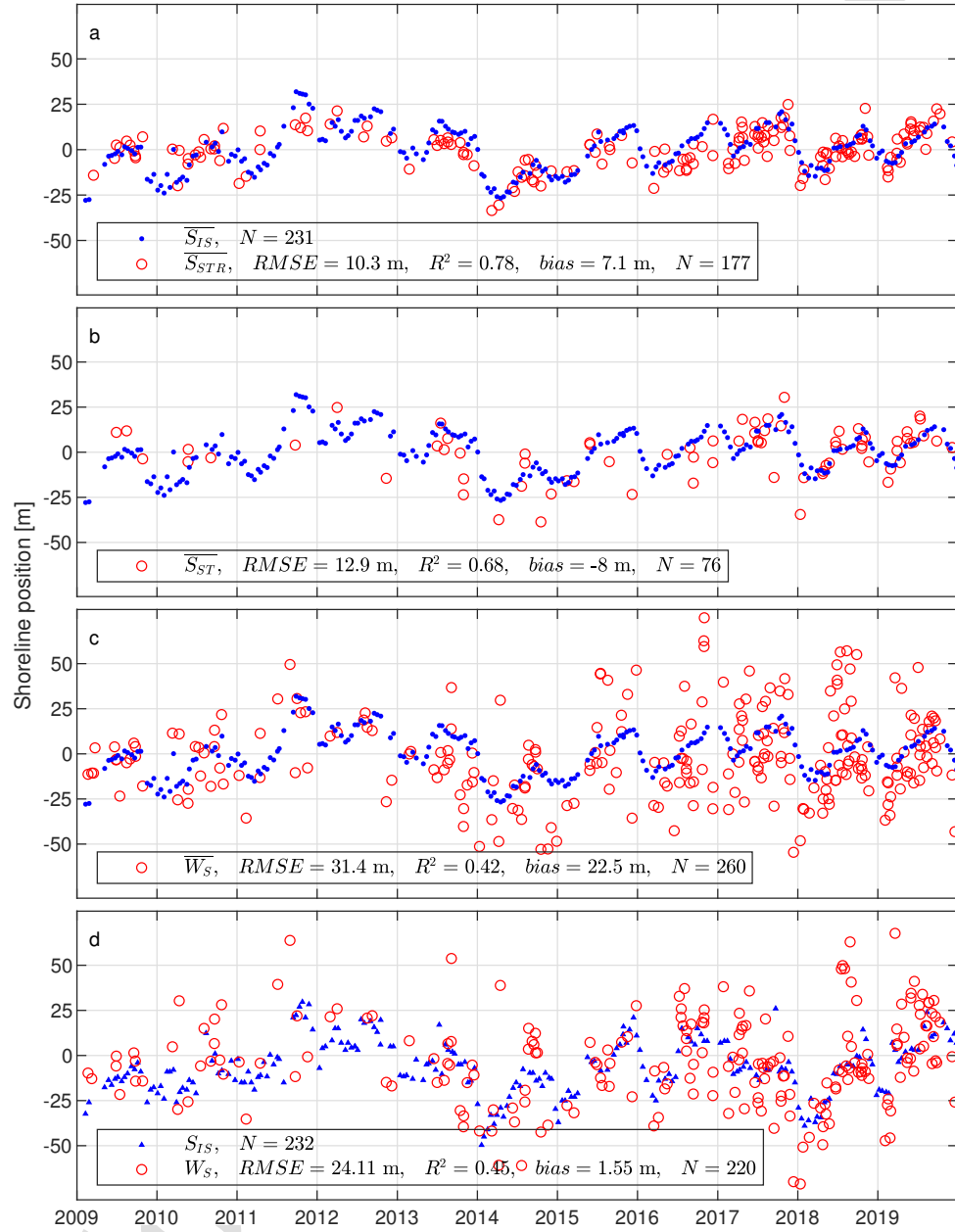


Figure 3: The four different satellite derived shorelines are depicted together with the in situ derived single transect (S_{IS}) and alongshore averaged ($\overline{S_{IS}}$) +1.5 m AMSL shoreline proxy. The $RMSE$, R^2 and $bias$ compared to the $\overline{S_{IS}}$ and S_{IS} as well as the total number of unique observations N for each data set are indicated in the legend.

230 3. Shoreline numerical modelling

231 3.1. Equilibrium shoreline model

232 In the present work the empirical equilibrium shoreline model ShoreFor
 233 developed by Davidson et al. (2013) was used to simulate shoreline evolu-
 234 tion. In ShoreFor the shoreline displacement is defined as a function of the
 235 nearshore wave power and a disequilibrium state of the beach. In the ap-
 236 proach of Davidson et al. (2013) the rate of shoreline change dx/dt (m/s) is
 237 defined as:

$$\frac{dx}{dt} = c^{\pm} P^{0.5} (\Omega_{eq} - \Omega) \quad (1)$$

238 where the model's forcing term is the product of the incident wave power
 239 P (W) computed using linear wave theory, and the model free parameter
 240 c^{\pm} representing the response rate of the shoreline with units of velocity per
 241 measure incident wave power. The parameter c^{\pm} is separated into accretion
 242 c^{+} when $\Omega_{eq} > \Omega$ and erosion c^{-} when $\Omega_{eq} < \Omega$ components, accounting for
 243 the fact that accretion and erosion are observed to evolve at different rates.
 244 Davidson et al. (2013) included a term b in their formulation accounting for
 245 linear trends stemming from longer term processes that are not explicitly
 246 addressed in the model. In the present work this term is disregarded due
 247 to the relatively small trend calculated from the SDS data, and the absence
 248 of significant shoreline trend over the last 70 years (Castelle et al., 2018b).
 249 The term inside the parenthesis in equation 1 is a disequilibrium term which
 250 is based on the premise that shoreline state and morphological change are
 251 inter-related. Ω is the so called dimensionless fall velocity defined as:

$$\Omega = \frac{H_s}{T_p w_s} \quad (2)$$

252 where H_s and T_p are the instantaneous significant wave height and peak wave
 253 period respectively and w_s is the terminal fall velocity of the beach's median
 254 grain diameter d_{50} calculated using Stoke's law. The time varying equilib-
 255 rium condition Ω_{eq} is a weighted average of the antecedent dimensionless fall
 256 velocity Ω defined as:

$$\Omega_{eq} = \sum_{j=0}^{2\phi} \Omega_j 10^{-j/\phi} \left[\sum_{j=0}^{2\phi} 10^{-j/\phi} \right]^{-1} \quad (3)$$

257 where j is the number of days prior to the present time and the memory
 258 decay ϕ is a model free parameter indicating the number of days it takes for
 259 the weighting to reach 10%, 1% and 0.1% of the instantaneous value at ϕ ,
 260 2ϕ and 3ϕ days prior to the present. The formulation used in the present
 261 work and shown in Equation 3 incorporates all past beach state information
 262 for the past 2ϕ days, yielding a minimum weighting factor of 1%.

263 Following the work of D'Anna et al. (2022) a constant SLR_{rate} of 3.31
 264 mm/year is applied, the contribution of which to shoreline retreat is calcu-
 265 lated using the Bruun rule (Bruun, 1962). The SLR driven shoreline retreat
 266 is negligible in the time scales addressed in the present work.

267 3.2. Calibration

268 The model requires the calibration of two model free parameters, namely
 269 the accretion/erosion rate c^\pm and the memory decay ϕ . An extra term is
 270 added allowing the model to adjust its initial position by dx_0 . This term is
 271 introduced to account for uncertainties in the first shoreline data point.

272 To calibrate the model free parameters the simulated annealing algorithm
 273 proposed by Bertsimas and Tsitsiklis (1993) was implemented. Simulated
 274 annealing is a non-linear probabilistic method, that can be used to find the
 275 global minimum of a cost function without getting stuck in local minima. The
 276 implementation of the simulated annealing algorithm was already successful
 277 in the calibration of equilibrium models in Castelle et al. (2014), D'Anna
 278 et al. (2020), Labarthe et al. (2023) and more. In this contribution, the
 279 mean squared error (*MSE*) between the observed and simulated shoreline
 280 was used as a cost function in the optimization without accounting for any
 281 sources of uncertainty.

282 A timeseries of simulated shoreline evolution and the corresponding cost
 283 function C , are calculated based on a set of initial model parameters \mathbf{P}_0 .
 284 Successively, one of the model parameters is randomly selected and modified
 285 within the defined range, based on a defined noise. The cost function is
 286 calculated for the new set of model parameters $\mathbf{P}(\mathbf{i})$ and compared to the
 287 initial value. As long as the new solution is an improvement $C(i) < C$, the
 288 same step is repeated with the new solution as initial value $\mathbf{P}_0 = \mathbf{P}(\mathbf{i})$ &
 289 $C = C(i)$ until the number of iterations defined by the user is reached. In
 290 case the new solution is not an improvement $C(i) \geq C$ then the next step is
 291 defined based on the following probability:

$$\mathbb{P}(\mathbf{P}_0, \mathbf{P}(\mathbf{i}), T(i)) = \exp[-(C(i) - C)/T(i)]$$

292 where $T(i)$ is a positive integer called the temperature parameter. The tem-
 293 perature controls the probability of accepting worse solutions. Initially, the
 294 temperature is high, allowing the algorithm to accept worse solutions with rel-
 295 atively high probability. The algorithm uses a cooling schedule to gradually

296 decrease the temperature parameter with every iteration based on a defined
297 cooling coefficient. As the temperature decreases, the algorithm becomes
298 more selective, preferring only better solutions. The temperature parameter
299 plays a crucial role in Simulated Annealing. A high temperature allows the
300 algorithm to explore a wide range of solutions, including worse ones, helping
301 to escape local minima.

302 The initial model parameters \mathbf{P}_0 are defined as the average value of the
303 considered range. The noise amplitude used to inflate each parameter, cor-
304 responds to 5% of the bounds' difference. Our preliminary analysis showed
305 that in order to achieve an acceptable solution, the algorithm needed to be
306 initialized with a large temperature T_0 , slowly decreasing and allow for a
307 large number of iterations ($O \geq 10^5$).

308 3.3. Simulation setup

309 The present work aims to evaluate the performance of the state of the art
310 equilibrium shoreline evolution model proposed by Davidson et al. (2013),
311 when calibrated against satellite-derived waterline and shoreline datasets
312 with different water level corrections and sampling frequencies, and thus
313 varying uncertainties (see Figure 3). To assess the performance of the model
314 and further explore the requirements in SDS quality and quantity to ro-
315 bustly calibrate an equilibrium shoreline model, three different numerical
316 experiments have been designed. All the experiments were conducted under
317 the assumption that there is no a priori knowledge of the simulated coastal
318 environment. This was implemented by investigating a range of calibration
319 parameters (Table 1) beyond the limits found in the literature (e.g. Davidson
320 et al., 2013; Splinter et al., 2014; D'Anna et al., 2020, 2022).

Model parameter	Simulated annealing range	Units
c^+ / c^-	$[0; 2.5] \times 10^{-6} / [0; 1.0] \times 10^{-6}$	$\text{m}^{1.5} \text{s}^{-1} \text{W}^{0.5}$
ϕ	[25; 1400]	days
dx_0	[-10; 10]	m

Table 1: Range of values considered in the present work.

321 As an initial test the model has been calibrated against all five datasets
 322 depicted in Figure 3, using the entire period (January 2009 - December 2019)
 323 and comparing the model results with the in situ derived shoreline data $\overline{S_{IS}}$
 324 and S_{IS} . This experiment was designed to assess whether the information of
 325 the shoreline position can be extracted from the different datasets and to
 326 which extent each of the five datasets can be used to calibrate the empirical
 327 equilibrium shoreline model and provide accurate hindcast.

328 Given the alongshore variability in shoreline position due to prominent
 329 megacusp embayments, the next experiment was designed to investigate a
 330 minimum threshold in the alongshore averaging window necessary to obtain
 331 satisfactory model results. To do so, 40 different shoreline datasets were
 332 generated from the satellite-derived waterlines W using alongshore averag-
 333 ing windows extending from 100 m to 4000 m around the origo point (see
 334 Figure 1), in increments of 100 m. All of these alongshore averaged datasets
 335 were used to calibrate the model against the entire period (January 2009
 336 - December 2019). Model performance was systematically assessed against
 337 in situ derived shoreline data $\overline{S_{IS}}(y)$ after 2016, using the same window as
 338 the calibration dataset. The variable y represents the alongshore distance
 339 considered for each window (see Figure 1). Importantly, in order to avoid

340 erroneous interpretations of the results, account for the stochastic nature of
341 the simulated annealing algorithm and ensure repeatability, the calibration
342 was run 20 times for every dataset.

343 The final numerical experiments were designed to explore the amount and
344 quality of data required to obtain fair model skill. These experiments were
345 inspired by the work of Splinter et al. (2013), where they investigated the
346 influence of noise, morphological sampling interval and calibration duration
347 in empirical equilibrium shoreline models including Davidson et al. (2013).
348 Similar to the work of Splinter et al. (2013) and more recently Alvarez-Cuesta
349 et al. (2024), in order to properly investigate the influence of sampling fre-
350 quency as well as noise in the dataset, a synthetic shoreline was generated
351 S_{SYN} using Eq. 1 and the wave timeseries depicted in Figure 2. Subse-
352 quently the synthetic shoreline was inflated by normally distributed noise
353 with a magnitude, equal to 100% and 200% of the standard deviation of the
354 synthetic shoreline timeseries to account for measurement errors and other
355 unresolved processes. Finally the synthetic shoreline timeseries were subsam-
356 led in intervals of $dt = 1, 7, 14, 30, 60, 90, 182$ & 365 days. The resulting 24
357 synthetic shoreline timeseries were used to calibrate the model, which perfor-
358 mance was evaluated against the daily subsampled synthetic shoreline with
359 0% noise. The duration of an adequate calibration period was investigated in
360 increments of 6 months for all aforementioned synthetic shorelines as well as
361 the four observed alongshore averaged shoreline timeseries depicted in Figure
362 3. The performance of the models calibrated using the alongshore averaged
363 shoreline and waterline data was evaluated against the true shoreline ($\overline{S_{IS}}$)
364 timeseries of the subsequent period. All simulations for both the synthetic

365 and observed datasets, were repeated 10 times to account for the stochastic
 366 nature of the simulated annealing algorithm.

367 Lastly the importance of sampling frequency was further investigated
 368 using the alongshore averaged uncorrected waterline data $\overline{W_S}$ over the entire
 369 period from January 2009 to December 2019. In this experiment, N amount
 370 of data points were randomly sampled from the entire dataset which were
 371 then used to calibrate the model over the entire period. Successively the
 372 model's performance was evaluated against the true shoreline ($\overline{S_{IS}}$). Eleven
 373 datasets were investigated in total with the most scarce one being populated
 374 by $N = 25$ points randomly distributed over the entire period and increasing
 375 the amount of points in increments of 25 arriving at the complete dataset.
 376 The experiment was repeated 30 times for each dataset.

377 4. Results

378 4.1. Model calibration with different datasets

379 Figure 4 shows model results when calibrated with each of the five datasets
 380 (namely $\overline{S_{IS}}$, $\overline{S_{STR}}$, $\overline{S_{ST}}$, $\overline{W_S}$ and W_S), which are compared against the in-
 381 situ shoreline proxies $\overline{S_{IS}}$ and S_{IS} . For all five datasets, the model was
 382 calibrated using the entire period depicted in Figure 4. All the alongshore
 383 averaged datasets, both in-situ and satellite derived, produce an acceptable
 384 model with $RMSE < 10$ m and $R^2 \approx 0.6$ (Figure 4). This is not surprising
 385 for in-situ shoreline proxy $\overline{S_{IS}}$, with model skill similar to previous equilib-
 386 rium model applications at Truc Vert (Castelle et al., 2014; Splinter et al.,
 387 2014; D'Anna et al., 2020). More unexpected is that similar model skill is
 388 obtained with all the alongshore-averaged SDS despite the error and noise

389 in the dataset (see Figure 3). This is particularly true for the uncorrected
390 waterline \overline{W}_S , with RMSE of approximately 30 m and seasonal and interan-
391 nual patterns barely depictable (Figure 3). Results improve as uncertainties
392 are reduced with each applied correction (tide and/or runup correction), de-
393 spite the fact that both these datasets contain less data points (Figure 3). In
394 contrast, the model calibrated with the single transect waterline dataset W_S
395 (Figure 4e) shows very poor performance with a coefficient of determination
396 of $R^2 \approx 0.2$ and a RMSE > 10 m, which will be discussed later in the paper.

397 Given that only the single transect dataset yielded poor results, the influ-
398 ence of alongshore averaging window on model skill was investigated (Figure
399 5). Results show that the minimum window width to obtain good model skill
400 is $L \geq 1.2$ km. Both the RMSE of the model and the correlation coefficient
401 improve significantly with $L \geq 1.2$ km, while a slight further improvement
402 is observed when $L \geq 2.2$ km. These values coincide with approximately
403 1.5 and 3 times the wavelength of the megacusp embayments (~ 700 m) ob-
404 served in Truc Vert beach. It should be noted that the in situ data are limited
405 to a window of ~ 2.4 km. Thus, beyond this point the calibration results
406 have been compared against alongshore averaged shoreline positions using
407 the largest available window (~ 2.4 km). The findings of this experiment are
408 discussed in detail in Section 5.

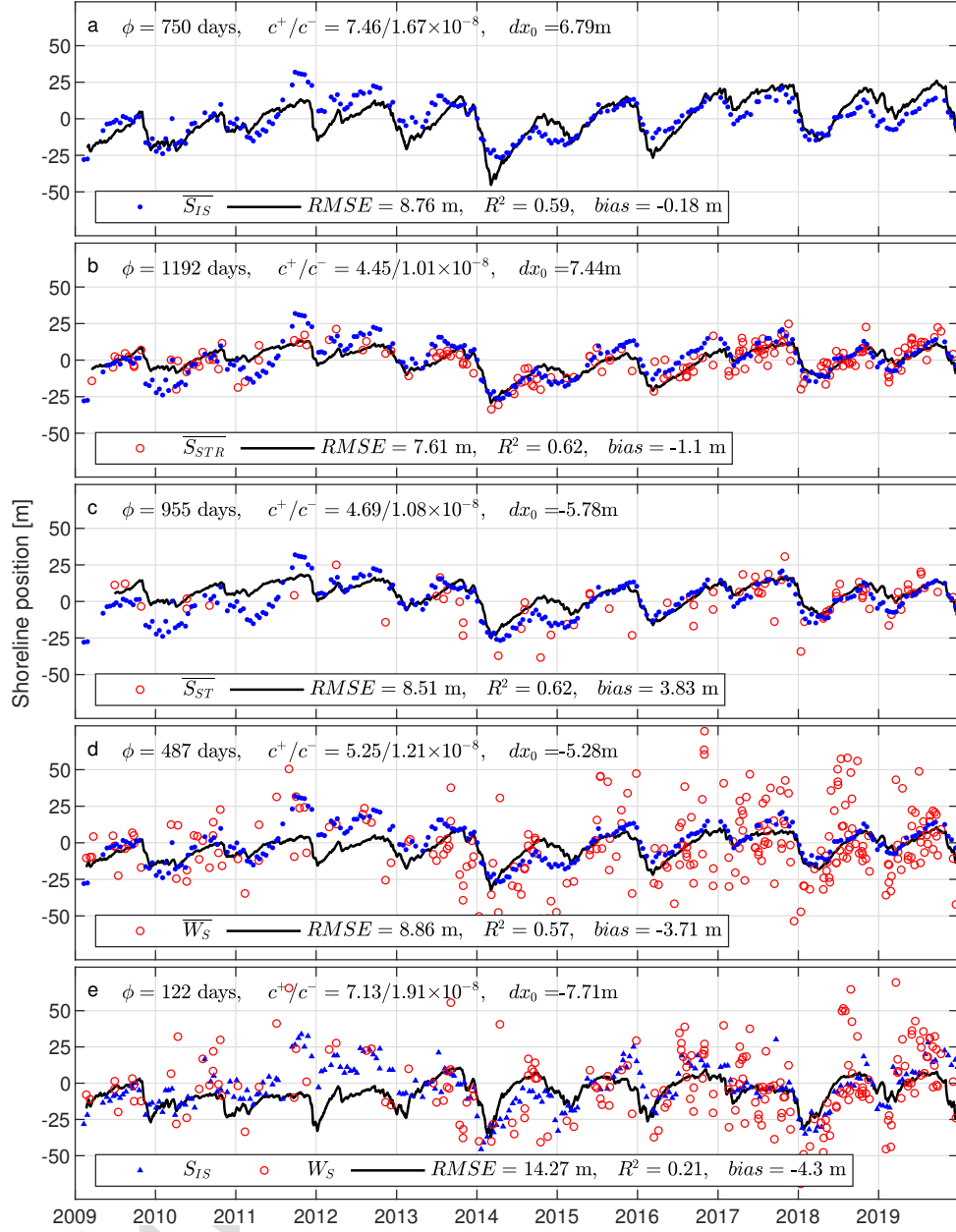


Figure 4: Model results using the simulating annealing algorithm to calibrate the model over the entire period based on the five different datasets and comparing with the in-situ derived shoreline data \overline{S}_{IS} (blue dots) and S_{IS} (blue triangles). Performance metrics and calibrated model parameters are indicated in each panel.

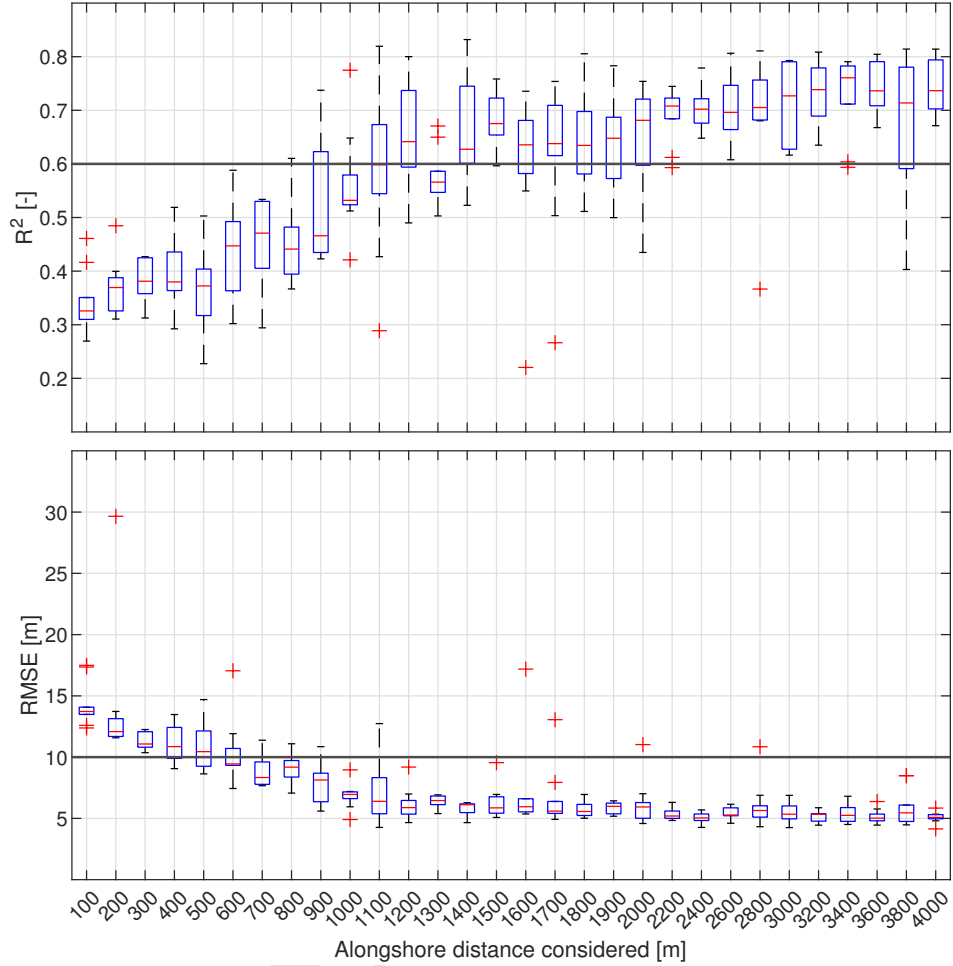


Figure 5: Performance indicators ($RMSE$ and R^2) of the model when calibrated using the alongshore averaged satellite derived waterline (\overline{W}_S) with a varying alongshore window size. The performance indicators of the model results are calculated against in-situ shoreline data with a matching window size ($\overline{S}_{IS}(y)$). Each box summarizes the results of 10 calibration runs. The horizontal red line inside the box, indicates the median value and the top and bottom edges of the blue boxes indicate the 25th and 75th percentiles respectively. Maximum whisker length extends up to 1.5 times the interquartile range and any value outside this range is considered an outlier and depicted as a red cross.

409 *4.2. How much data is enough ?*

410 In Figures 6 and 7 the results of the investigation on the adequate calibra-
411 tion period, influence of noise and sampling frequency on model performance
412 using a synthetic shoreline are summarized for the case of 0 % and 200 % noise
413 respectively. The sampling frequency of the shoreline used for calibration is
414 indicated in the upper right corner of each panel. The mean (squares) and
415 standard deviation (circles) R^2 and $RMSE$ of the 10 simulation ensemble
416 are plotted in the left and right hand column respectively.

417 The influence of sampling frequency is weak in the 0 % noise case for dt
418 ≤ 90 days (see Figure 6). Further reducing sampling frequency significantly
419 reduces model skill, especially when less than 4 years of data are used for
420 calibration. Considering a calibration period of 4 years or more, all four
421 datasets enable the generation of models with very similar skill. The larger
422 $RMSE$ around the 5 year calibration duration is due to the model producing
423 an erroneous trend.

424 The effect of noise in the dataset on model skill is almost negligible as
425 long as the sampling frequency is kept within $dt \leq 30$ days (see Figures 6
426 and 7). Reducing sampling frequency to $dt \geq 90$ days in the dataset with
427 200 % noise significantly reduces model skill, however when a calibration
428 period larger than 3 years is considered results improve. Further reducing the
429 sampling frequency to $dt = 365$ days, yields a model that fails to reproduce
430 the shoreline evolution. When calibrating over 4 years or more, the model
431 manages to capture the shoreline variability while still fails to reproduce the
432 shoreline trend. These findings are very promising and are discussed in detail
433 in Section 5.

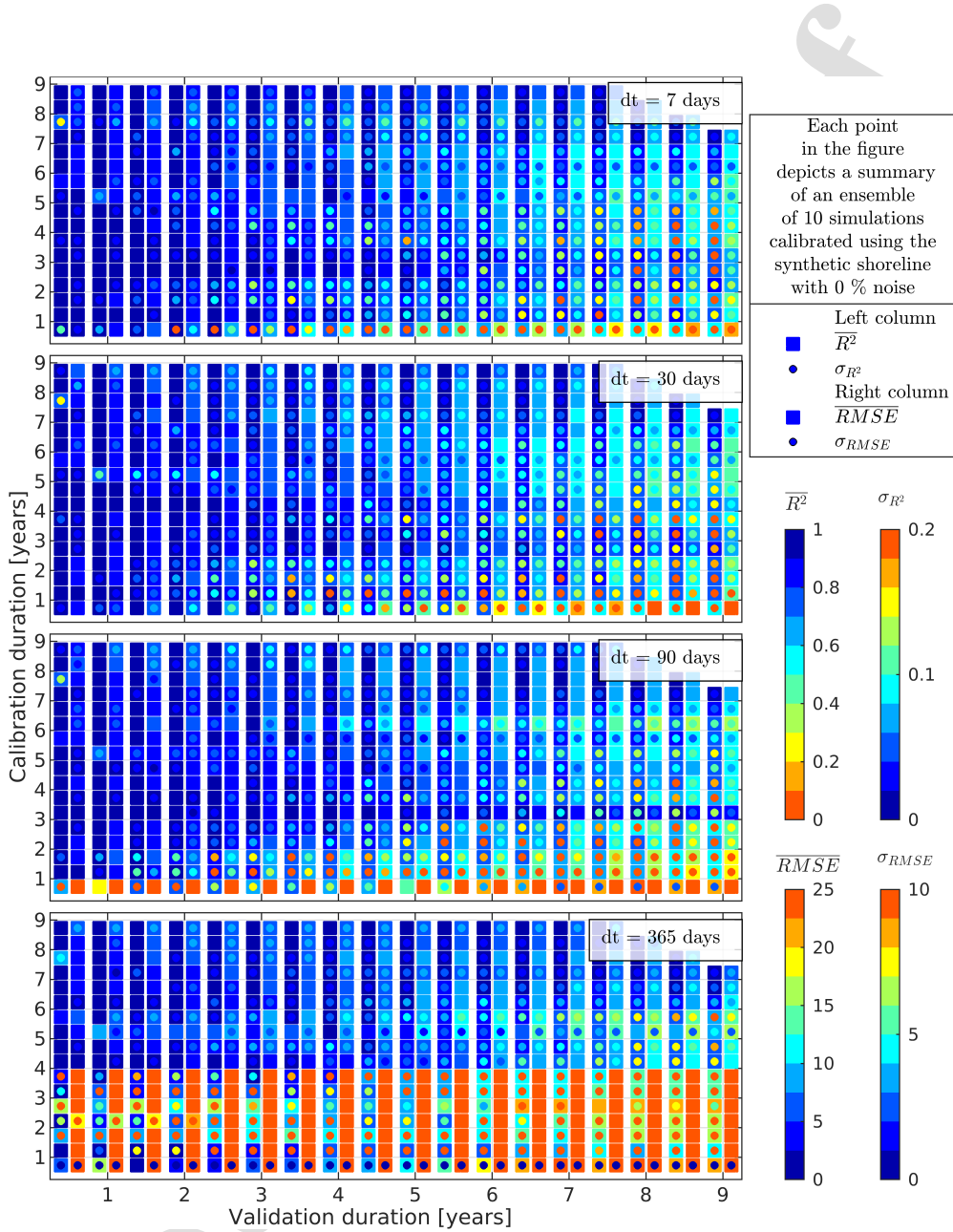


Figure 6: Model performance calibrated using synthetic shoreline with 0 % noise subsampled at $dt = 7, 30, 90$ and 365 days. $RMSE$ and R^2 plotted in the left and right column respectively, are calculated based on the daily subsampled synthetic shoreline considering the period following the calibration.. The squares and the circles represent the mean and standard deviation of an ensemble of 10 simulations.

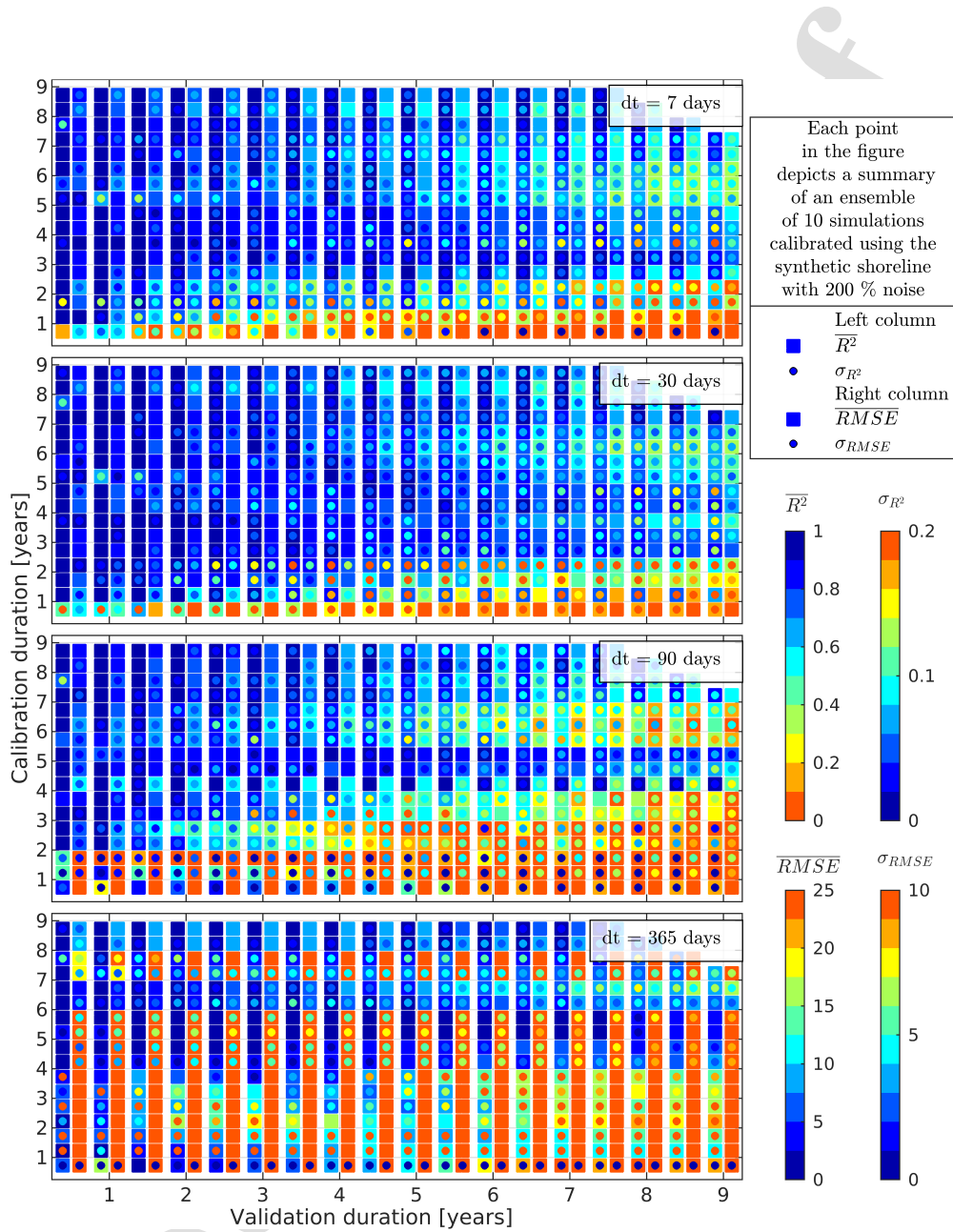


Figure 7: Model performance calibrated using synthetic shoreline with 200 % noise subsampled at $dt = 7, 30, 90$ and 365 days. $RMSE$ and R^2 plotted in the left and right column respectively, are calculated based on the daily subsampled synthetic shoreline considering the period following the calibration.. The squares and the circles represent the mean and standard deviation of an ensemble of 10 simulations.

434 In Figure 8 the predicted shorelines from the investigation on the adequate
435 calibration period using the four alongshore averaged datasets are depicted
436 together with the dataset used for the calibration. In Figure 9 the results
437 of the analysis are depicted in the same format as for the synthetic cases.
438 Results for all datasets, indicate a pivot point in model skill when calibration
439 duration exceeds 4 years. This finding agrees with the work of Splinter
440 et al. (2014) and our tests on the synthetic shoreline dataset. Excluding
441 the $\overline{S_{ST}}$ dataset the models produced considering a calibration period of 4
442 years or more, show very good model skill. The increase in $RMSE$ in the
443 model calibrated with the $\overline{W_s}$ considering a 6 year period is attributed to
444 an erroneous trend generated by the model. This trend is present in the
445 $\overline{W_s}$ dataset between 2009 and 2015, leading to model parameters that would
446 reproduce it. These findings open new perspectives for SDS applications
447 which are discussed in more detail in Section 5.

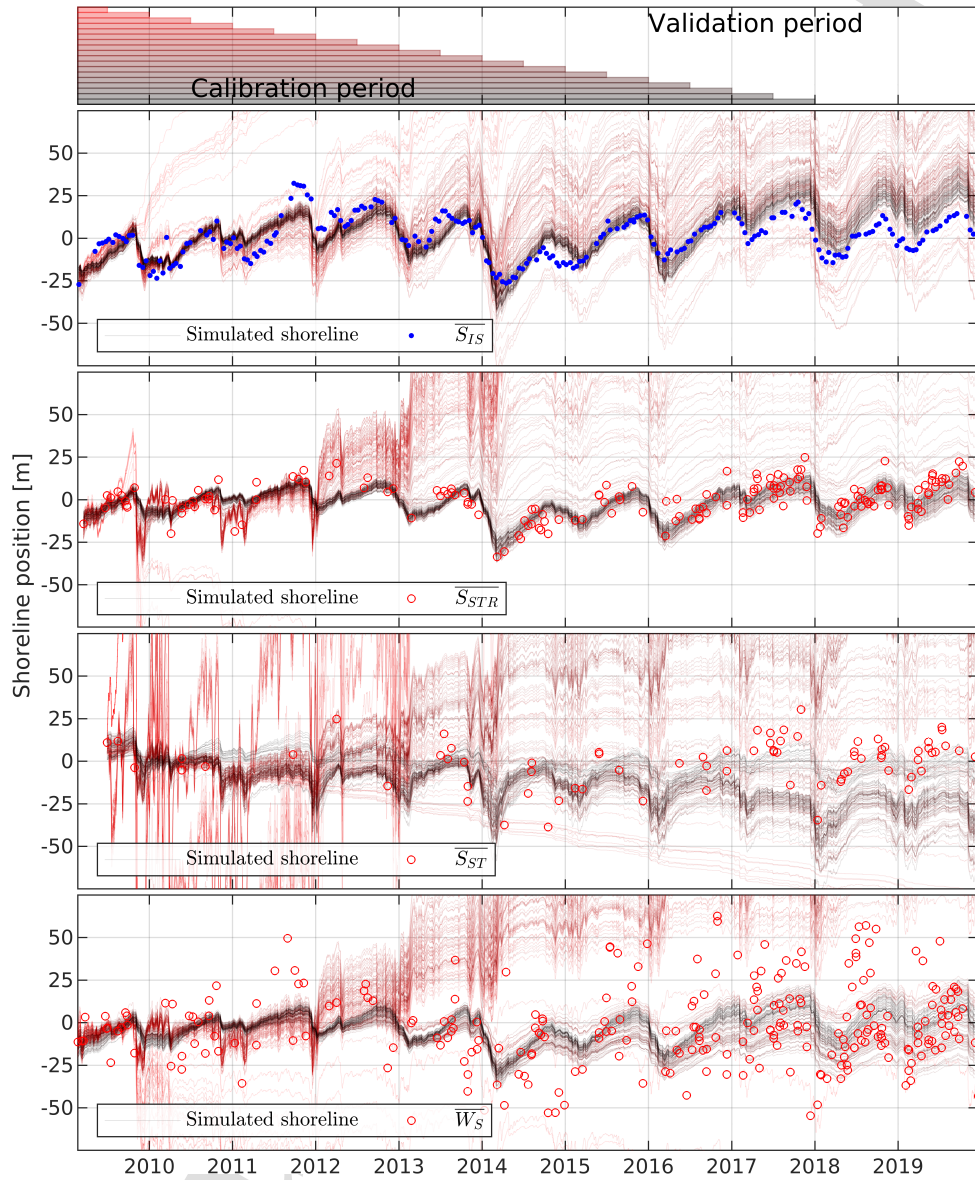


Figure 8: Model results of the investigation on the sufficient calibration window for all four alongshore averaged datasets. The considered calibration periods are indicated in the upper panel. The considered calibration periods are indicated in the upper panel, transitioning from red to black as the calibration duration increases. The simulated shorelines are plotted in red for the model calibration finishing at 07/2009 gradually transitioning to black as the calibration window increases. Model performance was evaluated against the \bar{S}_{IS} dataset considering the period following the calibration.

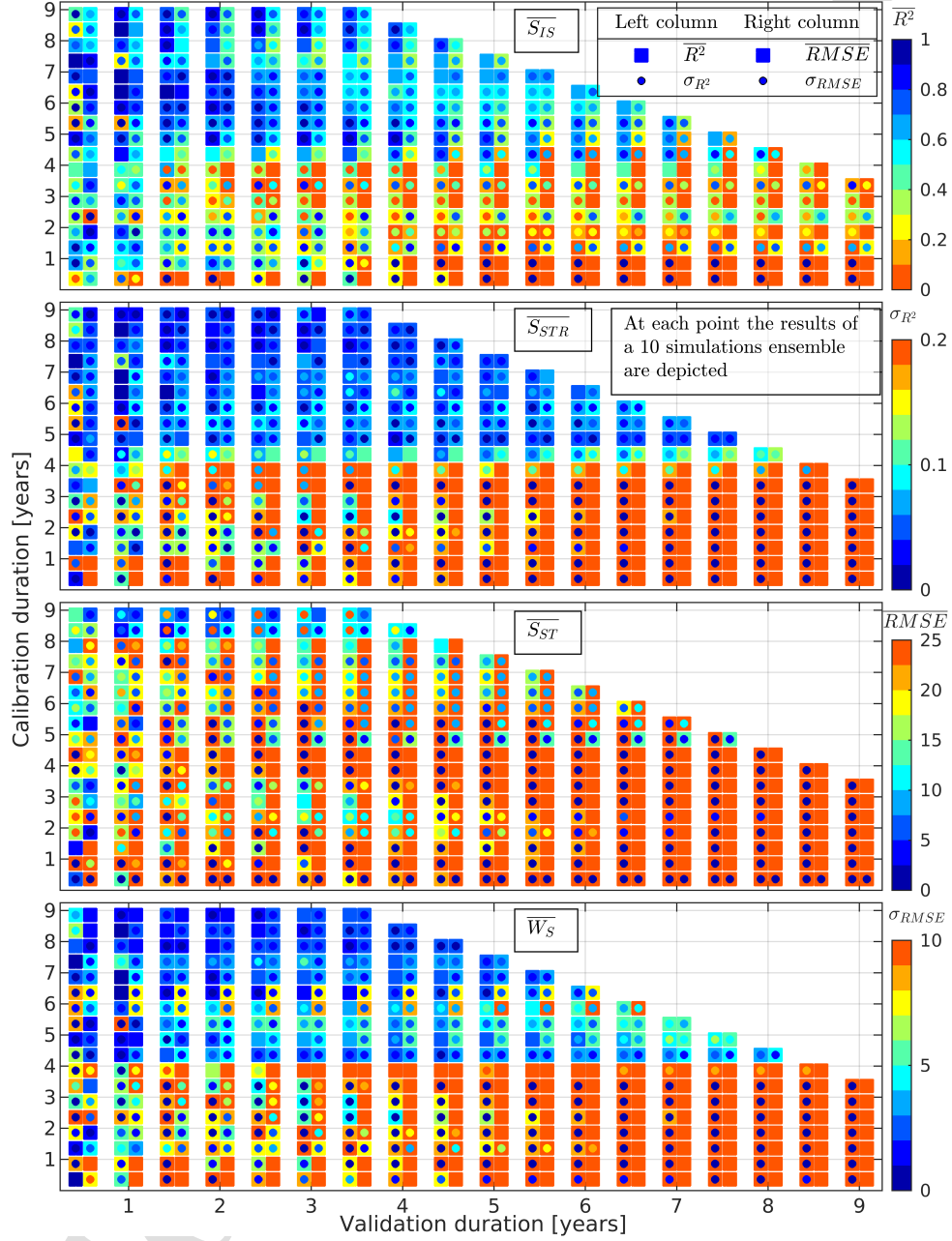


Figure 9: Model performance calibrated using the four alongshore averaged observed datasets, evaluated against the $\overline{S_{IS}}$ dataset considering the period following the calibration. $RMSE$ and R^2 plotted in the left and right column respectively. The squares and the circles represent the mean and standard deviation of an ensemble of 10 simulations.

448 Finally the results on the influence of sampling frequency in the along-
449 shore averaged uncorrected SD waterline $\overline{W_S}$ on model skill are depicted in
450 Figures 10 and 11. In Figure 10 four examples are shown having a total
451 number of observations over the entire 11 year period of $N = 25, 100, 175$
452 and 275 plotted from the upper to the lower panel, respectively. The results
453 are summarised in Figure 11 in terms of performance metrics ($RMSE$ and
454 R^2). These findings indicate that even with a dataset of 25 points distributed
455 randomly over the 11 year period the simulated annealing algorithm man-
456 ages to find an acceptable solution. However, the majority of the runs based
457 on calibration with only 25 points yield very poor results. Increasing the
458 number of points shows a significant improvement in the repeatability of the
459 solution. When using the complete dataset ($N_{max} = 275$ points), the algo-
460 rithm never fails to find an acceptable solution. These results are discussed
461 in detail in section 5.

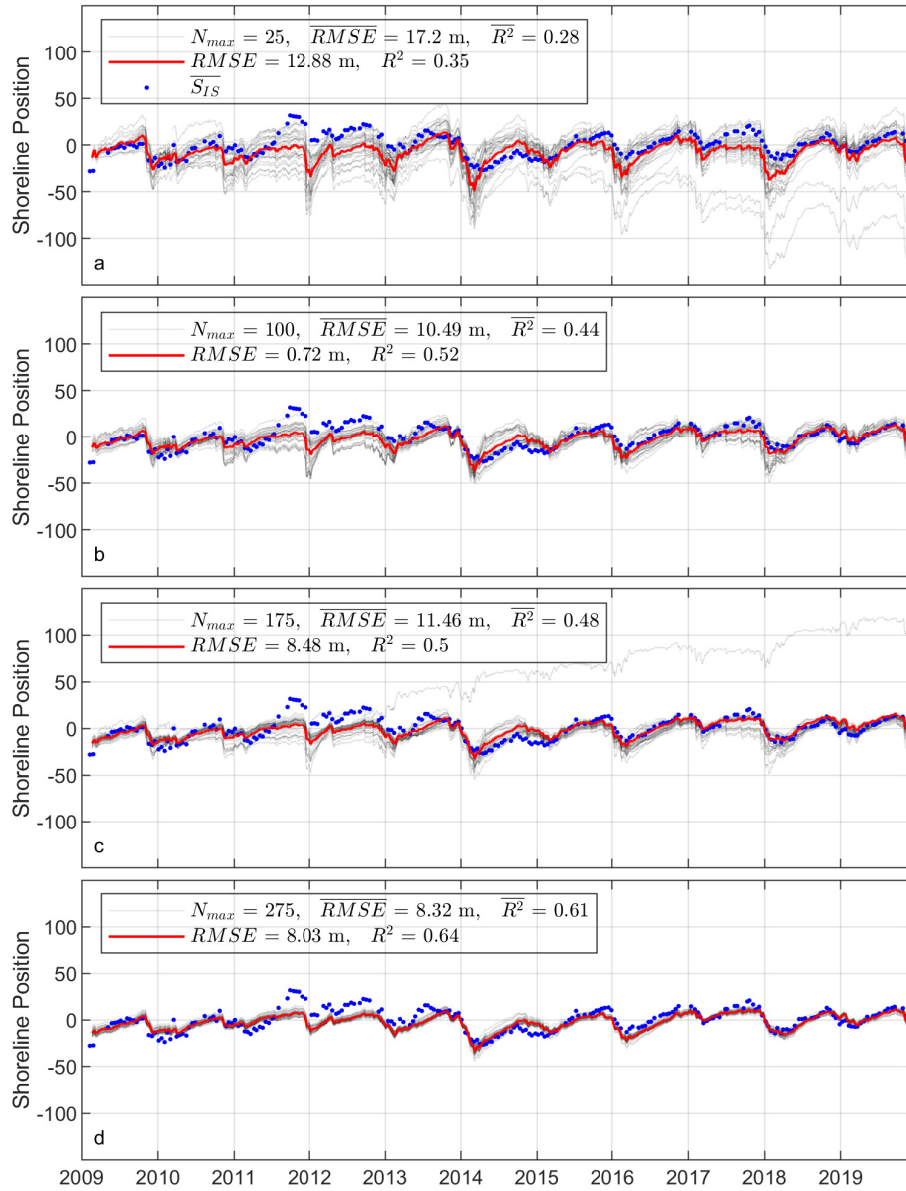


Figure 10: Predicted shoreline obtained from an ensemble of 30 different model calibrations using N number of randomly selected points from the \overline{W}_S data set. The ensemble mean is plotted in red while all the rest are plotted in light grey. The model's performance is evaluated against the \overline{S}_{IS} (blue dots). The amount of data points N_{max} used for the calibration of the model is indicated in the legend together with the average performance indicators \overline{RMSE} and \overline{R}^2 of the ensemble.

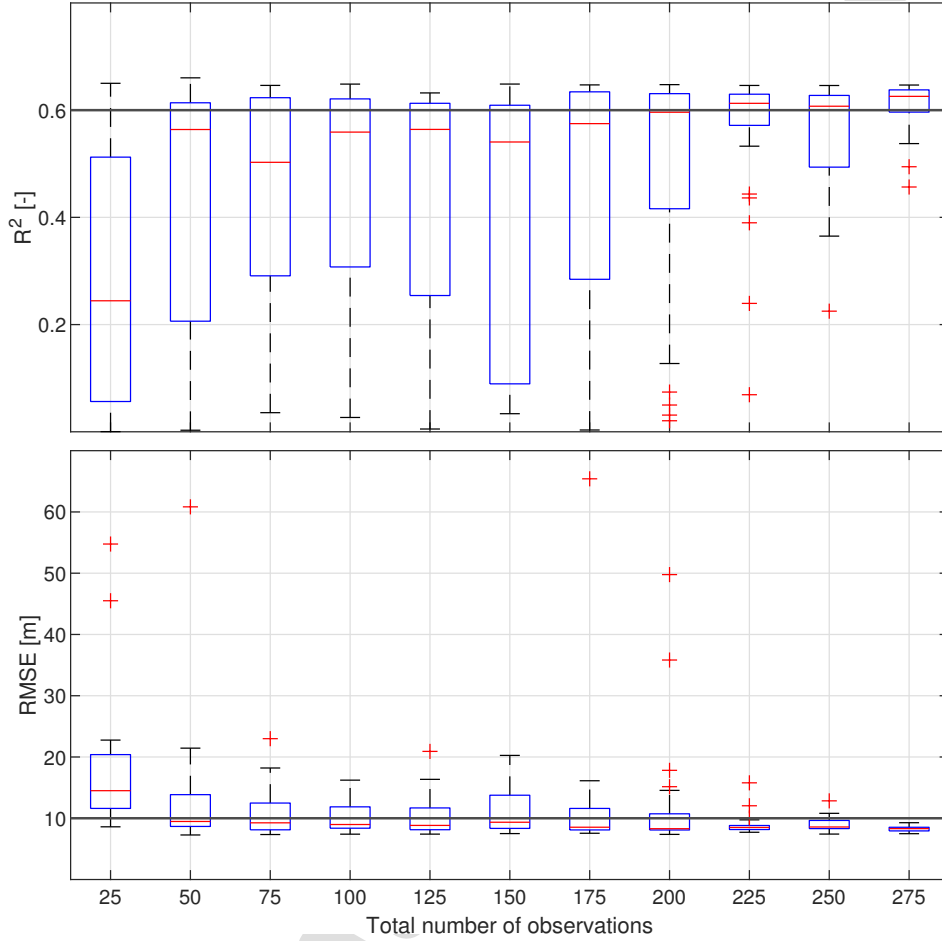


Figure 11: Performance indicators $RMSE$ and R^2 depicted in the lower and upper panel of the figure plotted against the number of data points used for the calibration. Each box corresponds to an ensemble of 30 simulations using N amount of data points randomly selected from the $\overline{W_S}$ dataset. The horizontal red line inside the boxes, indicates the median value and the top and bottom edges of the blue boxes indicate the 25th and 75th percentiles respectively. Maximum whisker length extends up to 1.5 times the interquartile range and any value outside this range is considered an outlier and depicted as a red cross.

462 5. Discussion

463 To the authors' knowledge the current study is the first ever successful
464 use of uncorrected SDS data for the calibration of an equilibrium shoreline
465 model in a high-energy, meso- macrotidal environment. Previous studies such
466 as Castelle et al. (2014); Splinter et al. (2014) have used either data collected
467 using traditional survey techniques such as GNSS or video-derived shorelines
468 (e.g. Holman et al., 2003, ARGUS). Existing work using SDS observations in
469 model calibration focused on microtidal environments (e.g. Alvarez-Cuesta
470 et al., 2021a,b; Ibaceta et al., 2022), where SDS RMSE are in the order
471 of 10 m. In their latest contribution Vitousek et al. (2023) applied a SDS
472 data assimilated shoreline model to hindcast and predict coastal change at
473 the entire coast of California. They used almost exclusively SDS data for
474 the calibration of the model, to which they applied water level corrections
475 achieving a RMSE between SDS and in situ observations in the order of 15
476 m.

477 There is a substantial amount of research aiming at reducing uncertainties
478 and improve quality of SDS data (Castelle et al., 2021; Konstantinou et al.,
479 2023). In the present application however the amount of data was found
480 to be the most important parameter of the SDS dataset rather than the
481 quality/accuracy of the shoreline position. Without applying any of the
482 corrections proposed in Castelle et al. (2021), SDS data extracted in a meso-
483 macrotidal, high-energy environment with a RMSE larger than 30 m, allowed
484 skillful equilibrium shoreline model calibration. The calibrated model showed
485 a very good performance with a $RMSE = 8.3$ m and a strong correlation of R^2
486 $= 0.63$. This result was unexpected considering the large RMSE associated

487 with the raw SDS data.

488 The effect of noise in the datasets (both synthetic and observed) seems
489 to be almost negligible as long as the sampling frequency is kept high ($dt \leq$
490 30 days) and an adequate calibration period is considered. This observation
491 stemming from the synthetic shoreline analysis experiment clearly explains
492 why the worst model skill is obtained when the tide corrected dataset $\overline{S_{ST}}$ is
493 used for calibration. The model seems to be sensitive to the period chosen
494 for calibration as this would influence the shoreline trend as well as the phe-
495 nomena included. Further analysis considering different calibration periods
496 while maintaining the same duration should be performed to investigate this
497 hypothesis.

498 It should be stated that the in situ data include a strong accretion spike
499 in 2012 which is due to sandbar-welding and could only be captured at spring
500 low tide which is when surveys take place at Truc Vert. This accretion signal
501 is not as pronounced in the SDS datasets since the satellite flyover time does
502 not necessarily coincide with spring low tide. Furthermore, as previously
503 discussed the water level corrected datasets disregard low tide images, which
504 results in smoothing of the accretion spike. Such an event could not be
505 captured by the physics of the model used, and is believed to have an impact
506 in the performance of the model when calibrated with this period of the
507 in-situ dataset. This could also be partly the reason for increasing model
508 performance as the influence of 2012 gets smoothed with larger calibration
509 period (see Figure 9).

510 The fact that the adopted methodology proved successful even in a very
511 challenging site such as Truc Vert, is very encouraging for potential future

512 applications of SDS data in equilibrium shoreline modelling even at sites
513 where no in-situ data are available. The spatio-temporal coverage of freely
514 available satellite imagery combined with the no a priori knowledge assump-
515 tion adopted in the current study, hint that the proposed methodology could
516 be universally applicable on cross-shore transport dominated coasts. The
517 model used in the present work requires information about the median sedi-
518 ment grain size D_{50} of the simulated environment. Although this information
519 is impossible to obtain via remote sensing, a reasonable guess would be suf-
520 ficient as this would serve as a scaling factor that would be compensated by
521 the calibration parameters.

522 Alongshore averaging was found to be the only necessary processing of
523 the SDS data prior to their application in model calibration at Truc Vert.
524 This can be explained by the presence of prominent mega-cusps, that typ-
525 ically form, migrate alongshore, and decay in time, which physics are not
526 represented by an equilibrium model like Davidson et al. (2013). Therefore
527 these features needed to be filtered out of the dataset, which was achieved
528 by alongshore averaging over a window approximately 1.5 times the features
529 wavelength. This approach does not violate the no a priori knowledge as-
530 sumption adopted, since megacusp spacing can be estimated by simply study-
531 ing the satellite images, and an averaging window of say 3-4 time this spacing
532 be applied. Alternatively, filtering out megacusps, which are quite common
533 on intermediate coastlines (Wright and Short, 1984), can be performed by
534 applying a conservative alongshore window width in the order of a couple of
535 km as Truc Vert shows larger rip spacing than most of the reported sandy
536 beaches. Critically, our findings are in line with recent work suggesting that

537 spacial averaging can reduce SDS noise (Castelle et al., 2022; Warrick et al.,
538 2023), and demonstrate that global SDS datasets with transects spaced by
539 10s of kilometers are not relevant to address shoreline change on most coasts
540 (Warrick et al., submitted).

541 A dataset covering 4 to 5 years with a monthly sampling frequency was
542 found to be sufficient for the calibration of the model applied to hindcast ~ 6
543 years of shoreline evolution in Truc Vert. This result, obtained with raw SDS
544 data in a high energy, meso- macrotidal shoreline, is in line with the find-
545 ings of Splinter et al. (2013) where they investigated the influence of noise,
546 morphological sampling interval and dataset duration in equilibrium shore-
547 line model calibration and the recent work of Alvarez-Cuesta et al. (2024)
548 who performed a similar analysis on data assimilation. The fact that similar
549 results with previous studies are obtained in the present work, further illus-
550 trates the strength of the simulated annealing algorithm considering that the
551 investigated noise level in the synthetic time series is 4 times larger compared
552 to previous studies (200% of the standard deviation) and so is the order of
553 magnitude of the observation error ($O \sim 30$ m). It should be noted that the
554 SDS data after 2013, improve both in terms of image quality and sampling
555 frequency. Therefore, the aforementioned result can be considered conserva-
556 tive and the models obtained using the methodology presented in this work
557 are only expected to improve.

558 Our findings regarding the adequate sampling frequency indicate that
559 even with as few as 25 points randomly spread over an 11 year period, the sim-
560 ulated annealing algorithm was able to find a very good solution. This is par-
561 ticularly encouraging for applications in higher latitudes where the amount

562 of cloud-free satellite images are significantly reduced (Konstantinou et al.,
563 2023). On average however, the performance of the models calibrated with
564 the scarcely populated datasets ($N_{max} \leq 200$) is considered poor. Results
565 could be significantly improved for all datasets by narrowing the range of in-
566 vestigated model free parameters which would guide the algorithm towards
567 a desired solution.

568 The alongshore averaging window width and adequate spatiotemporal
569 resolution of the SDS data, should be regarded as site specific variables.
570 Given that Truc Vert is a challenging coastline, conservative estimates of
571 these variables are provided in the current work. Exception would be high-
572 latitude coastlines where cloud coverage can significantly affect the sampling
573 frequency. The limited availability of cloud free satellite images that would
574 significantly affect the temporal resolution could be addressed through an
575 iterative approach. In addition larger waves associated with higher latitudes
576 would influence the size of cusps and megacusps which in turn would control
577 the width and spatial resolution of the alongshore window. The sufficient
578 width and resolution of the alongshore window are not seen as limitations but
579 rather as site-specific information readily available in the satellite imagery.

580 The present results suggest that the introduced methodology could be
581 potentially applicable to any cross shore dominated sandy shoreline. To
582 verify this hypothesis such approach should be applied to several diverse
583 sites around the world investigating the influence of beach type, wave climate
584 and tidal amplitude in model skill. Furthermore, applying such method to
585 complex coasts where other processes (e.g. longshore sediment transport
586 gradients) are at play should also be explored using one-line models. Finally

587 applying the same approach to different model types would further challenge
588 the findings of the present study. Although previous work using several
589 models like Yates et al. (2009); Splinter et al. (2014); Vitousek et al. (2017);
590 D’Anna et al. (2022) suggest similar performance, further validation of the
591 proposed methodology should be conducted.

592 The simulated annealing algorithm has proven to be a very useful tool,
593 enabling the proposed methodology. The stochastic nature of the algorithm
594 should be accounted for by repeating the experiment enough times such as
595 to achieve convergence of the error statistics. Any application of the intro-
596 duced methodology would require accurate inshore wave data (hindcast and
597 /or forecast), that capture the wave climate variability (e.g. seasonal, in-
598 terannual). Such data may be obtained from publicly available global wave
599 hindcasts spanning over several decades such as Mentaschi et al. (2023);
600 Hersbach et al. (2023), and either used directly as a forcing or as a bound-
601 ary condition to produce high resolution nearshore wave forcing for shoreline
602 modelling.

603 **6. Conclusion**

604 The present work introduces a novel approach using uncorrected, noisy,
605 SDS data for the calibration of equilibrium based shoreline models. The
606 simulated annealing algorithm proposed by Bertsimas and Tsitsiklis (1993)
607 guided by high quality wave forcing, extracts information from uncorrected
608 noisy SDS data, even when assuming no a priori knowledge of the site. Rather
609 than data quality, the amount of data (e.g sampling frequency) was found to
610 be critical in the modelling application. The only required processing of the

611 SDS data for the model calibration was alongshore averaging, while any other
612 site-specific corrections did not significantly improve model skill. Though
613 further validation is needed, our findings suggest that alongshore averaged
614 uncorrected SDS extracted at any cross shore dominated coastline can be
615 applied in the calibration of transect based equilibrium shoreline models.
616 The present work opens new perspectives in modelling, understanding and
617 predicting sandy shoreline change in sites lacking field data.

618 **7. Acknowledgements**

619 This work was done in the framework of the SHORMOSAT project and
620 funded by Agence Nationale de la Recherche (ANR) grant number ANR-21-
621 CE01-0015. This study includes the monitoring site of Truc Vert labelled by
622 the Service National d'Observation (SNO) Dynalit (<https://www.dynalit.fr>).
623 The Observatoire de la Côte de Nouvelle-Aquitaine (OCNA) and Observa-
624 toire Aquitain des Sciences de l'Univers (OASU) provide additional financial
625 support for the surveys. We thank Stéphane Bujan for performing the Truc
626 Vert beach field surveys. NORFAS-UG wave hindcast data was provided by
627 LOPS-Ifremer.

628 **References**

629 Aagaard, T., Davidson-Arnott, R., Greenwood, B., Nielsen, J., 2004. Sedi-
630 ment supply from shoreface to dunes: Linking sediment transport mea-
631 surements and long-term morphological evolution. *Geomorphology* 60,
632 205–224. doi:10.1016/j.geomorph.2003.08.002.

- 633 Alvarez-Cuesta, M., Toimil, A., Losada, I.J., 2021a. Modelling long-term
634 shoreline evolution in highly anthropized coastal areas. part 1: Model
635 description and validation. *Coastal Engineering* 169. doi:10.1016/j.
636 coastaleng.2021.103960.
- 637 Alvarez-Cuesta, M., Toimil, A., Losada, I.J., 2021b. Modelling long-term
638 shoreline evolution in highly anthropized coastal areas. part 2: Assessing
639 the response to climate change. *Coastal Engineering* 168. doi:10.1016/j.
640 coastaleng.2021.103961.
- 641 Alvarez-Cuesta, M., Toimil, A., Losada, I.J., 2024. Which data assimila-
642 tion method to use and when: unlocking the potential of observations in
643 shoreline modelling. *Environmental Research Letters* 19. doi:10.1088/
644 1748-9326/ad3143.
- 645 Antolínez, J.A., Méndez, F.J., Anderson, D., Ruggiero, P., Kaminsky, G.M.,
646 2019. Predicting climate-driven coastlines with a simple and efficient mul-
647 tiscale model. *Journal of Geophysical Research: Earth Surface* 124, 1596–
648 1624. doi:10.1029/2018JF004790.
- 649 Bertin, S., Floch, F., Dantec, N.L., Jaud, M., Cancouët, R., Franzetti,
650 M., Cuq, V., Prunier, C., Ammann, J., Augereau, E., Lamarche, S., Bel-
651 leney, D., Rouan, M., David, L., Deschamps, A., Delacourt, C., Suanez,
652 S., 2022. A long-term dataset of topography and nearshore bathymetry
653 at the macrotidal pocket beach of porsmilin, france. *Scientific Data* 9.
654 doi:10.1038/s41597-022-01170-3.

- 655 Bertsimas, D., Tsitsiklis, J., 1993. Simulated annealing. *Statistical Science*
656 8, 10–15.
- 657 Boudière, E., Maisondieu, C., Ardhuin, F., Accensi, M., Pineau-Guillou, L.,
658 Lepesqueur, J., 2013. A suitable metocean hindcast database for the design
659 of marine energy converters. *International Journal of Marine Energy* 3-4.
660 doi:10.1016/j.ijome.2013.11.010.
- 661 Bruun, P., 1962. Sea-level rise as a cause of shore erosion. *Journal of the Wa-*
662 *terways and Harbors Division* 88, 117–132. URL: <https://ascelibrary.org/doi/pdf/10.1061/JWHEAU.0000252?download=true>, doi:<https://doi.org/10.1061/JWHEAU.000025>.
- 665 Castelle, B., Bujan, S., Ferreira, S., Dodet, G., 2017. Fore-
666 dune morphological changes and beach recovery from the ex-
667 treme 2013/2014 winter at a high-energy sandy coast. *Ma-*
668 *rine Geology* 385, 41–55. URL: <https://www.sciencedirect.com/science/article/pii/S0025322716303620>, doi:<https://doi.org/10.1016/j.margeo.2016.12.006>.
- 671 Castelle, B., Bujan, S., Marieu, V., Ferreira, S., 2020. 16 years of topographic
672 surveys of rip-channelled high-energy meso-macrotidal sandy beach. *Sci-*
673 *entific Data* 7. doi:10.1038/s41597-020-00750-5.
- 674 Castelle, B., Dodet, G., Masselink, G., Scott, T., 2018a. Increased winter-
675 mean wave height, variability, and periodicity in the northeast atlantic
676 over 1949–2017. *Geophysical Research Letters* 45, 3586–3596. doi:10.
677 1002/2017GL076884.

- 678 Castelle, B., Guillot, B., Marieu, V., Chaumillon, E., Hanquiez, V., Bujan, S.,
679 Popeschi, C., 2018b. Spatial and temporal patterns of shoreline change of
680 a 280-km high-energy disrupted sandy coast from 1950 to 2014: Sw france.
681 Estuarine, Coastal and Shelf Science 200, 212–223. doi:10.1016/j.ecss.
682 2017.11.005.
- 683 Castelle, B., Marieu, V., Bujan, S., Ferreira, S., Parisot, J.P., Capo, S.,
684 Sénéchal, N., Chouzenoux, T., 2014. Equilibrium shoreline modelling of a
685 high-energy meso-macrotidal multiple-barred beach. Marine Geology 347,
686 85–94. doi:10.1016/j.margeo.2013.11.003.
- 687 Castelle, B., Marieu, V., Bujan, S., Splinter, K.D., Robinet, A., Sénéchal, N.,
688 Ferreira, S., 2015. Impact of the winter 2013-2014 series of severe western
689 europe storms on a double-barred sandy coast: Beach and dune erosion and
690 megacusp embayments. Geomorphology 238, 135–148. URL: [http://dx.
691 doi.org/10.1016/j.geomorph.2015.03.006](http://dx.doi.org/10.1016/j.geomorph.2015.03.006), doi:10.1016/j.geomorph.
692 2015.03.006.
- 693 Castelle, B., Masselink, G., 2023. Morphodynamics of wave-dominated
694 beaches. Cambridge Prisms: Coastal Futures 1, e1. doi:10.1017/cft.
695 2022.2.
- 696 Castelle, B., Masselink, G., Scott, T., Stokes, C., Konstantinou, A., Marieu,
697 V., Bujan, S., 2021. Satellite-derived shoreline detection at a high-energy
698 meso-macrotidal beach. Geomorphology 383. doi:10.1016/j.geomorph.
699 2021.107707.
- 700 Castelle, B., Ritz, A., Marieu, V., Lerma, A.N., Vandenhove, M., 2022.

- 701 Primary drivers of multidecadal spatial and temporal patterns of shore-
702 line change derived from optical satellite imagery. *Geomorphology* 413.
703 doi:10.1016/j.geomorph.2022.108360.
- 704 Cooper, J.A.G., Masselink, G., Coco, G., Short, A.D., Castelle, B., Rogers,
705 K., Anthony, E.J., Green, A.N., Kelley, J.T., Pilkey, O.H., Jackson,
706 D.W.T., 2020. Sandy beaches can survive sea-level rise. *Nature Climate*
707 *Change* 10, 993 – 995.
- 708 D’Anna, M., Idier, D., Castelle, B., Cozannet, G.L., Rohmer, J., Robinet, A.,
709 2020. Impact of model free parameters and sea-level rise uncertainties on
710 20-years shoreline hindcast: the case of true vert beach (sw france). *Earth*
711 *Surface Processes and Landforms* 45, 1895–1907. doi:10.1002/esp.4854.
- 712 D’Anna, M., Idier, D., Castelle, B., Rohmer, J., Cagigal, L., Mendez, F.J.,
713 2022. Effects of stochastic wave forcing on probabilistic equilibrium shore-
714 line response across the 21st century including sea-level rise. *Coastal En-*
715 *gineering* 175. doi:10.1016/j.coastaleng.2022.104149.
- 716 Davidson, M.A., Splinter, K.D., Turner, I.L., 2013. A simple equilibrium
717 model for predicting shoreline change. *Coastal Engineering* 73, 191–
718 202. URL: <http://dx.doi.org/10.1016/j.coastaleng.2012.11.002>,
719 doi:10.1016/j.coastaleng.2012.11.002.
- 720 Gallagher, E.L., MacMahan, J., Reniers, A., Brown, J., Thornton, E.B.,
721 2011. Grain size variability on a rip-channeled beach. *Marine Geology*
722 287, 43 – 53. doi:10.1016/j.margeo.2011.06.010.

- 723 Ghermandi, A., Nunes, P.A., 2013. A global map of coastal recreation values:
724 Results from a spatially explicit meta-analysis. *Ecological Economics* 86,
725 1–15. doi:10.1016/j.ecolecon.2012.11.006.
- 726 Hersbach, Bell, B., Berrisford, P., Biavati, G., Horányi, A., Sabater, J.M.,
727 Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons,
728 A., Soci, C., Dee, D., Thépaut, J.N., 2023. Era5 hourly data on single
729 levels from 1940 to present. Copernicus Climate Change Service (C3S)
730 Climate Data Store (CDS) (Accessed on 16-Oct-2023). doi:10.24381/
731 cds.adbb2d47.
- 732 Holman, R., Stanley, J., Ozkan-Haller, T., 2003. Applying video sensor net-
733 works to nearshore environment monitoring. *IEEE Pervasive Computing*
734 2, 14–21. doi:10.1109/MPRV.2003.1251165.
- 735 Ibaceta, R., Splinter, K.D., Harley, M.D., Turner, I.L., 2020. Enhanced
736 coastal shoreline modeling using an ensemble kalman filter to include non-
737 stationarity in future wave climates. *Geophysical Research Letters* 47.
738 doi:10.1029/2020GL090724.
- 739 Ibaceta, R., Splinter, K.D., Harley, M.D., Turner, I.L., 2022. Improving
740 multi-decadal coastal shoreline change predictions by including model pa-
741 rameter non-stationarity. *Frontiers in Marine Science* 9. doi:10.3389/
742 fmars.2022.1012041.
- 743 Konstantinou, A., Scott, T., Masselink, G., Stokes, K., Conley, D., Castelle,
744 B., 2023. Satellite-based shoreline detection along high-energy macroti-

- 745 dal coasts and influence of beach state. *Marine Geology* 462, 107082.
746 doi:<https://doi.org/10.1016/j.margeo.2023.107082>.
- 747 Labarthe, C., Castelle, B., Marieu, V., Garlan, T., Bujan, S., 2023. Ob-
748 servation and modeling of the equilibrium slope response of a high-energy
749 meso-macrotidal sandy beach. *Journal of Marine Science and Engineering*
750 11, 584. doi:10.3390/jmse11030584.
- 751 Laporte-Fauret, Q., Lubac, B., Castelle, B., Michalet, R., Marieu, V., Bom-
752 brun, L., Launeau, P., Giraud, M., Normandin, C., Rosebery, D., 2020.
753 Classification of atlantic coastal sand dune vegetation using in situ, uav,
754 and airborne hyperspectral data. *Remote Sensing* 12. doi:10.3390/
755 rs12142222.
- 756 Larson, M., Kraus, N.C., 1995. Prediction of cross-shore sediment transport
757 and temporal scales at different spatial. *Marine Geology* 126, 11–127.
- 758 Ludka, B.C., Guza, R.T., O'Reilly, W.C., Merrifield, M.A., Flick, R.E., Bak,
759 A.S., Hesser, T., Bucciarelli, R., Olfe, C., Woodward, B., Boyd, W., Smith,
760 K., Okihiro, M., Grenzeback, R., Parry, L., Boyd, G., 2019. Sixteen years
761 of bathymetry and waves at san diego beaches. *Scientific Data* 6. doi:10.
762 1038/s41597-019-0167-6.
- 763 Luijendijk, A., Hagenaaars, G., Ranasinghe, R., Baart, F., Donchyts, G.,
764 Aarninkhof, S., 2018. The state of the world's beaches. *Scientific Reports*
765 8. doi:10.1038/s41598-018-24630-6.
- 766 Masselink, G., Castelle, B., Scott, T., Dodet, G., Suanez, S., Jackson, D.,
767 Floc'H, F., 2016. Extreme wave activity during 2013/2014 winter and

- 768 morphological impacts along the atlantic coast of europe. *Geophysical*
769 *Research Letters* 43, 2135–2143. doi:10.1002/2015GL067492.
- 770 McCarroll, R., Valiente, N., Wiggins, M., Scott, T., Masselink, G., 2023.
771 Coastal survey data for perranporth beach and start bay in southwest eng-
772 land (2006–2021). *Scientific Data* 10. doi:10.1038/s41597-023-02131-0.
- 773 Mentaschi, L., Vousedoukas, M., Garcia-Sanchez, G., Montblanc, T.F.,
774 Roland, A., Voukouvalas, E., Federico, I., Abdolali, A., Zhang, Y.J.,
775 Feyen, L., 2023. A global unstructured, coupled, high-resolution hind-
776 cast of waves and storm surges. *EarthArXiv* URL: [https://arxiv.org/](https://arxiv.org/abs/2306.16337)
777 [abs/2306.16337](https://arxiv.org/abs/2306.16337), doi:<https://doi.org/10.48550/arXiv.2306.16337>.
- 778 Michaud, H., Pasquet, A., Leckler, F., Baraille, R., Dalphinnet, A., Aouf, L.,
779 2016. Improvements of the new french coastal wave forecasting system
780 and application to a wave-current interaction study. 14th International
781 Workshop on Wave Hindcasting and Forecasting & 5th Coastal Hazard
782 Symposium SHOM & Meteo France. URL: [https://www.researchgate.](https://www.researchgate.net/publication/312919454)
783 [net/publication/312919454](https://www.researchgate.net/publication/312919454), doi:10.13140/RG.2.2.13218.02243.
- 784 Montaña, J., Coco, G., Antolínez, J.A., Beuzen, T., Bryan, K.R., Cagi-
785 gal, L., Castelle, B., Davidson, M.A., Goldstein, E.B., Ibaceta, R., Idier,
786 D., Ludka, B.C., Masoud-Ansari, S., Méndez, F.J., Murray, A.B., Plant,
787 N.G., Ratliff, K.M., Robinet, A., Rueda, A., Sénéchal, N., Simmons,
788 J.A., Splinter, K.D., Stephens, S., Townend, I., Vitousek, S., Vos, K.,
789 2020. Blind testing of shoreline evolution models. *Scientific Reports* 10.
790 doi:10.1038/s41598-020-59018-y.

- 791 Murray, A.B., 2007. Reducing model complexity for explanation and predic-
792 tion. *Geomorphology* 90, 178–191. doi:10.1016/j.geomorph.2006.10.
793 020.
- 794 Ojeda, E., Ruessink, B.G., Guillen, J., 2008. Morphodynamic response of
795 a two-barred beach to a shoreface nourishment. *Coastal Engineering* 55,
796 1185–1196. doi:10.1016/j.coastaleng.2008.05.006.
- 797 Pianca, C., Holman, R., Siegle, E., 2015. Shoreline variability from days
798 to decades: Results of long-term video imaging. *Journal of Geophysical*
799 *Research: Oceans* 120, 2159–2178. doi:10.1002/2014JC010329.
- 800 Pineau-Guillou, L., 2013. *Projet PJ0303 : Océanographie Côtière*
801 *Opérationnelle Action A030310P : CPER-PREVIMER volet 2-Etude*
802 *et validation de configurations modèles physiques Département*
803 *Océanographie et Dynamique des Ecosystèmes Unité Dynamiques*
804 *de l'Environnement Côtier Laboratoire Physique Hydrodynamique*
805 *et Sédimentaire-ODE/DYNECO/PHYSED/2013-05 version 1.0 PRE-*
806 *VIMER Validation des modèles hydrodynamiques 2D des côtes de*
807 *la Manche et de l'Atlantique. Technical Report. Ifremer. URL:*
808 *<https://archimer.ifremer.fr/doc/00157/26800/>.*
- 809 Ranasinghe, R., Turner, I.L., 2006. Shoreline response to submerged
810 structures: A review. *Coastal Engineering* 53, 65–79. doi:10.1016/j.
811 *coastaleng.2005.08.003.*
- 812 Robin, N., Billy, J., Castelle, B., Hesp, P., Lerma, A.N., Laporte-Fauret, Q.,
813 Marieu, V., Rosebery, D., Bujan, S., Destribats, B., Michalet, R., 2021.

- 814 150 years of foredune initiation and evolution driven by human and natural
815 processes. *Geomorphology* 374. doi:10.1016/j.geomorph.2020.107516.
- 816 Robinet, A., Castelle, B., Idier, D., Cozannet, G.L., Déqué, M., Charles,
817 E., 2016. Statistical modeling of interannual shoreline change driven by
818 north atlantic climate variability spanning 2000–2014 in the bay of biscay.
819 *Geo-Marine Letters* 36, 479–490. doi:10.1007/s00367-016-0460-8.
- 820 Robinet, A., Castelle, B., Idier, D., Harley, M.D., Splinter, K.D., 2020.
821 Controls of local geology and cross-shore/longshore processes on embayed
822 beach shoreline variability. *Marine Geology* 422. doi:10.1016/j.margeo.
823 2020.106118.
- 824 Robinet, A., Idier, D., Castelle, B., Marieu, V., 2018. A reduced-complexity
825 shoreline change model combining longshore and cross-shore processes:
826 The lx-shore model. *Environmental Modelling and Software* 109, 1–16.
827 doi:10.1016/j.envsoft.2018.08.010.
- 828 Senechal, N., Coco, G., Bryan, K.R., Holman, R.A., 2011. Wave runup during
829 extreme storm conditions. *Journal of Geophysical Research: Oceans* 116.
830 doi:10.1029/2010JC006819.
- 831 Small, C., Nichols, J.R., 2003. A global analysis of human set-
832 tlement in coastal zones. *Journal of Coastal Research* 19, 584–
833 589. URL: <https://www.researchgate.net/publication/244956994>,
834 doi:10.2307/4299200.
- 835 Splinter, K.D., Turner, I.L., Davidson, M.A., 2013. How much data is
836 enough? the importance of morphological sampling interval and dura-

- 837 tion for calibration of empirical shoreline models. *Coastal Engineering* 77,
838 14–27. doi:10.1016/j.coastaleng.2013.02.009.
- 839 Splinter, K.D., Turner, I.L., Davidson, M.A., Barnard, P., Castelle, B.,
840 Oltman-Shay, J., 2014. A generalized equilibrium model for predicting
841 daily to interannual shoreline response. *Journal of Geophysical Research:*
842 *Earth Surface* 119, 1936–1958. doi:10.1002/2014JF003106.
- 843 Tran, Y.H., Barthélemy, E., 2020. Combined longshore and cross-shore
844 shoreline model for closed embayed beaches. *Coastal Engineering* 158.
845 doi:10.1016/j.coastaleng.2020.103692.
- 846 Turner, I.L., Harley, M.D., Short, A.D., Simmons, J.A., Bracs, M.A.,
847 Phillips, M.S., Splinter, K.D., 2016. A multi-decade dataset of monthly
848 beach profile surveys and inshore wave forcing at narrabeen, australia.
849 *Scientific Data* 3. doi:10.1038/sdata.2016.24.
- 850 Vitousek, S., Barnard, P.L., Limber, P., Erikson, L., Cole, B., 2017. A model
851 integrating longshore and cross-shore processes for predicting long-term
852 shoreline response to climate change. *Journal of Geophysical Research:*
853 *Earth Surface* 122, 782–806. doi:10.1002/2016JF004065.
- 854 Vitousek, S., Vos, K., Splinter, K.D., Erikson, L., Barnard, P.L., Survey,
855 U.S.G., 2023. A model integrating satellite-derived shoreline observations
856 for predicting fine-scale shoreline response to waves and sea-level rise across
857 large coastal regions a model integrating satellite-derived shoreline observa-
858 tions for predicting fine-scale shoreline response to waves and sea-level rise
859 across large coastal regions 2. *Journal of Geophysical Research: Earth Sur-*

- 860 face URL: <https://doi.org/10.22541/essoar.167839941.16313003/>
861 v1, doi:10.22541/essoar.167839941.16313003/v1.
- 862 Vos, K., Harley, M.D., Splinter, K.D., Simmons, J.A., Turner, I.L., 2019a.
863 Sub-annual to multi-decadal shoreline variability from publicly available
864 satellite imagery. *Coastal Engineering* 150, 160–174. doi:10.1016/j.
865 *coastaleng*.2019.04.004.
- 866 Vos, K., Splinter, K., Palomar-Vázquez, J., Pardo-Pascual, J., Almonacid-
867 Caballer, J., Cabezas-Rabadán, C., Kras, E., Luijendijk, A., Calkoen,
868 F., Almeida, L., Pais, D., Klein, A., Mao, Y., Harris, D., Castelle, B.,
869 Buscombe, D., Vitousek, S., 2023. Benchmarking satellite-derived shore-
870 line mapping algorithms. *Communications Earth and Environment* 4.
871 doi:10.1038/s43247-023-01001-2.
- 872 Vos, K., Splinter, K.D., Harley, M.D., Simmons, J.A., Turner, I.L., 2019b.
873 Coastsat: A google earth engine-enabled python toolkit to extract shore-
874 lines from publicly available satellite imagery. *Environmental Modelling*
875 and Software 122. doi:10.1016/j.*envsoft*.2019.104528.
- 876 Vousdoukas, M.I., Ranasinghe, R., Mentaschi, L., Plomaritis, T.A., Athana-
877 siou, P., Luijendijk, A., Feyen, L., 2020. Sandy coastlines under
878 threat of erosion. *Nature Climate Change* 10, 260–263. doi:10.1038/
879 *s41558-020-0697-0*.
- 880 Warrick, J.A., Buscombe, D., Vos, K., R., B.K., Castelle, B., Cooper, A.,
881 Harley, M.D., T., J.D.W., Ludka, B., Masselink, G., Palmsten, L., R.,
882 A.A.A., Sénéchal, N., Sherwood, C.R., D., S.A., Sogut, E., D., S.K.,

- 883 Stephenson, W.J., Syvitski, J., Woodroffe, C.D., Young, A.P., submitted.
884 Evaluating climate signals on global shoreline position : A commentary
885 on “influence of el niño on the variability of global 2 shoreline position”.
886 EarthArXiv doi:<https://doi.org/10.31223/X5W66T>.
- 887 Warrick, J.A., Vos, K., Buscombe, D., Ritchie, A.C., Curtis, J.A., 2023.
888 A large sediment accretion wave along a northern california littoral cell.
889 Journal of Geophysical Research: Earth Surface 128, e2023JF007135.
890 doi:<https://doi.org/10.1029/2023JF007135>.
- 891 Wright, L., Short, A., 1984. Morphodynamic variability of surf zones
892 and beaches: A synthesis. Marine Geology 56, 93–118. URL: [http://](http://linkinghub.elsevier.com/retrieve/pii/0025322784900082)
893 linkinghub.elsevier.com/retrieve/pii/0025322784900082, doi:10.
894 1016/0025-3227(84)90008-2.
- 895 Yates, M.L., Guza, R.T., O'Reilly, W.C., 2009. Equilibrium shoreline re-
896 sponse: Observations and modeling. Journal of Geophysical Research:
897 Oceans 114. doi:10.1029/2009JC005359.

Satellite-derived equilibrium shoreline modelling at a high-energy meso-macrotidal beach

Highlights :

- Model calibration using uncorrected satellite-derived shoreline data.
- Simulated annealing extracts information from raw satellite derived shoreline data.
- New perspective in modelling sandy shoreline change even when lacking field data.
- Sampling frequency more critical than data quality in model calibration.

Declaration of interests

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

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Journal Pre-proof