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Sensitivity of a one-line longshore shoreline change model to the mean wave direction

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Keywords: beach morphodynamics, one-line model, longshore transport, shoreline change, sensitivity analysis, wave angle bias

Highlights:

- One-line shoreline change models often produce artifacts in beach planform
- One-line longshore models are highly sensitive to small incident wave angle biases
- Wave angle bias corrections can be obtained using a Monte Carlo approach
- Accurate observations or simulations of wave breaking conditions are necessary

Abstract

The sensitivity of a one-line longshore shoreline change model to the incident wave direction is evaluated at Narrabeen Beach (Australia). As previously observed, the application of the one-line model using wave conditions generated along the 10-m depth contour produces a long-term reorientation of the coastline, with an initial transition period and then a new stable equilibrium during the 10-year period from 2005 to 2015. However, this coastline change in shoreline planform shape is not observed in the shoreline position measurements. The source of this error is investigated by assuming that it is caused by biases in the incident wave direction and by using a Monte Carlo approach to search for the optimal set of wave angle bias corrections to apply at each cross-shore transect. The obtained optimal values enable the one-line model to reproduce accurately the shoreline planform, and they are coherent with estimates of the wave breaking angle obtained independently using a nearshore wave propagation model. Then, using the corrected wave angle time series as a reference, a second Monte Carlo analysis is completed to investigate the sensitivity of the model to errors in the mean wave direction drawn from Gaussian distributions with varying standard deviations. The analysis shows the range of expected errors in shoreline position for an estimated range of errors in the mean wave direction at Narrabeen beach. This work highlights the importance of considering the sensitivity of one-line longshore model simulations to errors in the incident wave angle, which can be relatively large given the uncertainties in spectral wave model estimates of wave direction, in wave buoy observations, and in wave propagation methods or input bathymetry used to estimate wave breaking conditions.

1 Introduction

The littoral zone is a complex environment. It is both a physically dynamic interface, as well as a highly important social and economic zone, given the dense population and high concentration of human activities. In addition, the littoral zone and surrounding coastal areas are highly sensitive to marine flooding and erosion hazards, including shoreline retreat. Thus, it is essential to be able to understand and predict shoreline evolution, in particular at spatial scales of a beach and at medium to long temporal scales, as well as during extreme events.

43 To achieve this goal, a wide variety of morphological evolution models exist, ranging in complexity from
44 three-dimensional, physics-based models (e.g. MIKE21 (Warren & Bach 1992), Delft3D (Roelvink & Banning
45 1995), XBeach (Roelvink et al. 2009)) to one-line models representing only cross-shore (e.g. Miller & Dean
46 2004, Yates et al. 2009, Davidson et al. 2013) or longshore (e.g. Ashton & Murray 2006, Turki et al. 2013,
47 Bouchette et al. 2014) processes. The choice of an appropriate model thus depends on the dominant physical
48 processes that must be represented or parameterized at the spatial and temporal scales of interest, and
49 predicting coastal evolution at seasonal to decadal or longer timescales remains a significant challenge (Safak
50 et al. 2017, Davidson et al. 2017, Montañó et al. 2020). Given the limits of numerical models at these
51 temporal and spatial scales, empirical, process-based models may be an optimal alternative to physics-based
52 models (Murray 2007, Ranasinghe R. 2013, French et al. 2016). This family of models allows simulating
53 shoreline evolution at temporal and spatial scales given their numerical simplicity, low computational cost,
54 and accuracy once calibrated.

55 At short (e.g. storm) to seasonal timescales, cross-shore processes are often dominant, while over longer
56 time timescales (e.g. interannual to decadal), longshore processes may become increasingly important. To
57 reproduce shoreline changes at these scales, both cross-shore and longshore processes must be taken into
58 account. Recent work has thus focused on developing “hybrid” models that incorporate both cross-shore and
59 longshore processes, including CoSMoS-COAST of Vitousek et al. (2017), LX-Shore of Robinet et al. (2018),
60 the COCOONED model of Antolínez et al. (2019), and the combined model of Tran & Barthélemy (2020).
61 These models are forced by hydrodynamic conditions (e.g. waves) and typically have several free parameters
62 that must be calibrated for each study site.

63 In hybrid approaches, the one-line longshore transport model is the most commonly used approach to
64 account for longshore processes (e.g., Vitousek et al. 2017, Robinet et al. 2018, Antolínez et al. 2019). For
65 embayed beaches, additional approaches have been developed to simulate longshore processes, including semi-
66 empirical approaches based on decomposing the mean and fluctuating components of the wave field (e.g. Tran
67 & Barthélemy 2020, which is then combined with a cross-shore model), or by modeling directly the beach
68 orientation using an equilibrium approach (Turki et al. 2013, Jaramillo et al. 2021).

69 Here, the focus is on the classical one-line model, which was first introduced by Pelnard-Considére (1956).
70 It assumes that at long timescales, beach cross-shore profiles maintain an equilibrium shape in balance with
71 the incoming wave field. The beach thus responds to perturbations by restoring the equilibrium shape.
72 Therefore, gradients in longshore sediment fluxes cause landward or seaward shifts in the equilibrium profile,
73 based on the hypothesis that cross-shore processes can be neglected at long temporal scales (Hanson 1989).
74 The longshore sediment flux can be estimated using different formulae (e.g. CERC (1984) (USACE 1984),
75 Kamphuis (1986) (Kamphuis et al. 1986)) that empirically relate the hydrodynamic conditions (e.g. breaking
76 wave height and direction) and the beach geological characteristics (e.g. sediment porosity or grain size) to
77 the longshore sediment flux. This simple approach depends on the quality of both the input data and the
78 choice of model free parameters.

79 Recently, several studies have focused on identifying and evaluating sources of uncertainties in coastal
80 morphological models. For example, Davidson et al. (2017) tested the sensitivity of the cross-shore empirical
81 model ShoreFor (Davidson et al. 2013, Splinter et al. 2014) to variations in the potential future wave climate.
82 D’Anna et al. (2020) went one step further using the hybrid LX-Shore model (where cross-shore changes
83 are based on the ShoreFor model) by estimating the contribution of different input parameters to the total
84 model uncertainty in a test case applied at Truc Vert beach. In addition, recent studies have also quantified
85 uncertainties related to climate change impacts (Toimil et al. 2020), in particular focusing on the importance
86 of changes in the mean water level on long-term shoreline change (Le Cozannet et al. 2019, Athanasiou et al.
87 2020).

88 The one-line longshore model is a simple and therefore widely used model (Larson et al. 1997). It is
89 thus important to study the uncertainties associated with this approach, and several recent studies have
90 investigated the sensitivity of the model to a series of different assumptions and input parameters. Ruggiero
91 et al. (2010) illustrated the relative importance of the wave climate (wave height, peak period and wave
92 direction) and sediment supply (by varying the model sediment flux at the boundary) in simulations with
93 the Unibest model (Delft Hydraulics 1994) by evaluating the model skill in reproducing observed shoreline
94 changes. They showed that altering the offshore mean wave angle generated an important increase in the
95 model error. Kroon et al. (2020) analyzed the relative contribution of errors in different model parameters
96 and wave climate variability to the total model uncertainties as a function of the considered timescales. The
97 model sensitivity to the wave climate is also demonstrated in George et al. (2019), where the longshore flux
98 uncertainties are estimated by incorporating errors in the input wave height and direction. Previous studies
99 have highlighted the sensitivity of the one-line model to wave climate uncertainties, including uncertainties
100 in the wave direction, without directly quantifying the impacts on the modeled shoreline position.

101 Depending on the inherent complexity of the study site and the quality of the input data, the one-line

102 longshore model may generate changes in the beach planform (e.g. reorientation) that are different from
103 observations. For example, this was observed recently using hybrid models when modeling shoreline changes
104 in the North Beach Sub-cell of the Columbia River Littoral Cell (Washington, USA, (Antolínez et al. 2019)),
105 and the highly studied Narrabeen Beach (Australia, (Robinet et al. 2020)).

106 The reorientation “artefact” is corrected for in Antolínez et al. (2019) by replacing the initial shoreline
107 position with the computation of a new long-term average shoreline. This long-term average shoreline is
108 generated by running their hindcast wave climate for 500 years, following Anderson et al. (2018). The
109 authors assume that using the long-term average shoreline as the baseline should correct problems inherited
110 from the wave climate, such as a wave direction bias in the offshore wave conditions or errors in the nearshore
111 wave propagation.

112 Similarly, in Robinet et al. (2020), the beach reorientation observed in a 5-year-long simulation at
113 Narrabeen Beach is corrected by running the model in two steps. First, the model simulates the 5-year
114 period, and then the final shoreline position at the end of the first simulation is used as the initial shoreline
115 position in the second simulation. The authors assume that the shoreline changes and not the shoreline
116 position simulated in the second step are more accurate. Finally, the simulation results are corrected to
117 account for the difference in the initial shoreline position in order to compare to the observations. Despite
118 applying this two-step method, changes in the shoreline planform shape are still observed in the first year of
119 the second simulation, and this time period is thus excluded from the remainder of their analysis.

120 These two studies (Antolínez et al. 2019, Robinet et al. 2020) used pre- and post-processing methods to
121 manage the change in the coastline orientation introduced by the one-line longshore model. The authors
122 suggest that the errors are potentially caused by errors in wave direction and/or nearshore propagation.
123 However, they do not attempt to demonstrate this in their work. The current study is focused on under-
124 standing the source of the coastline reorientation simulated by the one-line model, as well as applying a simple
125 approach to correct for this error. This work therefore aims to study the overall sensitivity of the one-line
126 modeling approach to biases or errors in the wave conditions. The epistemic uncertainties introduced by the
127 longshore one-line model have two potential sources: the model formulation or the input wave conditions. In
128 this study, it is assumed that the formulation of the one-line model is accurate, and the input wave direction
129 is studied as a potential source of model uncertainties.

130 Previous studies have used Monte Carlo-based approaches in applications of the one-line model by gen-
131 erating variations in the wave climate based on existing wave distributions (Wang & Reeve 2010, Bergillos
132 et al. 2018) or from measured wave statistics (Reeve et al. 2014, Kroon et al. 2020). Here, two Monte Carlo
133 approaches are used to evaluate the sensitivity of a one-line longshore model to the mean wave direction and
134 wave height at Narrabeen Beach.

135 ~~In the first analysis, a spatially variable, random bias is added to the wave angle time series at each
136 cross-shore transect to find the optimal values minimizing the difference in the simulated and observed
137 shoreline position. Then, the second analysis starts with the wave angle time series corrected with the optimal
138 values obtained in the first analysis, and then adds spatially variable random biases drawn from specified
139 Gaussian distributions to test the sensitivity of the shoreline position results to these types of errors. Here,
140 it is assumed that the distribution of potential errors in measured (e.g. wave buoy observations) or modeled
141 (e.g. large-scale spectral wave models) wave direction are Gaussian. The sensitivity of the one-line longshore
142 model to biases in the wave direction is evaluated by calculating the induced coastline reorientation. This
143 study is applied at Narrabeen beach, where an optimal set of wave angle bias values are estimated to minimize
144 the errors between the observed and modeled shoreline changes. Then, in the second analysis, the impacts
145 of errors in the input wave angle on the modeled shoreline changes are quantified, and although this study is
146 conducted using the data from Narrabeen Beach, the results can be generalized to other sites.~~

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148 cross-shore transect to find the optimal values minimizing the difference between the simulated and observed
149 shoreline position. Then, the second analysis aims to test the sensitivity of the shoreline model to spatially
150 variable random biases drawn from specified Gaussian distributions. Here, it is assumed that the distribution
151 of potential errors in measured (e.g. wave buoy observations) or modeled (e.g. large-scale spectral wave
152 models) wave direction are Gaussian. Although this study is conducted using the data from Narrabeen
153 beach, the results can be generalized to other sites.~~

154 In the following, the characteristics of the study site are presented (section 2) before describing the one-
155 line longshore model (section 3) and the Monte Carlo approach applied in the analysis (section 4). The
156 optimal bias values and the sensitivity of the model to the input wave angle and wave height are then
157 evaluated (section 5), before discussing the hypotheses and limitations of this study, and the generalization
158 of the approach to other sites (section 6). Finally, a synthesis of the results, as well as perspectives for future
159 studies (section 7) are presented.

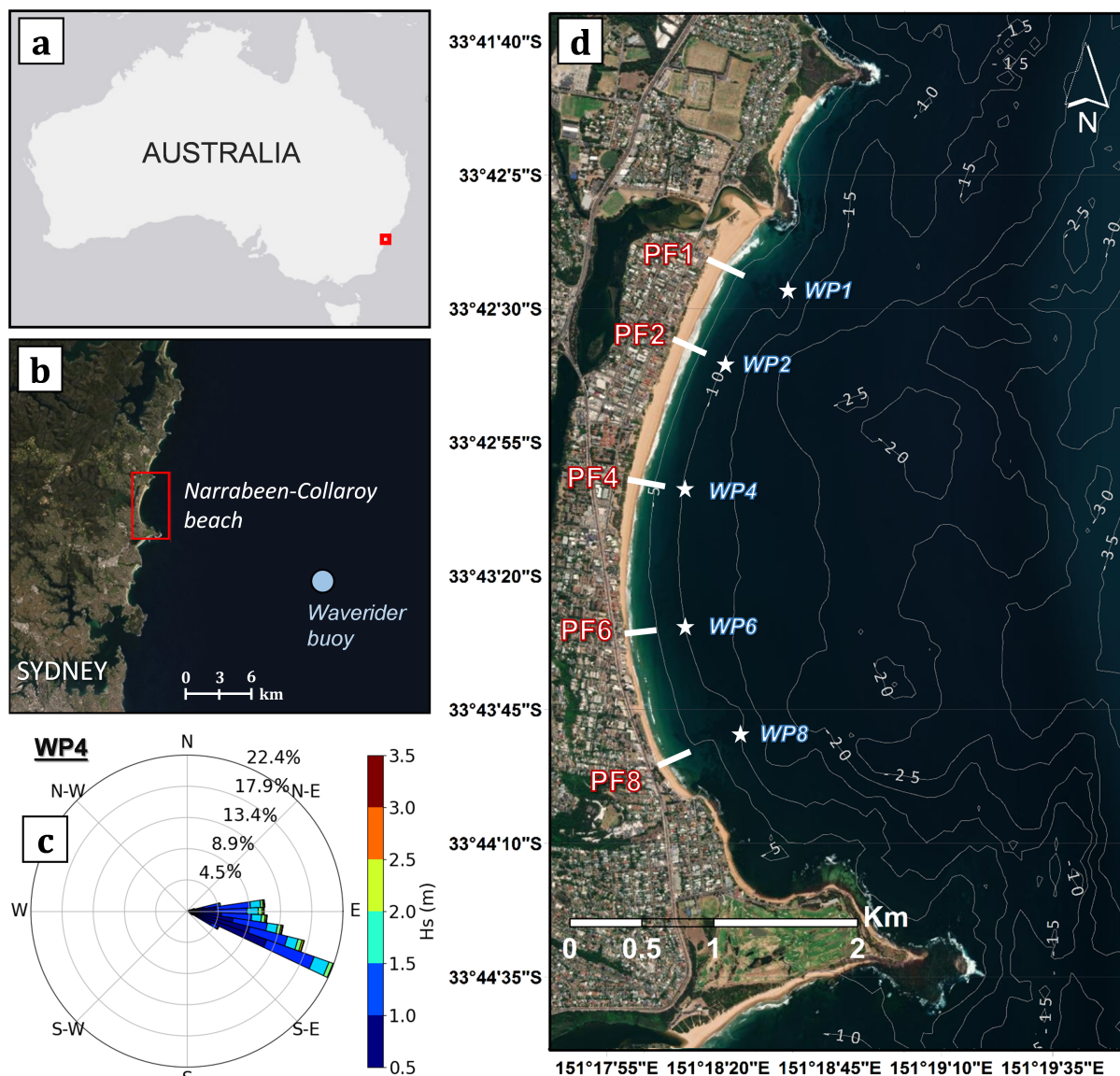


Figure 1: Study site location and wave characteristics: (a) map of Australia indicating the zoom shown in (b), (b) the area around Narrabeen beach, showing the location of Sydney and the offshore wave buoy. (c) The wave rose indicates the percent occurrence of each wave height (colorbar) and wave direction (between 1979-2015), and (d) a satellite image of Narrabeen-Collaroy Beach showing the location of the 5 surveyed cross-shore profiles (named PF1, PF2, PF4, PF6, and PF8) and the 5 locations where wave conditions are available (WP1, WP2, WP4, WP6, and WP8). The bathymetry contours are shown at 5 meter depth intervals (in grey).

161 The Narrabeen-Collaroy embayment is a 3.6 km-long sandy beach located in southeast Australia, to the
 162 north of Sydney (Fig. 1). The embayment consists of Narrabeen beach at the northern end and Collaroy
 163 beach at the southern end, and is hereafter referred to as Narrabeen beach for simplicity. The beach is
 164 bordered by two rocky headlands at the northern and southern extremities, and the rocky substrate extends
 165 underwater to approximately 60 m depth. Reefs are also present from 5 m to 10 m water depth in front of
 166 both beach extremities (as can be seen partially in the satellite image in Fig. 1d in front of cross-shore profiles
 167 PF1 and PF8). The beach is backed by low dunes at the northern end and by a seawall at the southern end.
 168 An estuary forms a lagoon landward of the beach at the northern extremity, and the mouth of the estuary
 169 breaches the dune intermittently.

170 The beach is characterized by fine to medium quartz sand ($D_{50} \approx 0.3$ mm) that is nearly uniform
 171 alongshore (Turner et al. 2016). The headlands at the extremities of the beach and the curvature of the

172 bay generate alongshore gradients in wave energy caused by wave sheltering and refraction processes. The
173 effects of wave sheltering are more dominant at the southern end of the beach owing to the presence of the
174 1.5 km-long rocky headland and the predominantly southeasterly incident waves, but wave sheltering also
175 occurs at the northern end of the beach for less-frequent northerly incident waves. Differences in the wave
176 exposure cause differences in the morphodynamic beach state, changing from a higher-energy, longshore-bar
177 trough beach state in the north to a lower energy, low tide terrace/reflective beach state in the south (Wright
178 & Short 1984, Harley et al. 2011).

179 Narrabeen beach is a semi-diurnal, micro-tidal environment with a mean spring tide of less than 1.5 m.
180 The Sydney waverider buoy, located 11 km offshore in 80 m water depth (Fig. 1b), has recorded directional
181 wave conditions since 1992, which are supplemented by hourly hindcast waves from the Centre for Australian
182 Weather and Climate Research (Durrant et al. 2014) to fill data gaps due to buoy maintenance/dysfunction.
183 The offshore wave climate ranges from moderate to high wave energy (mean $H_s \simeq 1.6$ m and $T_p \simeq 10$ s),
184 with dominant long-period swell waves impacting the beach from the south-south-east (SSE) direction. In
185 addition, storm waves (defined as $H_s > 3$ m) are generated from tropical cyclones from the northeast,
186 east-coast lows from the east, and cyclones from the south (Turner et al. 2016). The regional wave climate
187 induces a relatively subtle seasonal cycle with higher energy conditions in the austral winter and lower energy
188 conditions in the austral summer. Furthermore, the beach is influenced by the El Niño-Southern Oscillation
189 (ENSO) at interannual timescales (approximately 3 to 7 years), resulting in more energetic and easterly waves
190 impacting Narrabeen beach during La Niña periods and less energetic and more southerly waves during El
191 Niño periods (Harley et al. 2010). Overall, nearshore currents dynamics are primarily driven by waves, given
192 the generally mild wind conditions and microtidal regime.

193 Beach sand levels have been measured along 5 historical profiles (PF1, PF2, PF4, PF6, and PF8, as
194 shown in Fig. 1d) at approximately monthly intervals since 1976. The offshore wave data is transformed
195 into wave conditions along the 10 m depth contour in front of each profile (Fig. 2c-e) using a look-up table
196 generated with a series of hundreds of SWAN spectral model runs (Turner et al. 2016). This high spatial
197 and temporal resolution dataset consisting of topographic measurements and hourly wave conditions at 5
198 cross-shore profiles along Narrabeen beach (described in detail by Turner et al. (2016)) is freely available at
199 <http://narrabeen.wrl.unsw.edu.au>.

200 Observed morphological changes at the 5 cross-shore profiles show limited long-term changes (maximum
201 linear trend = -0.54m/yr at PF4) in shoreline position (estimated as the cross-shore location of the $z=0$ m
202 altitude, Harley et al. 2011). However, significant seasonal, annual, and interannual variability is observed,
203 with a mean value of 71 m for the overall range (min/max) of variability of the shoreline position, estimated
204 across all profiles (e.g. PF4 and PF8, Fig. 2a,b). Seasonal variations in shoreline position show primarily
205 accretion during the austral summer and erosion during the austral winter. Offshore of the 10m depth contour,
206 bathymetric variations are nearly negligible, whereas in the surf zone, observed bathymetric variations are
207 on the order of 1m, and thus may influence nearshore wave refraction.

208 The alongshore differences in wave conditions show more northerly waves and larger wave heights at PF4
209 than at PF8 (Fig. 2c,e comparing the WP4 and WP8). The peak period (T_p , Fig. 2d) is assumed to be
210 homogeneous along the 10 m depth contour for the 5 alongshore profiles since it is taken as equal to the
211 offshore value (Turner et al. 2016). Fig. 2e also highlights the seasonal dependence of the variability in the
212 wave direction, with reduced variability in wave direction during the austral winter.

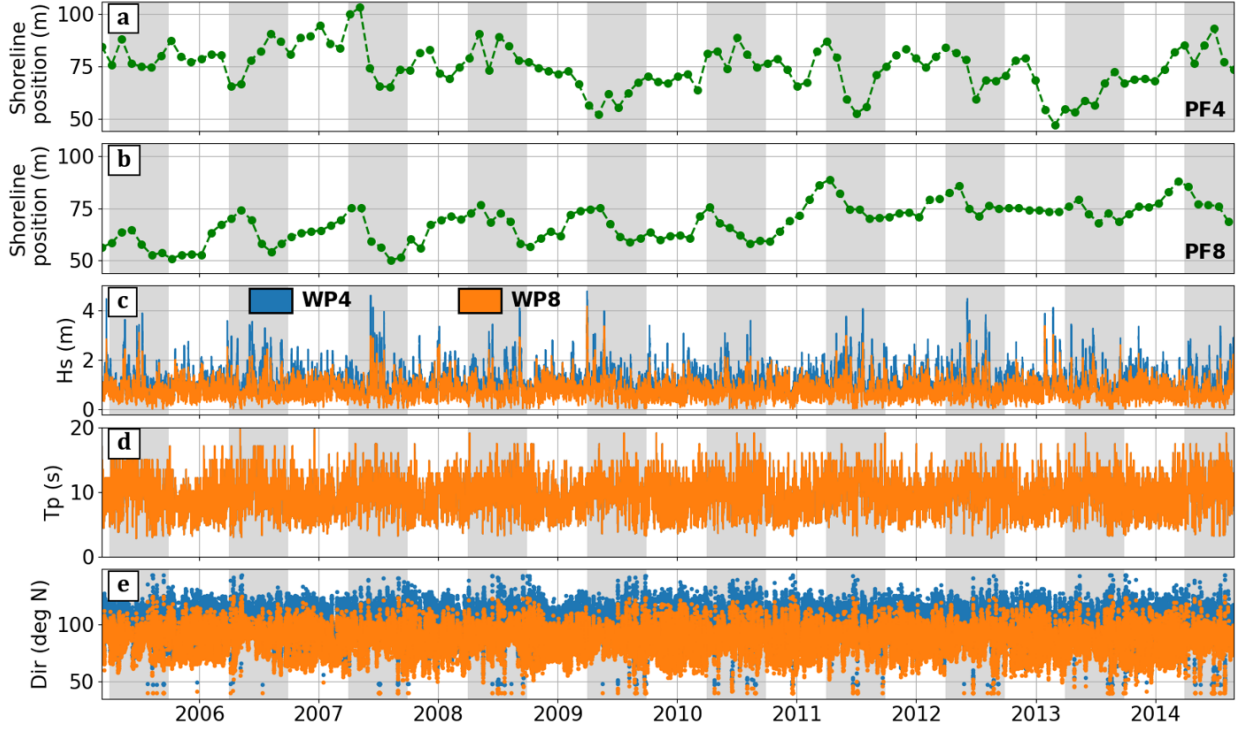


Figure 2: Observations of the shoreline position ($z=0$ m altitude) at (a) PF4 and (b) PF8, and the corresponding wave conditions at WP4 (blue) and WP8 (orange) showing the: (c) significant wave height (H_s), (d) peak wave period (T_p), and (e) wave direction. The gray-shaded areas indicate austral winters.

3 Model and sensitivity test description

3.1 Mathematical model

In this study, alongshore sediment transport processes are modeled using a simple one-line approach based on the work of Pelnard-Considére (1956). The one-line model estimates changes in the shoreline position S generated by alongshore gradients in the alongshore sediment flux Q :

$$\frac{\partial S}{\partial t} = -\frac{1}{Dc} \frac{\partial Q}{\partial x}, \quad (1)$$

where Dc is the depth of closure. The longshore sediment flux Q is defined as:

$$Q = Q_0 \sin(2\alpha), \quad (2)$$

where

$$Q_0 = \frac{\rho K H_b^{2.5} \sqrt{g/\gamma_b}}{16(\rho_s - \rho)\lambda}, \quad (3)$$

and

$$\alpha = \alpha_b - \alpha_{shore}. \quad (4)$$

Here, K is a dimensionless empirical parameter, H_b is the breaking wave height, g is the gravitational acceleration, γ_b is the breaker index ratio, ρ and ρ_s are the water and sediment density, respectively, λ is the sediment porosity, and α_b and α_{shore} are the breaking wave angle and the shoreline angle (Fig. 3), respectively. The shoreline angle is calculated as:

$$\alpha_{shore} = \arctan\left(\frac{\partial S}{\partial x}\right). \quad (5)$$

Equation (1) thus can be rewritten as:

$$\frac{\partial S}{\partial t} = -\frac{1}{Dc} \frac{K \sqrt{g/\gamma_b}}{16(\rho_s - \rho)\lambda} \frac{\partial}{\partial x} \left[H_b^{2.5} \sin(2(\alpha_b - \arctan \frac{\partial S}{\partial x})) \right]. \quad (6)$$

226 The mathematical model is discretized at predefined transects along the coast (Fig. 3), and first-order,
 227 centered finite difference schemes are used:

$$\frac{S_n^{i+1} + S_n^i}{\Delta t} = -\frac{1}{Dc} \frac{Q_{n+1/2} - Q_{n-1/2}}{\Delta X_n}. \quad (7)$$

228 As shown in Fig. 3, n is the transect index, X_n is the alongshore distance between adjacent transects, and i
 229 is the time index.

230 Following Robinet et al. (2018), the wave characteristics at breaking (e.g. H_b , α_b , and γ_b) are calculated
 231 by numerically refracting and transforming the wave conditions from 10m water depth (e.g. WP points shown
 232 in Fig. 1d) using the method of Larson et al. (2010).

233 The wave characteristics at breaking (e.g. H_b , α_b , and γ_b) are calculated by numerically refracting and
 234 transforming the wave conditions from 10 m water depth (e.g. WP points shown in Fig. 1d) using the method
 235 of Larson et al. (2010). The limitations and hypotheses of this empirical approach are discussed in Section 6.

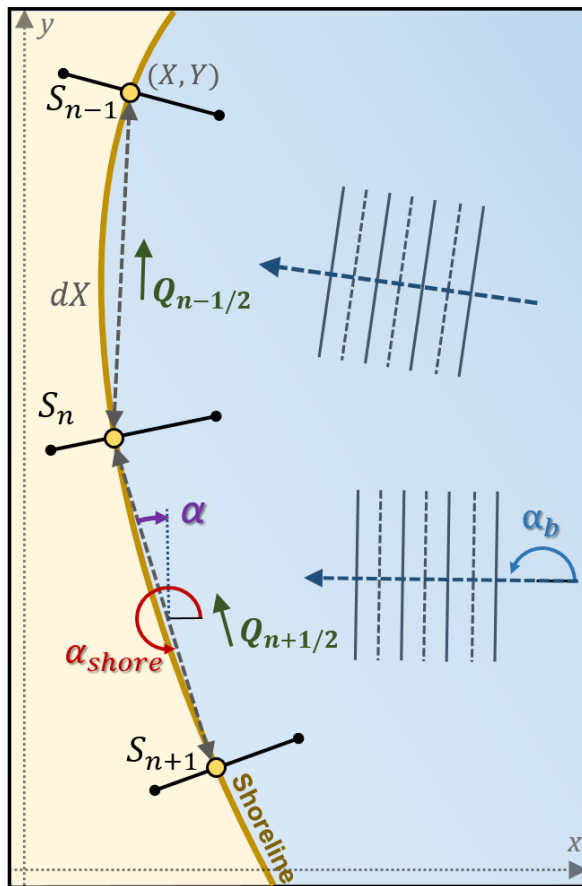


Figure 3: Schematic representation of the model setup for cross-shore transects (index n), showing the shoreline position S , the relative wave angle α (Eq.4), the alongshore sediment flux Q , and the local reference frame (X, Y) .

236 3.2 Model application at Narrabeen Beach

237 The one-line longshore model is applied at Narrabeen beach at 15 cross-shore transects distributed uniformly
 238 alongshore ($\Delta X = 250$ m). Wave conditions along the 10m depth contour were interpolated from the time
 239 series provided at the 5 cross-shore profiles. Wave time series are unavailable at the 2 boundary transects, so
 240 the wave conditions at these locations are initially assumed to be the same as those of the adjacent profiles.

241 Although measurements of sediment fluxes at the domain boundaries are unavailable, given the presence
 242 of the rocky outcrops limiting alongshore sediment transport, they are assumed to be small, and zero-flux
 243 conditions are applied at the boundaries. This hypothesis will be discussed further in section 6.

244 The K parameter is set to 0.02 for all transects based on qualitative comparisons of the amplitude
245 of simulated and observed shoreline position variability. This parameter is often difficult to determine, and
246 typical values in the literature range between 0.014 and 2.3 (Pilkey & Cooper 2002). The relative contribution
247 of the K parameter in this study will be discussed further in section 6. The depth of closure D_c is estimated
248 using the formula proposed by Hallermeier (1983), and an alongshore mean value of 12 m is used for all
249 transects in agreement with the bathymetric observations of Turner et al. (2016).

250 The one-line model is applied for a 10-year time period, from 2005 to 2015, to simulate shoreline changes
251 caused by longshore processes using a hourly time step. Cross-shore processes are neglected by assuming
252 that they are dominant at interannual timescales and do not contribute significantly to observed trends at
253 pluriannual timescales. Harley et al. (2015) completed an EOF (empirical orthogonal function) analysis of
254 5 years of extensive 2D topographic surveys, identifying two principal modes of shoreline variability: cross-
255 shore migration and beach rotation, explaining 55% and 22% of the variance, respectively. Beach rotation is
256 typically attributed to longshore sediment processes, but the authors suggested that alongshore variability in
257 cross-shore processes and differences in sandbar dynamics may also contribute. However, the contributions
258 of these processes are not able to be quantified, and the temporal mode of the beach rotation EOF shows
259 seasonal oscillations and no significant long-term trends.

260 Thus to compare the observations and the model, the mean annual shoreline position $\bar{S}(t)$, where the
261 overline indicates the mean over a 12-month period, is calculated to focus predominantly on longshore pro-
262 cesses and to evaluate the long-term trends in shoreline position. The simulation shows that, when forced
263 with the wave time series along the 10 m depth contour, the one-line model causes a change in the shoreline
264 planform shape, as seen in (Fig. 4b), where the final annual mean simulated ($\bar{S}_{f,mod}$) and observed ($\bar{S}_{f,obs}$)
265 shoreline position are compared.

266 In comparison to the observed shoreline position at the end of the simulated time period, the simulated
267 coastline shows significant erosion at the southern end (around 150m at PF8), nearly no difference in the
268 middle of the beach (with a pivot point near PF6), and accretion at the northern end (between +30m to
269 +60m between PF1 and PF4)(Fig. 4b). Similar results producing large changes in the beach planform shape
270 were also observed by Robinet et al. (2020) (as discussed previously) with the LX-Shore hybrid model over
271 the 5-year time period from 2005 to 2010.

272 The beach reorientation simulated by the one-line model is caused by a disequilibrium between the
273 coastline orientation and the incident wave direction. For a simplified case with a constant wave incidence
274 angle, the one-line model is equivalent to a diffusion equation, bringing the shoreline position toward an
275 equilibrium state. This equilibrium is reached when the coastline orientation is perpendicular to the incident
276 wave direction. When the one-line model is applied at a natural site with temporal variations in the wave
277 direction, the same response is achieved if the mean incident wave direction does not vary significantly in
278 time. Thus, assuming that the one-line model concept is correct, the simulated beach reorientation observed
279 here is hypothesized to be caused by errors in the model input variables or parameters, and in particular by
280 biases in the incident wave direction. The potential contribution of bias errors in the wave height will be also
281 be discussed in section 6.

282 4 Methods: wave angle bias assessment

283 To evaluate the sensitivity of the model to the incident wave angle, two different analyses are completed
284 by: (1) first searching for the optimal set of bias values that minimize the differences between the simulated
285 and observed shoreline evolution, and then (2) systematically testing the sensitivity of the model to sets of
286 random wave angle biases generated from specified Gaussian distributions. For both analyses, Monte Carlo
287 simulations are completed to evaluate the impacts of the wave angle biases on the simulated shoreline position
288 and resultant coastline orientation.

289 In this analysis, it is important to distinguish between a wave angle bias and a wave angle error. A wave
290 angle bias is variable in space but constant in time (systematic error), whereas a wave angle error is variable
291 in both space and time (non-systematic or random error). In this study, wave angle biases are examined
292 because in the long term, random wave angle errors were observed to compensate for each other in time (not
293 show here) and did not generate long-term coastline reorientation in the one-line longshore model, as will be
294 discussed further in section 6.4.

295 4.1 Wave angle bias estimation

296 In the first analysis, the impact of wave angle biases in the input wave time series at 10 m depth is evaluated
297 with a 3-step method.

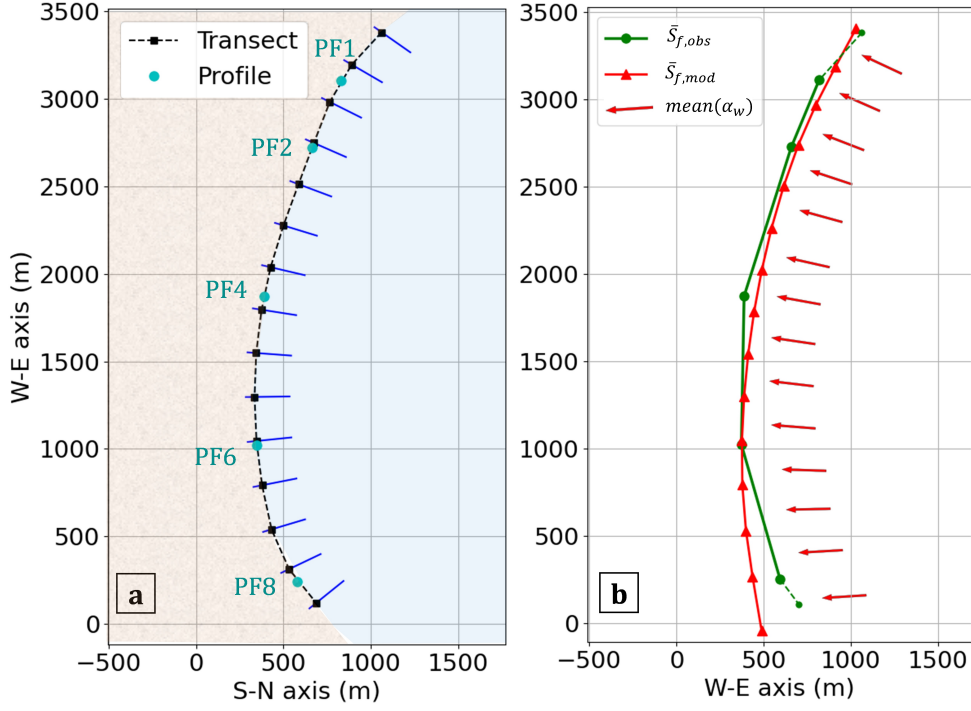


Figure 4: (a) Longshore model setup at Narrabeen beach, showing the 15 defined cross-shore transects. (b) Observed (green line) and simulated (red line) annual mean shoreline position at the end of the 10-year simulation. For each cross-shore transect, the red arrow indicates the temporal mean wave angle (α_w) at 10 m water depth.

298 First, at each position between adjacent transect, a random wave angle bias (τ) that is constant in time,
 299 is drawn from a uniform, univariate distribution using a Monte Carlo approach. The uncorrelated
 300 wave angle biases ($\tau_{n+1/2}$) are then added to the wave direction time-series at each position $n + 1/2$ such
 301 that the new wave angle $\tilde{\alpha}_{w,n+1/2}(t)$ in 10 m water depth is:

$$\tilde{\alpha}_{w,n+1/2}(t) = \alpha_{w,n+1/2}(t) + \tau_{n+1/2}. \quad (8)$$

302 Then, the one-line longshore model is run using the modified wave direction time series $\tilde{\alpha}_{w,n+1/2}(t)$, while
 303 the input wave height $H_{s,10}$ and wave period $T_{p,10}$ remain unchanged.

304 Lastly, the normalized root mean square error (NRMSE) is computed to quantify the difference between
 305 the observed and simulated shoreline position. The root mean square error (RMSE) is computed as:

$$RMSE = \sqrt{\sum_{n=1}^N \sum_{t=1}^T (\tilde{S}_{mod,n}(t) - \tilde{S}_{obs,n}(t))^2} \quad (9)$$

307 with \tilde{S}_{obs} the annual moving average observation (to remove the seasonal variability) computed every month
 308 and \tilde{S}_{mod} the simulated shoreline position at the corresponding time, summed over all observations times T
 309 and all transects N .

310 The NRMSE is calculated as the RMSE normalized by the minimum of the all the RMSE values after
 311 the Monte Carlo process. This method is applied twice, in a nested approach. A first set of 15,000 Monte
 312 Carlo realizations of wave angle biases is generated, allowing τ to vary from -30° to $+30^\circ$, following a uniform
 313 univariate distribution. The results are then used to define smaller angle intervals for each transect $n + 1/2$
 314 (as shown by the vertical cyan bars in Fig. 5a), and a second set of 10,000 Monte Carlo realizations were
 315 completed to determine the set of wave angle biases $\tau_{n+1/2}$ yielding the minimum NRMSE.

316 Since morphological observations are not available at the domain boundaries during the simulated period,
 317 the existing 2D survey data, which spans part of the simulated period, are used to estimate the long-term
 318 trends at the two boundary transects. No trends are observed, thus it is assumed shoreline position remains
 319 unchanged for the 10-year period.

4.2 Model sensitivity analyses

In order to test the sensitivity of the model to the magnitude of the wave angle bias, the wave angle time series $\tilde{\alpha}_{w,n+1/2}(t)$ are corrected using the optimal set of biases obtained in the previous analysis. These new time series are then used as the reference simulation in the sensitivity analyses. Then, new randomly generated wave angle biases $\tau'_{n+1/2}$ are drawn from Gaussian distributions with specified standard deviations and are added to each cross-shore transect. The new wave angle time series $\alpha'_{w,n+1/2}(t)$ at each cross-shore transect are thus defined as:

$$\alpha'_{w,n+1/2}(t) = \tilde{\alpha}_{w,n+1/2}(t) + \tau'_{n+1/2}. \quad (10)$$

For each test, the $\tau'_{n+1/2}$ values are drawn from independent Gaussian distributions with a specified standard deviation $\sigma_{\tau'}$. Six different tests with 1000 Monte Carlo realizations were carried out for $\sigma_{\tau'}$ ranging from 1° to 6° .

A second sensitivity analysis testing the relative importance of biases in the wave height is carried out for comparison. The same approach is used, and the wave height time series are adjusted by a bias β' that is a percentage of the wave height, such that:

$$H'_{sw,n+1/2}(t) = (1 + \beta'_{n+1/2})H_{sw,n+1/2}(t). \quad (11)$$

For each test, the $\beta'_{n+1/2}$ values are drawn from independent Gaussian distributions with a specified standard deviation $\sigma_{\beta'}$. Four different tests with 1000 Monte Carlo realizations were carried out for $\sigma_{\beta'}$ ranging from 5% to 30%.

Finally, the associated error is quantified as the difference between the final, simulated annual mean shoreline position for each realization with a specified $\sigma_{\tau'}$ or $\sigma_{\beta'}$ and for the reference simulation.

The distribution of the differences is obtained for each value of $\sigma_{\tau'}$ or $\sigma_{\beta'}$, which is then characterized by its standard deviation $\sigma_{\Delta S}$. The standard deviation serves as a metric to estimate the order of magnitude of shoreline position errors for a given distribution of wave angle bias errors.

5 Results

5.1 Optimal wave angle analysis

In Fig. 5a, the 50 best Monte Carlo realizations with a NRMSE within 30% of the minimum value vary within a range of up to 10° for each transect and show generally positive values of τ in the north (with two exceptions just north of PF2 and PF4), and then increasingly negative values south of PF4. The optimum set of τ values (purple curve, Fig. 5a) between PF1 to PF8 ranges from 10° to -20° (Table 1).

Table 1: Approximate optimum set of τ values for each cross-shore profile that minimize the NRMSE between the simulated and observed shoreline changes.

Profile	PF1	PF2	PF4	PF6	PF8
Optimum τ	-0.5°	4.8°	4.5°	-13.2°	-19.9°

It is important to note that the model depends not only on $\tau_{n+1/2}$, but also on alongshore gradients in $\tau_{n+1/2}$. In the one-line longshore model, changes in the shoreline position are caused by alongshore gradients in the sediment flux, which are calculated from alongshore gradients in the wave angle α_b and in the wave height H_b , as shown in Eq.(7). The alongshore gradients in $\tau_{n+1/2}$ for the 50 best realizations (Fig. 5b) have a similar, concave shape with the highest values at the extremities of the beach.

The optimal τ values correct for the potential wave angle bias at breaking, caused either by biases in the 10 m depth wave time series or by wave refraction occurring between the 10 m depth contour and the wave breaking point. The large values of $\tau_{n+1/2}$ obtained near the boundary transects (Fig. 5a) may also be attributed to two additional sources that impact more significantly the transects at or near the domain boundaries. They correct for errors induced by extrapolating the wave conditions from the WP points to the domain boundaries, likely generating the largest errors at these transects. They also correct for the assumption that there are no sediment fluxes at the boundaries.

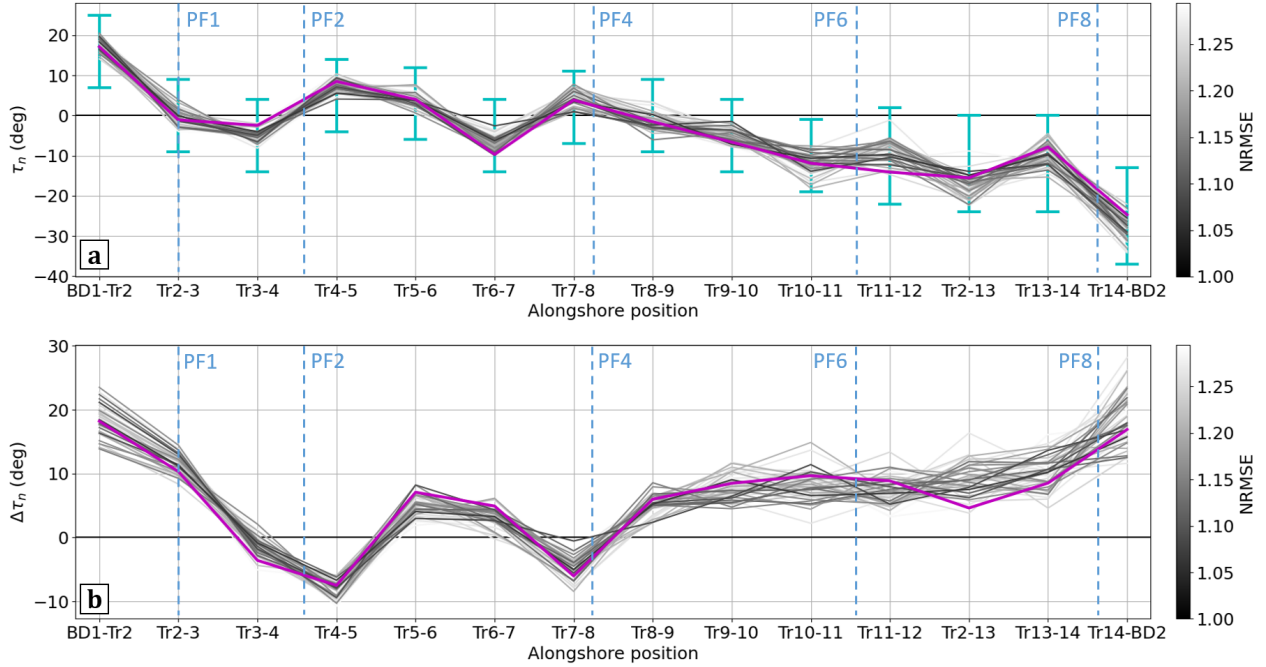


Figure 5: Wave angle bias tests: (a) wave angle bias correction ($\tau_{n+1/2}$) and (b) gradient in wave angle bias correction between adjacent transects plotted for the 50 best Monte Carlo realizations. The vertical cyan bars indicate the range of values used to define the second set of refined Monte Carlo realizations. The color of each curve indicates the NRMSE (gray color scale ranging from 1.0 to 1.3), and the optimal set of $\tau_{n+1/2}$ values are shown in magenta.

361 5.2 Optimal wave angle bias values

362 Using the optimal set of $\tau_{n+1/2}$ values in the one-line longshore model reproduces a simulated coastline
 363 shape similar to the observed coastline shape (Fig. 6a). The wave angle time series are corrected with small
 364 changes in the mean wave angle (e.g. Table 1 for PF1-PF8) relative to the original mean wave angle (Fig. 6a),
 365 except close to the domain boundaries at the extremities of the beach. The difference between the annual
 366 mean initial, observed and final, observed or modeled shoreline position is calculated as: $\Delta \bar{S} = \bar{S}_f - \bar{S}_i$. The
 367 difference $\Delta \bar{S}$ calculated for the corrected wave time series is similar to the observed changes $\Delta \bar{S}_{obs}$ (Fig. 6b).

368 The simulated shoreline position changes using the original wave angle time series ($\alpha_{n+1/2}$ red triangles
 369 in Fig. 6b) are generally larger than or of the same order of magnitude as the seasonal variability over the
 370 10-year period (Fig. 6b, gray bars). However, the simulated shoreline position changes using the corrected
 371 wave time series are smaller than the observed seasonal variability (Fig. 6b, gray bars) and agree more closely
 372 with the observations. Finally, this simple analysis demonstrates how a **relatively** small bias in the input wave
 373 angle can cause significant changes in the shoreline planform shape that are different from the observations.

374 5.3 Model sensitivity analyses

375 Using the wave angle time series $\tilde{\alpha}_w$ corrected with the optimal set of bias values $\tau_{n+1/2}$ as the reference
 376 case, a sensitivity analysis is completed to evaluate the impacts of randomly distributed wave angle biases
 377 on the simulated shoreline position.

378 Six different tests of 1000 Monte Carlo realizations were carried out for $\sigma_{\tau'}$ ranging from 1° to 6° , and the
 379 model error is quantified as the standard deviation $\sigma_{\Delta S}$ of a Gaussian distribution fit to the distribution of
 380 the estimated shoreline position differences (e.g. Fig. 7a,c, for $\sigma_{\tau'} = 5^\circ$). The standard deviation of shoreline
 381 position errors $\sigma_{\Delta S}$ increases approximately linearly as a function of the standard deviation of the wave angle
 382 biases $\sigma_{\tau'}$ (Fig. 7b). Shoreline position errors are on the order of 5m for wave angle biases as small as 1° , and
 383 increase to more than 30m for wave angle biases of only $5-6^\circ$.

384 With respect to the sensitivity of the model to a bias in the wave height, with $\sigma_{\beta'} = 5\%$, 10% , 20% , 30% ,
 385 the associated shoreline position errors $\sigma_{\Delta S}$ are approximately one order of magnitude smaller than for the
 386 wave angle bias tests (comparing Fig. 7d, e and f). For example, shoreline position errors are typically less
 387 than 1m for wave height biases of 5% and reach only 3m for wave height biases as large as 30%.

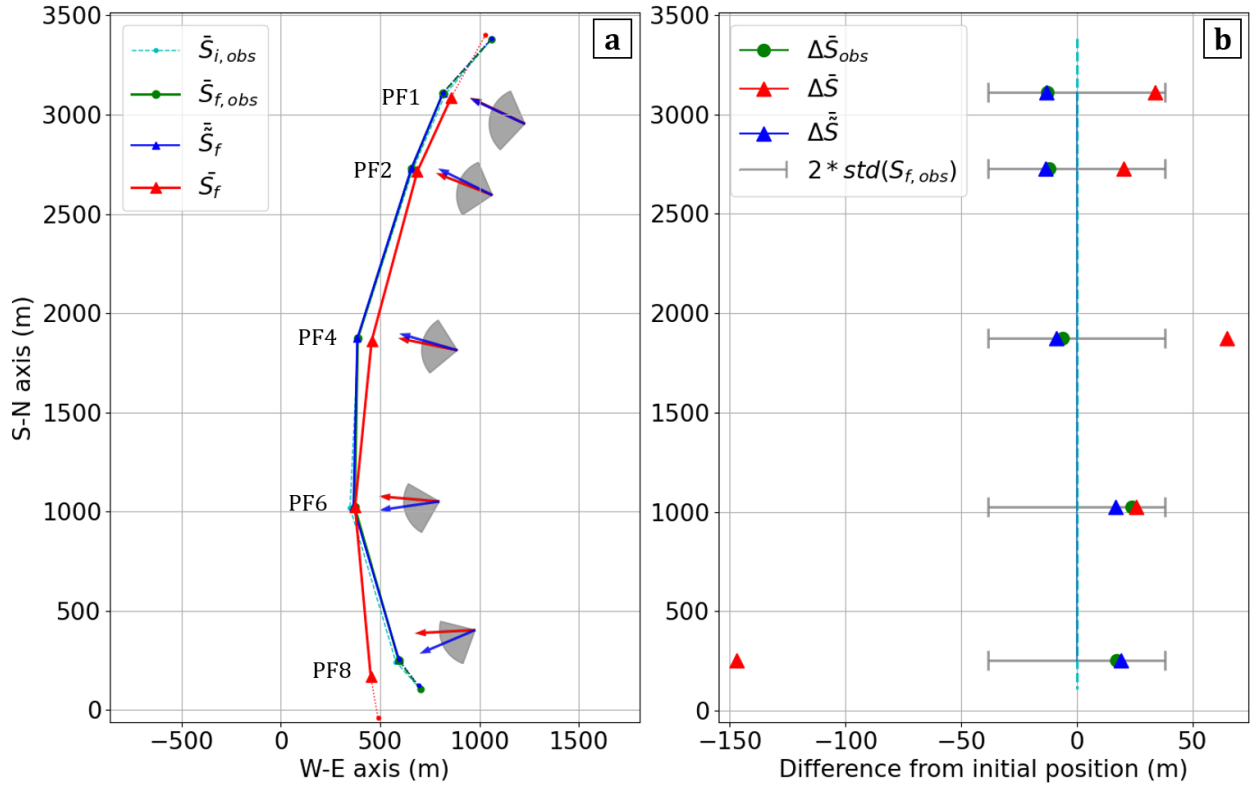


Figure 6: Comparison of the observed and simulated shoreline position: (a) aerial view of the observed initial $\bar{S}_{i,obs}$ (cyan) and final $\bar{S}_{f,obs}$ (green) shoreline position and the simulated final shoreline position for the original \bar{S}_f (red) and corrected $\tilde{\bar{S}}_f$ (blue) wave angle time series. Also shown are the temporal mean wave direction of the original α_w (red arrow) and corrected $\tilde{\alpha}_w$ (blue arrow) time series and the wave direction envelop (grey shading) in 10 m water depth. (b) Difference in the shoreline position relative to the initial observations (cyan) for: the final observed ($\Delta\bar{S}_{obs}$, green) and simulated shoreline position for the original ($\Delta\bar{S}$, red) and corrected ($\Delta\tilde{\bar{S}}$, blue) wave angle time series, and beach shoreline position variance (gray).

388 6 Discussion

389 6.1 One-line model limitations

390 The one-line longshore model is a simple approach for estimating large-scale longshore sediment transport
 391 that has several important conceptual limitations (see Pilkey & Cooper 2002). Two potential sources of error
 392 can be distinguished: the conceptual framework of the one-line model and the longshore flux estimation.

393 In the conceptual model, one limitation is the estimation of the depth of closure D_c , which determines the
 394 active profile length. The assumption that a well-defined depth of closure exists remains controversial, and it
 395 is difficult to identify this limit *in situ*. While a physical, cross-shore limit to the active profile (zone within
 396 which wave-breaking induced sediment transport occurs) likely exists, this limit varies in time as a function
 397 of the wave characteristics and sediment characteristics and availability, and depends on the considered time
 398 period (Valiente et al. 2019). Therefore, assuming a constant value in time and in space (e.g. for a beach)
 399 is convenient for modeling purposes but may contribute to intrinsic errors in one-line models (D’Anna et al.
 400 2021). A second limitation is the assumption of a constant equilibrium profile and a uniform cross-shore
 401 distribution of the longshore sediment flux (Bayram et al. 2001). In addition, factors like the instantaneous
 402 tide level, which would be more important on a meso- or macrotidal beach, or total water depth likely impact
 403 the cross-shore distribution of sediments.

404 In estimating the longshore sediment flux, a second potential source of errors in the one-line model is
 405 the choice or calibration of the K parameter in the CERC formula. This free parameter determines the
 406 longshore flux magnitude, and its magnitude and even use are highly controversial (see Pilkey & Cooper
 407 2002). However, in this study the value of K does not impact the estimation of τ since K is constant for
 408 all transects and thus the one-line model can be simplified to a diffusion equation. Therefore, in long-term
 409 simulations where the coastline reaches a new equilibrium shape, the K value primarily impacts the value of

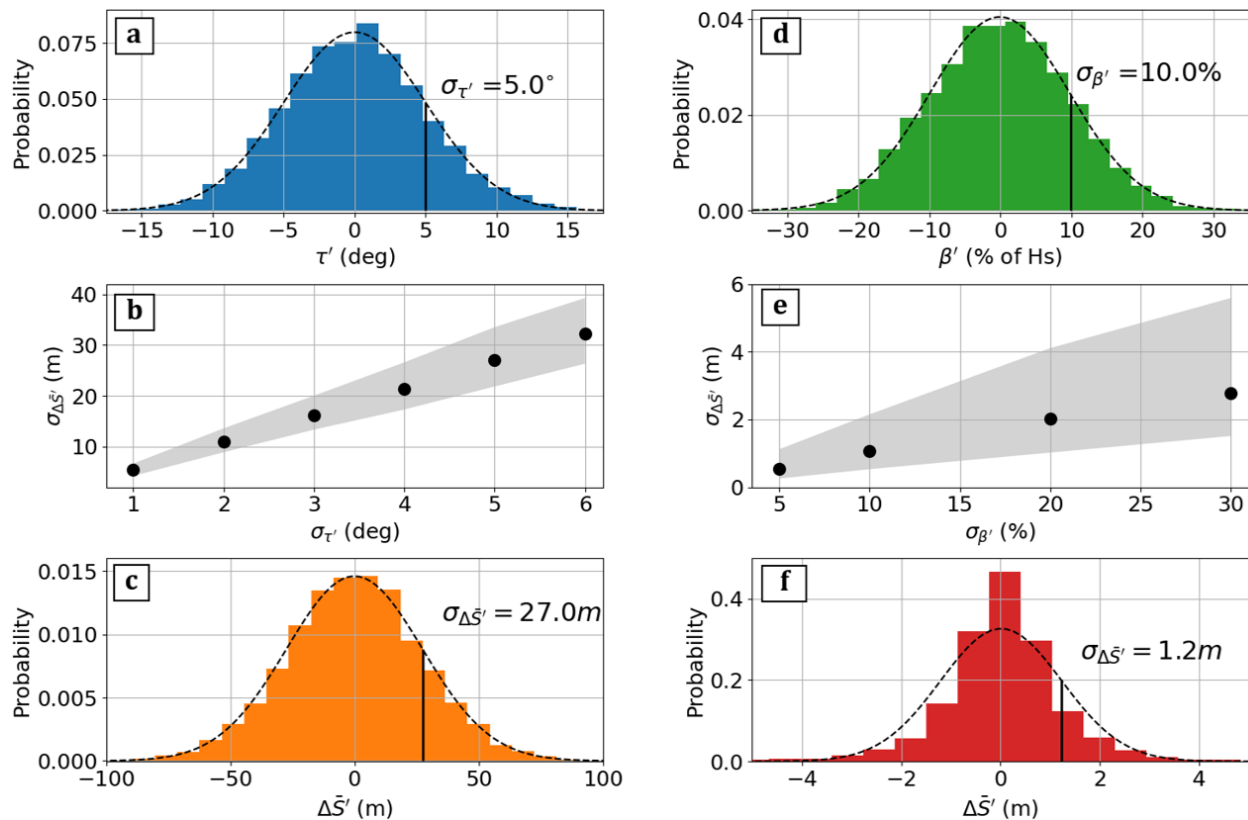


Figure 7: Wave angle bias sensitivity analysis: (a) wave angle bias distribution for $\sigma_{\tau'} = 5^\circ$, (b) standard deviation of shoreline position differences ($\sigma_{\Delta\bar{S}'}$) as a function of $\sigma_{\tau'}$, showing the mean (black stars) and envelope (range of minimum and maximum values) over all transects (gray shading) (c) shoreline position difference (in comparison to the reference case) distribution for all transects for $\sigma_{\tau'} = 5^\circ$, (d) β' distribution for $\sigma_{\beta'} = 10\%$, (e) standard deviation of shoreline position differences ($\sigma_{\Delta\bar{S}'}$) as a function of $\sigma_{\beta'}$, showing the mean (black stars) and envelope (range of minimum and maximum values) over all transects (gray shading), and (f) shoreline position difference distribution for all transects for $\sigma_{\beta'} = 10\%$.

410 the diffusion coefficient, which controls the coastline adjustment timescale to changes in the wave angle,
 411 but does not impact the coastline shape.

412 Finally, the one-line model conserves sediment, and therefore the [choice of](#) boundary conditions may have
 413 strong impacts on the simulated shoreline changes. In this study, it is assumed that there are no sediment
 414 fluxes at the boundaries since the beach is bounded by rocky outcrops. The only likely sediment sources or
 415 sinks are associated with the lagoon mouth at the northern end of the beach. [However, the corresponding](#)
 416 [fluxes are unable to be quantified accurately and are assumed to be](#) negligible in comparison to the estimated
 417 longshore fluxes (Harley et al. 2011), so they are not considered in the model.

418 6.2 Wave bias analysis assumptions and limits

419 In this study, several assumptions are made in applying a Monte Carlo approach to finding the optimal set
 420 of wave angle bias corrections and then in completing sensitivity [analyses](#) to randomly generated wave angle
 421 [and wave height](#) bias errors. Firstly, it is assumed that the errors observed in the one-line model simulation
 422 (e.g. reorientation of the coastline) are caused by errors in the input wave angle time series and not in the
 423 general model formulation.

424 This study focused on evaluating the effects of random wave angle biases rather than random, time-variable
 425 errors because [in preliminary tests \(not shown here\), the effects of random wave angle errors compensated](#)
 426 [for each other in time over the 10-year period, causing no long-term trends in shoreline position changes.](#)
 427 Time-variable errors induce short-term shoreline changes, at timescales of the model time-step, which are
 428 affected by the K parameter. Thus, the sensitivity of the model to time-variable errors is linked intrinsically
 429 to the estimation of K , and therefore these two issues should be addressed simultaneously (as in Kroon et al.
 430 2020).

431 Secondly, a Monte Carlo approach is chosen to generate the random wave angle biases $\tau_{n+1/2}$. A simpler

432 hypothesis would be to consider an alongshore homogeneous τ , assuming that the wave angle bias originates
 433 at the wave buoy **and remains constant as the waves propagate to the 10m depth contour**. In this case, the
 434 corrected wave angle time series would become:

$$\alpha_{w,n+1/2}^*(t) = \alpha_{w,n+1/2}(t) + \tau. \quad (12)$$

435
 436 The effects of adding an alongshore homogeneous τ (ranging from $-30^\circ \leq \tau \leq 30^\circ$) show that it is
 437 insufficient to correct **changes in the shoreline planform shape because it induces different responses at**
 438 **different alongshore locations**. For example, an alongshore homogeneous change in mean wave direction is
 439 able to correct the shoreline **position changes** at PF8 with $\tau \approx -10^\circ$ (Fig. 8b), but it is unable to **do so** at
 440 PF4 (Fig. 8a). At PF4, adding a spatially homogeneous τ value does not allow reproducing the observed
 441 shoreline changes since all of the simulations predicted significant long-term trends that were not observed.

442 At Narrabeen beach, local wave refraction contributes to alongshore gradients in wave angle. **Alongshore**
 443 **variable biases thus allow to correct** for errors associated with local wave refraction that varies alongshore
 444 owing to the curvature of the coastline and the alongshore variable bathymetry. In particular, these errors
 445 may become large at the extremities of the beach near PF1 and PF8 where reefs located in -5 to -10 m water
 446 depth likely have significant impacts on wave refraction.

447 Extending this work beyond Narrabeen beach, this analysis emphasizes the importance in representing
 448 well not only the wave angle time series, but also alongshore gradients in the wave angle time series used to
 449 force one-line longshore models.

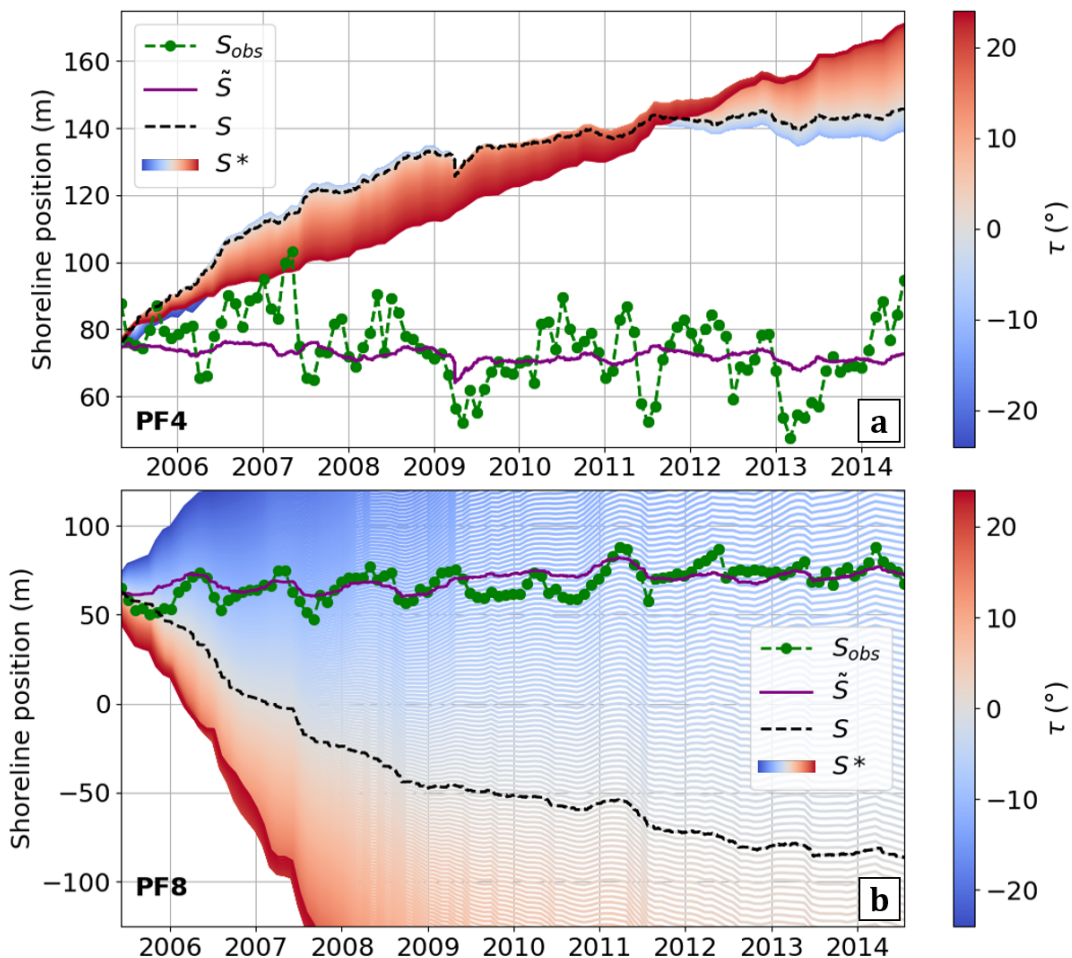


Figure 8: Sensitivity analysis with alongshore homogeneous τ showing the shoreline position evolution from observations S_{obs} (green), the original model simulation S (black), the model simulation forced with the corrected wave angle time series \tilde{S} (purple), and the model simulations S^* forced with wave angle time series adjusted with alongshore homogeneous τ ranging from -30° to 30° (blue-red colorbar).

450 6.3 Planform beach orientation

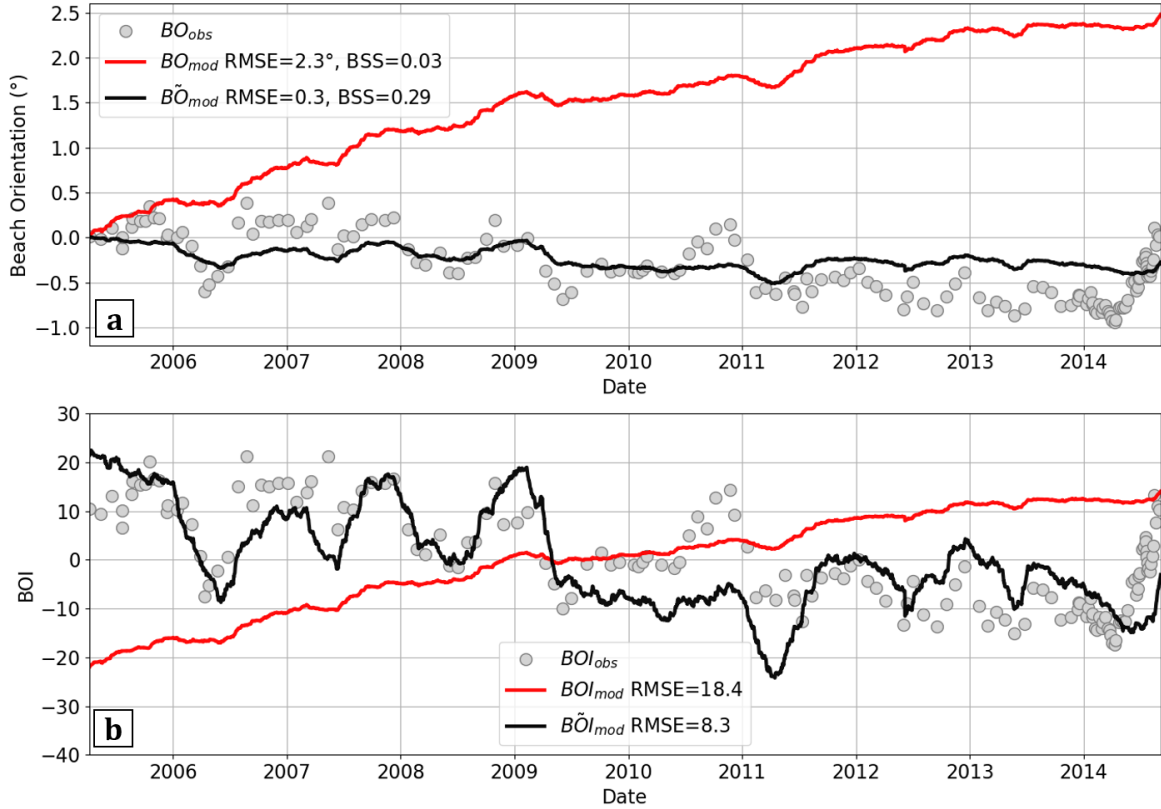


Figure 9: Comparison of (a) Beach Orientation (BO) and (b) Beach Orientation Index (BOI) for shoreline observation (grey dotted), original model simulation (red) and model simulation forced with correct wave angle time series (black).

451 To evaluate the capacity of the one-line model to accurately reproduce the beach orientation and it
 452 evolution in time, the Beach Orientation BO and Beach Orientation Index BOI were calculated following
 453 Harley et al. (2014) and Jaramillo et al. (2021). The BO and BOI are calculated using the observed
 454 shoreline position S_{obs} and both the original S and corrected \tilde{S} simulated shoreline positions at the 5 cross-
 455 shore transects PF1-8 (Fig. 9a, b). During the simulated period, the observed beach orientation BO_{obs} and
 456 beach orientation index BOI_{obs} show slightly negative trends and small seasonal oscillations (gray circles,
 457 Fig. 9). In comparison, beach orientation BO_{mod} and beach orientation index BOI_{mod} calculated from the
 458 simulations with the original wave angle time series (red curves, Fig. 9) shows significant differences with
 459 the observations. After correcting the wave angle time series with the optimal set of biases, the agreement
 460 between the observed and simulated beach orientation \tilde{BO}_{mod} and beach orientation index \tilde{BOI}_{mod} (black
 461 curves, Fig. 9) increases significantly. Jaramillo et al. (2021) also modeled shoreline changes at Narrabeen
 462 beach with an equilibrium-based shoreline rotation model, quantifying their model performance with the
 463 $RMSE$ between the simulated and observed BO and BOI time series. The results presented here (using
 464 only a one-line longshore model) obtain $RMSE$ of the same order of magnitude as their study (which covered
 465 a longer time period).

466 6.4 One-line model sensitivity to biases in the wave height and direction

467 Assuming that the one-line model is conceptually correct, this work shows that correcting a small wave
 468 angle bias (approximately $5-10^\circ$) has significant impacts on simulated long-term shoreline change trends.
 469 The comparison of the observed and corrected simulations of shoreline changes highlights that [this approach](#)
 470 [allows improving long-term \(10-year\) simulations](#) of shoreline evolution (\tilde{S} , purple line compared to S_{obs} , the
 471 dashed black line in Fig. 8). [As expected, the corrected mean wave angles in Fig. 6a are more perpendicular](#)
 472 [to the coastline orientation.](#) However, the difference between the mean wave and shoreline angles is not
 473 reduced to zero, which would result in no longshore sediment fluxes.

474 The sensitivity analyses quantified the impacts of a Gaussian distribution of wave angle biases in wave
 475 direction and wave height. The wave angle sensitivity analysis showed significantly larger impacts on the
 476 modeled final shoreline position than the wave height sensitivity analysis. For wave angle biases τ' drawn
 477 from a Gaussian distribution with a standard deviation of $\sigma_{\tau'}$, the associated alongshore gradients in wave
 478 direction are even larger, following a Gaussian distribution with a standard deviation of $\sqrt{2}\sigma_{\tau'}$. The observed
 479 increases in $\sigma_{\Delta\bar{s}'}$ are thus a result of the importance of alongshore gradients in wave angle and wave height in
 480 the one-line model, as well as the uncorrelated sampling method used to obtain each Monte Carlo realization.
 481 These gradients thus cause large gradients in alongshore sediment fluxes, resulting in significant shoreline
 482 position changes (e.g. on the order of 5 m to 30 m for wave angle biases ranging from 1° to 6°).

483 In this study, the set of optimal τ values (section 5.1) are the same order of magnitude as the uncertainties
 484 estimated by Turner et al. (2016) for transects PF1, 2, 4, and 6. The higher τ values obtained at PF8 and
 485 near the boundary transects BD1 and BD2 are likely caused by other factors, as suggested in section 5.1.
 486 One such contribution is the assumption that the wave conditions at BD1 and BD2 are the same as those at
 487 adjacent transects, even though the coastline angle changes. Secondly, the presence of reefs in the nearshore
 488 zone may cause wave refraction between the 10 m depth contour and the location of wave breaking that is not
 489 taken into account in the Larson et al. (2010) wave refraction approach used here. Finally, the assumption of
 490 no sediment fluxes at the boundaries forces the longshore model to conserve sediment, although the sediment
 491 budget is not necessarily strictly closed if sediment either bypasses the rocky outcrop at the southern end of
 492 the beach or is gained or lost at the lagoon mouth at the northern end of beach.

493 Finally, biases in the wave height have significantly smaller impacts on the resultant shoreline changes
 494 than biases in the wave angle (Fig. 7b,e), causing shoreline position changes on the order of 3 m for wave
 495 height biases as large as 30%. When generating wave conditions from wind-forced wave models, Komen et al.
 496 (1996) estimated that a 10% error in the surface wind speed can cause a 10–20% error in the wave height.
 497 Thus, similar to George et al. (2019), the range of wave height bias errors β' tested in this study ranged from
 498 5% to 30%, representing a potentially common range of errors encountered at sites with limited wave data.
 499 However, these biases are significantly larger than the expected values at Narrabeen beach, where Turner
 500 et al. (2016) estimated wave height biases on the order of only 3-4%.

501 6.5 Comparison of corrected and SWAN model breaking wave angles

502 To investigate the cause of the wave bias and the validity of the wave angle corrections $\tau_{n+1/2}$ proposed here,
 503 the corrected mean wave direction at the breaking point $\tilde{\alpha}_{b,n+1/2}$ obtained in this analysis (after using the
 504 Larson et al. (2010) method to propagate $\tilde{\alpha}_{w,n+1/2}$ to the breaking point) is compared to the breaking wave
 505 direction derived interdependently from a high resolution SWAN model (Harley et al. 2011) (Fig. 10b). These
 506 data are produced using a look-up table similar to that described in Turner et al. (2016), after extending it
 507 from producing wave conditions at 10 m water depth to the break point (thereby taking into account the
 508 additional refraction caused by nearshore reefs). The SWAN simulations were run using a single directional
 509 spreading value (30°) and were calibrated using nearshore wave data, showing a high correlation for the
 510 wave height and a slightly lower correlation for the wave direction (approximately 0.9 and 0.7, respectively
 511 Turner et al. 2016). While the SWAN model succeeds overall in reproducing the nearshore wave conditions, a
 512 deterministic wave model such as XBeach may be able to reproduce better the breaking wave conditions for
 513 this complex bathymetry. Before comparing the wave angles at the breaking point, it is important to note
 514 that the refraction calculated by the Larson et al. (2010) method between 10 m depth and the breaking point
 515 is small, ranging from 0° in the north to approximately -7° in the south (Fig. 10a). The estimated refraction
 516 effects are even smaller for the corrected wave angles $\tilde{\alpha}_{w,n+1/2}$ since on average the difference between the
 517 offshore wave angle and the coastline orientation decreased.

518 The comparison of the optimal breaking wave angles obtained in this analysis ($\tilde{\alpha}_b$) with the SWAN
 519 breaking wave angle ($\alpha_{b,SWAN}$) shows good overall agreement (Fig. 10b), supporting the hypothesis that
 520 the errors generated by the one-line model are caused by biases in the input wave angle. The corrected
 521 breaking wave angles are in general close to the SWAN breaking wave angles. The largest differences are
 522 observed at PF1, which is close to the model boundary, and PF6, where the wave angle bias is overestimated
 523 in comparison to the SWAN model look-up table. The largest change (nearly 20°) between the original (α_b)
 524 and corrected ($\tilde{\alpha}_b$) wave angle time series occurred at PF8, where $\tilde{\alpha}_b$ now agrees well with $\alpha_{b,SWAN}$. It is
 525 assumed that the optimal wave angle bias at this location primarily corrects for the underestimation of local
 526 wave refraction caused by a nearshore reef.

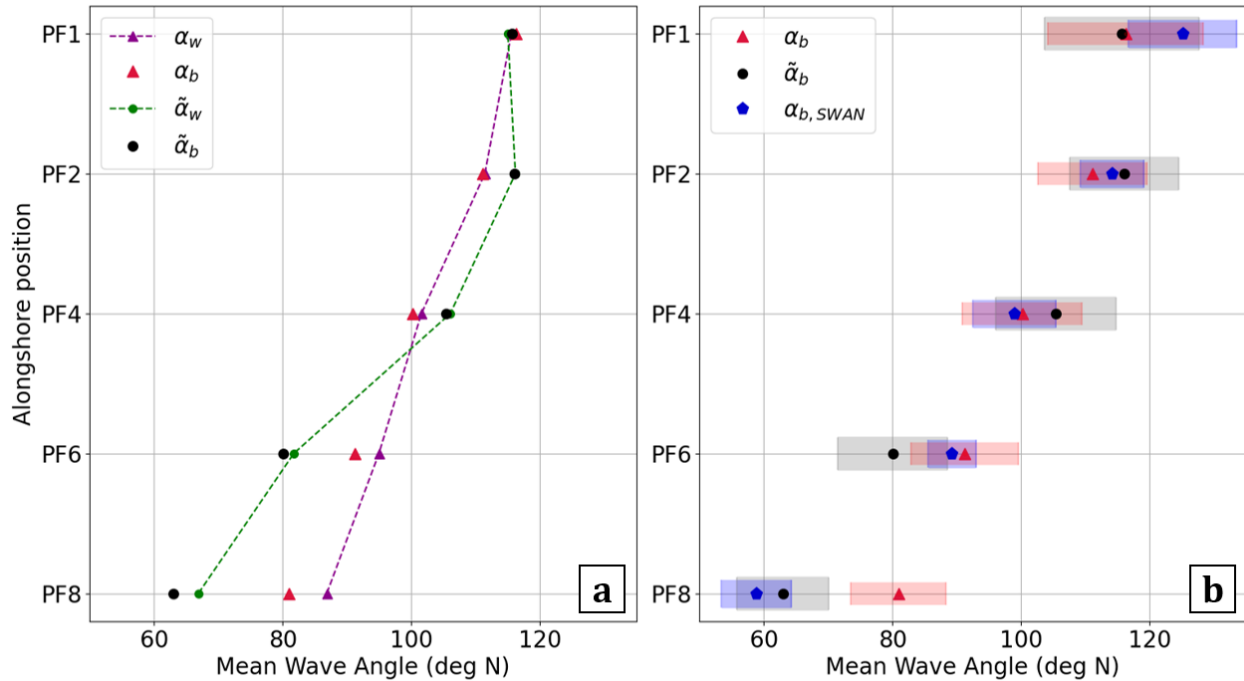


Figure 10: Temporal mean input and breaking wave angles: (a) Comparison between the mean original α_w (purple triangles) and corrected $\tilde{\alpha}_w$ (green points) 10 m depth wave angles, and the original α_b (red triangles) and corrected $\tilde{\alpha}_b$ (black points) breaking wave angles propagated using the Larson et al. (2010) method. (b) Comparison between the mean original (red triangles), corrected (black points), and SWAN (blue points) breaking wave angles, where the shaded zones indicate the standard deviation.

6.6 Wave data uncertainties

Morphological evolution models are forced with wave conditions derived from observations (e.g. wave buoys) and model outputs (e.g. spectral wave models). This study shows the sensitivity of a one-line longshore model to errors in the input wave direction, which then propagate through the modeling chain to cause errors in the predicted morphological changes. This is an important result because it is well known that the wave direction is difficult to estimate accurately with spectral wave models, often showing large uncertainties (e.g. Ardhuin & Roland 2013, Cavaleri et al. 2018), and that wave buoy observations also have errors in measured wave angles (e.g. Barstow et al. 2005). Even if the input wave conditions are known with high accuracy from one of these sources, wave conditions are often obtained at an offshore location and then must be propagated to the breaking point to be input in the one-line model flux calculation. Therefore, at the breaking point, it is often difficult to have highly accurate knowledge of the wave conditions, and in particular the incident wave angle, in particular in areas where refraction over complex bathymetry may be significant and not necessarily represented well when using simple wave transformation approaches. An additional limitation in one-line longshore models is that bulk wave parameters are used to force the model, and thus the potential complexity of the full-spectra is neglected (e.g. existence of secondary swells, bimodal spectra, or high wave angle spreading).

This study highlights the importance of propagating accurately offshore wave conditions to the nearshore zone to force morphological evolution models. One-line longshore models are particularly sensitive to the input wave angle, and even more so, to alongshore gradients in the input wave angle. In addition, this work also demonstrates that having high-quality estimates of nearshore wave conditions at 10 m depth may not be sufficient in particular cases where there is significant refraction shoreward of this location up to the breaking point (e.g. for embayed beach or beaches with complex nearshore bathymetry such as Narrabeen). However, it is not common to have access to high-quality, high-resolution, long-term estimates of wave conditions at the wave breaking point due to the high computational costs associated with nearshore wave propagation models. This emphasizes the need for further developments in nearshore in situ hydrodynamics monitoring and accurate and efficient nearshore wave propagation models, as well as the necessity to take into account uncertainties in morphological evolution studies.

7 Conclusions

In this study, the sensitivity of a commonly used one-line longshore sediment transport model to the input wave angle is evaluated using a statistical approach. The study is carried out at Narrabeen beach for the 10-year period from 2005 to 2015, where the model, forced with an available dataset of wave conditions at the 10 m depth contour, simulated a [change in the shoreline planform orientation that was different from that of the observations](#). The objective of the current work is to study the source of this error and to understand the sensitivity of the one-line longshore model to the input wave angle by using a Monte Carlo approach to correct the wave angle time series by adding randomly generated biases (spatially variable but temporally constant). The model sensitivity is further quantified by comparing the simulated shoreline position at the end of the 10-year period to the observations and to the reference test case corresponding to the optimal wave bias correction.

The results of the first analysis show that [by correcting the wave angle time series with the optimal set of biases](#) (in the range of -20° to 5°), [the simulated shoreline planform orientation agrees well with the observations](#). The shoreline position error distributions resulting from the wave angle and wave height bias sensitivity analyses [demonstrate that the one-line longshore model is highly sensitive to biases in the wave angle](#). For example, the standard deviation of the shoreline position errors increases by approximately 5 m for a 1° increase in the wave direction bias, [but by less than 1 m for a 10% bias in the wave height](#).

The breaking wave angles obtained from the optimal corrected [biases in this study generally agree well with the breaking wave angles obtained by propagating offshore wave conditions using the SWAN model](#). This comparison also demonstrated that [the corrections](#) to the mean wave direction are coherent with wave refraction processes in the nearshore zone, which are not taken into account in simple wave transformation models often used to estimate wave breaking conditions. Thus, the methodology presented in this paper is able to compensate for the lack of accurate breaking wave direction data by using available morphological observations.

Finally, this study highlights the need for high quality estimates of breaking wave conditions, and in particular, the wave breaking direction and its alongshore gradients, in longshore sediment transport models. Even when nearshore (e.g. 10 m depth) wave conditions are known, simple propagation methods like the approach of Larson et al. (2010) should be used with caution in areas with complex bathymetry, and the uncertainties associated with these simple modeling approaches should be evaluated.

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