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Ranking uncertainty: wave climate variability versus model uncertainty in probabilistic assessment of coastline change

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Abstract

Sand nourishments are increasingly applied as adaptive coastal protection measures. Predictions of the evolution of these nourishments and their impact on the surrounding coastline contain many uncertainties. The sources that add to this uncertainty can be delineated between intrinsic and epistemic uncertainty, i.e. inevitably in the system or related to knowledge limitations. Effects of intrinsic uncertainty (e.g. due to wave climate variability) on coastal evolution can be significant. In studying these effects, it has often been assumed that intrinsic uncertainty is dominant over epistemic uncertainty (e.g. introduced by the model), yet the magnitude of both contributions have not been explicitly quantified to assess the validity of this assumption. This paper examines the relative importance of intrinsic and epistemic uncertainty in coastline modeling of a large-scale nourishment. It uses a probabilistic framework in which sediment transport is considered to be a function of random wave forcing (intrinsic) and model (epistemic) uncertainty, calculating transport using a one-line model. The test case for this analysis is the mega-nourishment, the Sand Engine, located in the Netherlands. The applied wave climate variability is obtained from long term wave observations, whereas model uncertainty is quantified using

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the Generalized Likelihood Uncertainty Estimation (GLUE) method relying on monthly observations. We find that the confidence intervals on predicted volume losses increase substantially when including both intrinsic and epistemic sources of uncertainty. A global sensitivity analysis shows that ignoring model uncertainty would underestimate the variance by at least 50% after a 2.5-year simulation period for the Sand Engine, hence producing significant overconfidence in the results. These findings imply that for coastal modelling purposes a dual approach should be considered, evaluating both epistemic and intrinsic uncertainties.

Keywords: Large-scale nourishment, Model uncertainty, Wave climate variability, Generalized Likelihood Uncertainty Estimation (GLUE), Coastline modeling, Sensitivity Analysis

1. Introduction

Coastal sections around the world are increasingly protected with sand nourishments. Yet, using natural dynamics and materials in coastal protection is intrinsically associated with increased uncertainties of the coastal state with respect to more traditional hard protection measures. Recent nourishments along the Dutch coast such as the Sand Engine (de Schipper et al., 2016) and the Hondsbossche Dunes (Kroon et al., 2017) show a significant increase of nourishment volume compared to the more regular beach and foreshore nourishments (Stive et al., 2013). As intervention scales grow and natural variabilities are increasingly incorporated in these designs, the demand for predictions increases, while predictability of the state of the coast at any given time has decreased. In addition to this uncertain response to variable natural forces, many model related uncertainties are present, which are not always included in predicting these coastline changes.

In general, distinction is made between two types of uncertainty, intrinsic and epistemic uncertainty (e.g. Van Gelder, 2000; Van Vuren, 2005). The first is related to the random occurrence of processes in time and space and is irre-

18 ducible. The second is related to the present state of our process knowledge,
19 models and methods and is in theory reducible given appropriate resources.
20 In Fig. 1 the types of uncertainty in morphological coastline predictions are
21 schematized, adapted from the schematic subdivision of types of uncertainty in
22 design of civil structures by Van Gelder (2000).

23 In morphological coastline response on a yearly to decadal time-scale intrinsic
24 uncertainty can manifest in both space and time. For instance, the spatial
25 variability in the cross-shore bed levels can have significant influence on the
26 alongshore transport (Mil-Homens, 2016). Likewise, coastal morphology is very
27 sensitive to temporal variability such as the chronology and year to year variability
28 in wave forcing (Southgate, 1995).

29 Epistemic uncertainty is typically introduced by uncertainties in observations
30 and models. Model uncertainty can be attributed to model inadequacy,
31 parameter uncertainty (e.g. Ruessink, 2005; Simmons et al., 2017) and numerical
32 limitations (e.g. de Vriend, 1987). Model inadequacy can be caused by missing
33 processes (e.g. beach recovery, long waves, sediment sorting; Huisman et al.,
34 2016) or reduced complexity of processes, such as 1D or 2D models and sediment
35 transport formulae. Ruessink and Kuriyama (2008) show that unpredictability
36 of cross-shore sandbar migration during major wave events originates largely
37 from model inadequacy. Parameter uncertainties arise from limited knowledge
38 on actual values of model parameters (e.g. grain size, bed roughness or wind
39 shear). For instance, Villaret et al. (2016) show that model results are most
40 sensitive to settling velocity and grain size, which are often only locally known.
41 Numerical uncertainties can be introduced by the spatiotemporal model resolution,
42 the order of the numerical schematization and the acceleration technique
43 (Luijendijk et al., 2019). Finally, observation uncertainty is a result of accuracy
44 of the instruments and data processing used. For instance, sampling limitations
45 and measurement errors can significantly contaminate variability at resolved
46 scales, and may lead to errors in the representation of the scales of interest
47 (Plant et al., 2002; Kasprak et al., 2019).

48 In the last decades, large advances have been made to model and predict

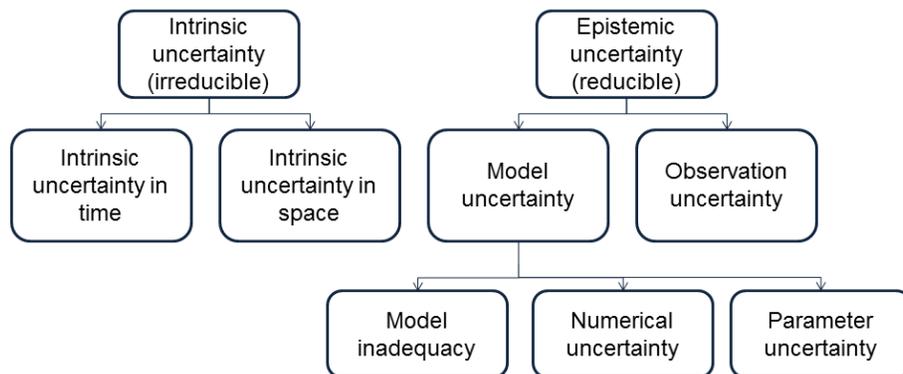


Figure 1: Types of uncertainty in the forecasting of morphological coastline response. Adapted from: Van Gelder (2000)

49 the morphological processes governing the changes of the coastal zone (Hanson,
 50 1988; Ashton and Murray, 2006; Lesser, 2009; Warner et al., 2010). Thereby
 51 making a significant contribution to the accuracy and skill of morphodynamic
 52 models, and thus reduction of model uncertainty. However, as focus has been on
 53 improvements and strenghts of the model, less detail is presented on the residual
 54 uncertainty. Recently, several of these tools have successfully been applied to the
 55 modeling of large-scale nourishment evolution (Luijendijk et al., 2017; Arriaga
 56 et al., 2017; Tonnon et al., 2018). Although, Arriaga et al. (2017) do acknowledge
 57 the sensitivity of the results to different wave climate scenario's, in general, only
 58 limited attention is paid to the uncertainties within the predictions.

59 On a track adjacent to model development and improvement, several of these
 60 deterministic models have been applied within probabilistic frameworks to allow
 61 for the effects of intrinsic uncertainty (Baquerizo and Losada, 2008; Ruggiero
 62 et al., 2010; Ranasinghe et al., 2012; Callaghan et al., 2013; Baart, 2013). The
 63 implicit assumptions underlying the focus on intrinsic uncertainty are that cli-
 64 mate variability is the most important source of uncertainty and that model

65 forcing and reliability are independent. That the validity of these assumptions
66 is debatable, is indicated by the results of Callaghan et al. (2013), who show
67 that model uncertainties have a significant influence on probabilistic estimates
68 of storm erosion: the predicted mean erosion and 95% confidence interval vary
69 greatly for each of the models presented and all models overestimate erosion for
70 higher return periods. For the long, climate change time scale, Le Cozannet
71 et al. (2019) show that model uncertainty can indeed be a significant contribu-
72 tion to variance in coastal recession predictions under a rising sea level.

73 Explicit quantification of model (parameter) uncertainty (epistemic uncer-
74 tainty) in morphological computations is possible, albeit at a large computa-
75 tional cost (e.g. Kroon et al., 2019; Simmons et al., 2017; Ruessink, 2005).
76 Similarly, it is possible to quantify intrinsic uncertainty in morphological model
77 applications in the coastal zone on a time scale of years (Baquerizo and Losada,
78 2008; Payo et al., 2008). Yet, combining these to assess the relative importance
79 of epistemic versus intrinsic uncertainty has not been investigated so far.

80 In coastal engineering the deterministic approach might dominate and proba-
81 bilistic approaches focus on intrinsic uncertainty, uncertainty analysis in climate
82 change predictions is common practice. In general, three main sources of un-
83 certainty in climate projections are identified: due to future emissions (scenario
84 uncertainty), due to internal climate variability, and due to inter-model differ-
85 ences (IPCC Working Group I, 2013; Hawkins and Sutton, 2011, 2009). Hawkins
86 and Sutton (2011) show clearly that for climate projections the dominant source
87 of uncertainty depends on lead time, climate indicator and spatial scale. Ex-
88 tending these results to coastal morphology, it seems unlikely that intrinsic
89 uncertainty or wave climate variability can be beforehand considered to be the
90 primary source of uncertainty for both short and long time scales. Therefore,
91 this paper includes both intrinsic and epistemic uncertainty in a probabilistic
92 framework to examine the relative importance of these uncertainties in coastline
93 modeling of a large-scale nourishment over time.

94 For this purpose, sediment transport and volume change are considered to
95 be a function of both intrinsic and epistemic uncertainty. As the principal

96 source of intrinsic uncertainty we choose the variability in wave climate and
97 as the principal source of epistemic uncertainty we assume model uncertainty.
98 The random wave forcing is based on the observed wave climate variability
99 whereas the distribution of the calibration settings for a simple one-line model
100 are quantified using observations of the Sand Engine nourishment. With a
101 comparison of the observed volume changes and several probabilistic forecasts
102 that include wave climate variability and/or model uncertainty, we show that
103 model uncertainty becomes dominant over wave climate variability for medium-
104 term time scales (years).

105 **2. Sand Engine nourishment**

106 The Sand Engine is a well measured nourishment project, and its large scale
107 results in a distinct and unique coastline response with a high signal to noise
108 ratio. The Sand Engine nourishment was placed between April and June 2011,
109 along the Dutch South Holland coast, as a hook shaped peninsula of 17 million
110 m^3 sand (Stive et al., 2013). The nourishment is exposed to a wind wave
111 climate with a predominant South-West and North-West direction. The spring-
112 neap tidal range varies approximately between 1.5 and 2 m and the local tidal
113 velocities around the peninsula can range up to 1 m/s (Radermacher et al.,
114 2017), but the main driver of the morphological evolution is the alongshore
115 sediment transport by oblique wave incidence (Luijendijk et al., 2017). The
116 bathymetric evolution has been monitored with a 1 to 3 month interval until
117 the end of 2016 and with a 3 to 6 month interval after that (Roest et al., 2017).
118 The grain size (d_{50}) of the Sand Engine varies over the cross-shore profile and
119 in time between approximately 200 and 400 μm (Huisman et al., 2016), and
120 morphological changes can be observed between -8 and 3 m+MSL (de Schipper
121 et al., 2016).

122 Our analysis starts with the bathymetrical survey of December 2012 because
123 the coastline curvature is too sharp for a one-line model to be stable prior to this
124 date. The remaining 5 year period between December 2012 and January 2018 is

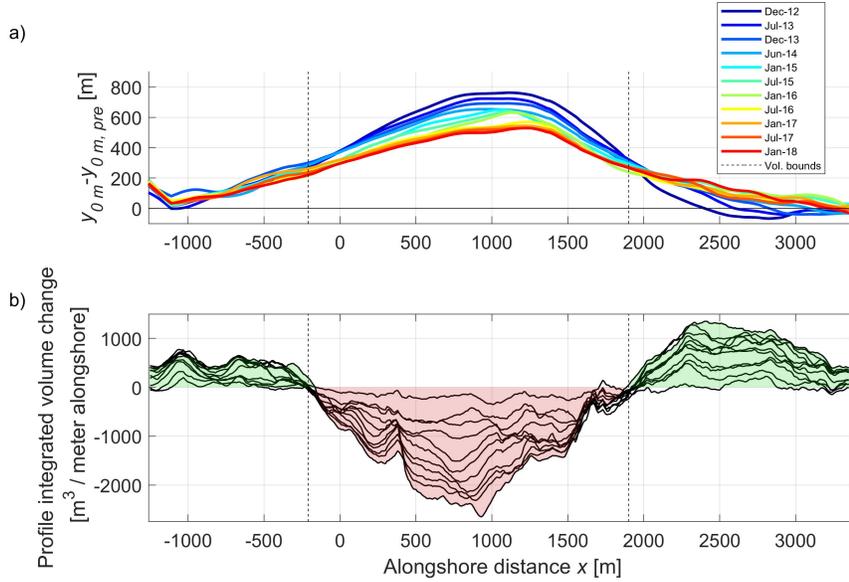


Figure 2: Morphological evolution of the Sand Engine since December 2012. Coastline position, y_{0m} , with respect to a reference coastline, $y_{0m,pre}$, prior to construction of the nourishment (a) and profile integrated volume change since December 2012 (b). The green shaded areas denote net sedimentation and the red shaded area denotes net erosion.

125 split in two 2.5-year periods: a calibration period and a validation period. The
 126 coastline is defined as the position of the most seaward 0 m+MSL depth contour,
 127 ignoring the lagoon. The resulting coastline positions since December 2012 are
 128 depicted in Fig. 2a. For each of the surveys the profile integrated volume
 129 change with respect to the bathymetry of December 2012 is calculated (Fig.
 130 2b). The total volume change (ΔV_{tot}) of the nourishment since December 2012 is
 131 calculated as the sum of the net eroding center part of the nourishment (shaded
 132 red in Fig. 2b) and shows a negative trend of approximately $500,000 \text{ m}^3/\text{yr}$
 133 (Fig. 3a). The volume changes between consecutive surveys (ΔV) vary between
 134 $100,000 \pm 160,000 \text{ m}^3$ (Fig. 3b). A large volume gain of $8,000 \text{ m}^3/\text{d}$, influenced
 135 by an observational error, is reported in August 2013. This volume gain is not
 136 excluded, exemplifying the effect of measurement errors in the analysis.

137 To derive model boundary conditions, offshore waves at nearby wave stations

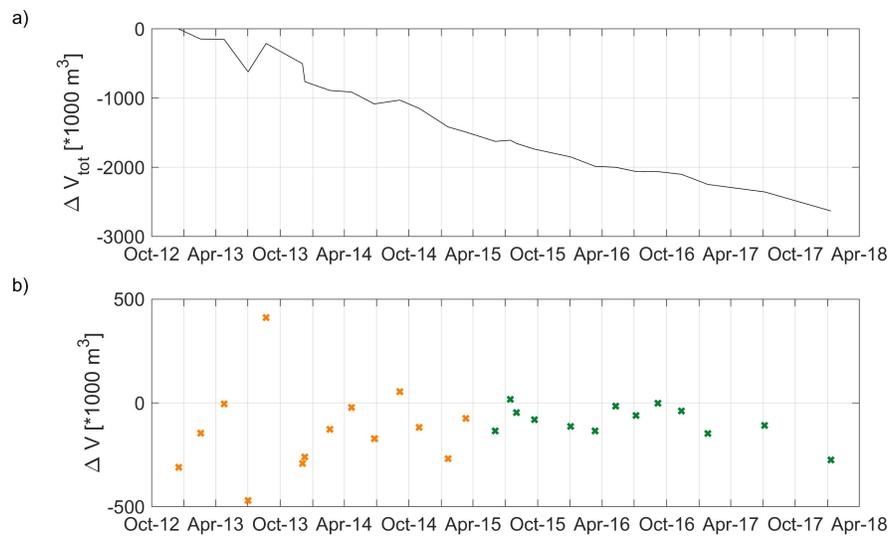


Figure 3: Total volume change (ΔV_{tot}) since December 2012 (a) and volume change (ΔV) between consecutive surveys (b) of the central, net eroding area of the Sand Engine. Orange crosses are used for model calibration and green crosses are used for validation. The positive volume change in August 2013 is influence by measurement errors.

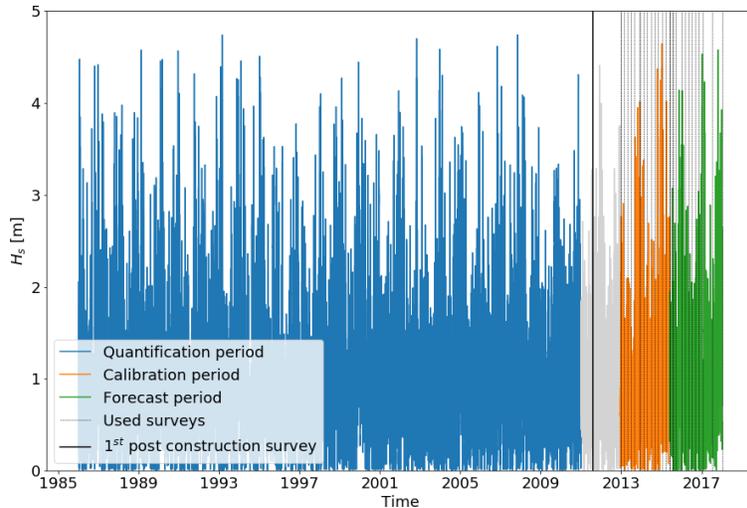


Figure 4: Wave height at the -10 m+MSL depth contour at the Sand Engine for the quantification period (1986-2011), the validation period (December 2012-June 2015) and the forecast period (June 2015-January 2018). Gray dotted lines depict the survey dates. The wave data from January 2011 to December 2012 are not used in the analysis (shown in gray).

138 are transformed to the -10 m+MSL depth contour with a SWAN model using
 139 a transformation matrix derived for the Sand Engine by Deltares (2011) in a
 140 similar way to Ly and Hoan (2018). A description of the mesh and a validation
 141 for a nearby measurement station can be found in Huisman et al. (2019). The
 142 resulting wave height time series (Fig. 4) are separated into three periods: a full
 143 25-year period to quantify the wave climate variability, (January 1986 - January
 144 2011), a 2.5-year calibration period (December 2012- June 2015) and finally a
 145 2.5-year forecasting period (June 2015-January 2018).

146 3. Methodology

147 3.1. Probabilistic approach

148 To examine the relative importance of model uncertainty versus the effects of
 149 wave climate variability in predicting coastline change a probabilistic simulation

150 procedure is followed (Fig. 5). For the morphological computations a one-line
151 model is chosen, to facilitate the large number of computations required to
152 achieve a high statistical accuracy.

153 The first step in the procedure is to quantify uncertainty. The variation in
154 wave climate is quantified using the statistics of 25 years of wave observations
155 (Fig. 5, left side of blue dotted box). Model uncertainty is quantified using
156 Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley,
157 1992) that seeks a distribution of appropriate model settings for the 2.5-year
158 calibration period, given a set of observations (Fig. 5, right side of blue dotted
159 box). The next step is to sample from the established distributions of wave
160 climate variability and model uncertainty. So, with a bootstrapping procedure
161 N model time series are generated that meet the observed wave statistics (Fig.
162 5 left orange box). Whereas N model settings are derived by Monte Carlo
163 sampling (Fig. 5 right orange box) from the derived distribution of model
164 settings. After the deduction of N wave time series and N model calibration
165 factors the uncertainty is propagated through the one-line model by running it
166 N times for the 2.5-year forecast period (Fig. 5, green box). For each of these
167 runs the volume change in the eroding part of the nourishment is determined,
168 and combining these results provides a probability density function of volume
169 change. We choose $N = 12,000$ samples, this means that we can be 95% sure
170 that the 50% fractile is located between the estimates of the 49% and 51%
171 fractile (Morgan et al., 1990).

172 In the next part of this section the details of the one-line model and the un-
173 certainty quantification steps are further elaborated upon. Finally, the relative
174 importance of wave climate variability and model uncertainty in this probability
175 density function of volume change is assessed with a global sensitivity analysis
176 (see paragraph 3.5).

177 3.2. One-line model

178 Many one-line models can be found in literature with a varying range of
179 complexity (e.g. Arriaga et al., 2017; Payo et al., 2002; WL—Delft Hydraulics,

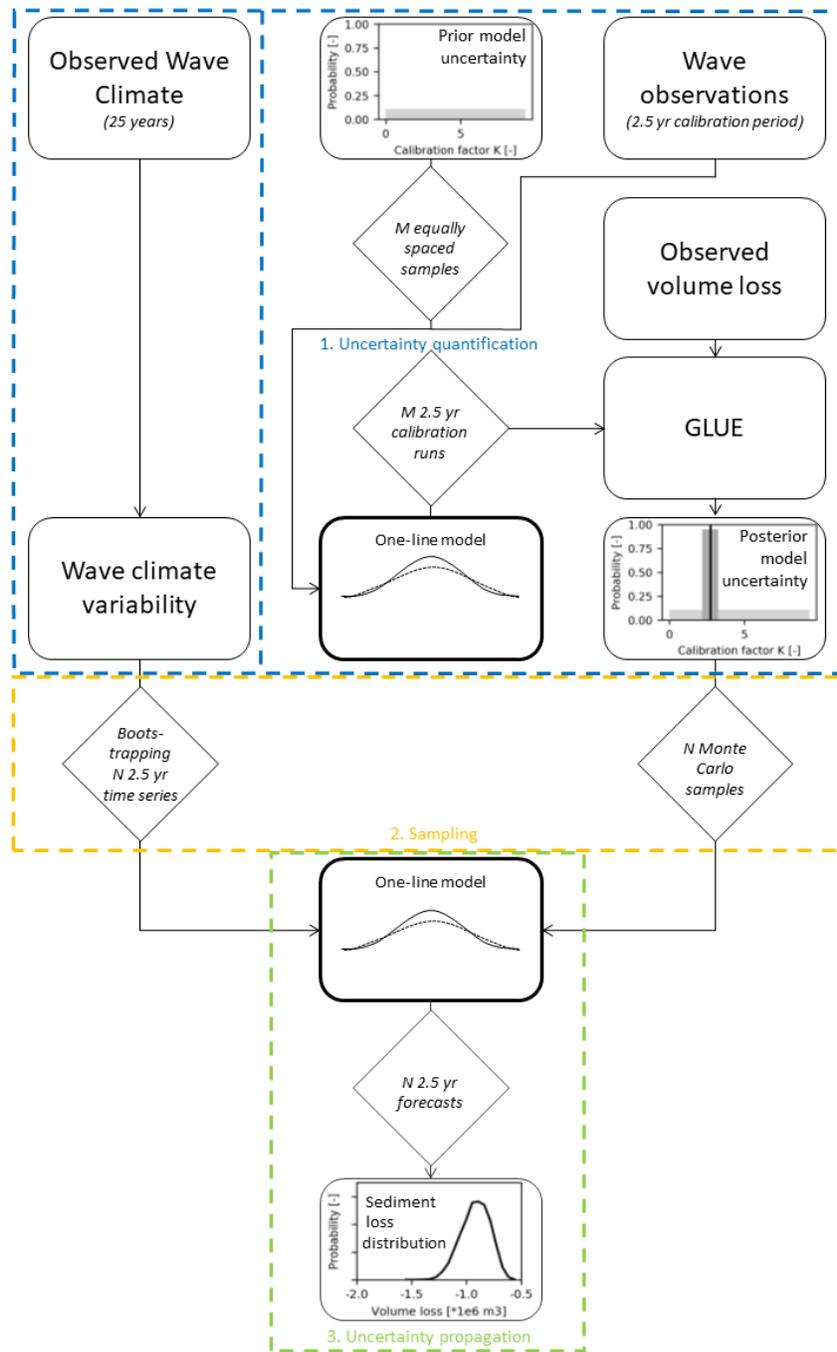


Figure 5: Schematic overview of probabilistic simulation steps: 1) uncertainty quantification, 2) sampling, and 3) uncertainty propagation in a 2.5 yr forecast of volume loss.

180 1994; Hanson, 1988). In this study a one-line model is used which updates
 181 the cross-shore coastline position based on the alongshore sediment transport
 182 gradient and neglects any sources or sinks:

$$183 \quad \frac{\delta y_s}{\delta t} + \frac{1}{D} \frac{\delta Q}{\delta x} = 0 \quad (1)$$

184 in which x is the alongshore coastline position, y_s is the cross-shore coastline po-
 185 sition, Q is the alongshore sediment transport, and D is the active profile height
 186 between closure depth and top of the berm. In this approach the alongshore
 187 sediment transport rate is calculated with the Kamphuis formula (Kamphuis,
 188 1991):

$$189 \quad Q = K \tan(\beta)^{0.75} d_{50}^{-0.25} \underbrace{H_{br}^2 T_p^{1.5} \sin^{0.6}(2\theta_{br})}_{\text{wave climate component } (w_{br})}, \quad (2)$$

190 where Q is expressed as kg immersed mass per second, K is the model calibration
 191 factor, $H_{s,br}$, T_p and θ_{br} are the significant wave height, peak period, and angle
 192 of wave incidence at the point of breaking relative to shore normal, $\tan(\beta)$ is the
 193 beach slope and d_{50} is the median particle size in the surf zone. For the purpose
 194 of this study we denote the term that is affected by varying wave forcing as the
 195 wave climate component, w_{br} .

196 To obtain volume change, ΔV_{tot} the coastline change is integrated over the
 197 active profile height, D , and the alongshore grid size, Δx , and then summed
 198 over the alongshore central section of the nourishment (Fig. 2, dashed lines).

199 We discretize the coastline of the Sand Engine in non-uniform spaced sections
 200 in the x -direction that vary between 200 and 225 m width. H_{br} and θ_{br} are
 201 calculated using linear wave theory from waves at a location beyond the closure
 202 depth, the -10 m+MSL depth contour. The wave conditions at the -10 m+MSL
 203 depth contour are assumed to be constant over the model domain. In addition,
 204 we assume $d_{50}=300 \mu\text{m}$, a beach slope of 1/50 and an active profile height $D=11$
 205 m. Note that, assuming these specific values may introduce uncertainty in time
 206 and space which will be accounted for via calibration of the model calibration
 207 factor K as a probability density distribution.

208 The model calibration factor K as originally proposed by Kamphuis (1991)

209 has a value of 2.33, assuming a sea water density of $\rho = 1029\text{kg/m}^3$. Later,
210 Schoonees and Theron (1996) use an extensive data set to find a value of $K =$
211 3.6 for exposed sites. In addition, Schoonees and Theron (1996) also reveal
212 significant uncertainty in the exact value of K . The re-calibrated formula still
213 shows deviations from observed transports up to a factor 5 and K values 50%
214 higher or lower only have a marginally higher standard error. Exemplifying that
215 K can be regarded a stochastic variable rather than a deterministic one.

216 *3.3. Quantification of wave climate variability*

217 To force the one-line model with varying wave time-series that follow local
218 wave statistics, the wave climate variability is quantified using available his-
219 torical wave time series for a 25 year period. This period precedes both the
220 model calibration period and the forecast period (Fig. 4). To maintain sea-
221 sonal fluctuations and the observed joint probability between H_s , T_p and θ ,
222 the time series is separated into monthly sections, providing 25 observations of
223 each month of the year. A bootstrapping procedure (Efron, 1979) is followed
224 to generate a 60-month time series (2.5 years). The forecast time series is built
225 as a sequence of a randomly selected January, followed by a randomly selected
226 February, etc., similar to the method used by Davidson et al. (2017). Using
227 this approach, 25^{60} possible sequences can be constructed. Climate fluctuations
228 such as El Nino and the North Atlantic Oscillation are neglected, meaning that
229 observed extreme months can occur in any year and after any other month. In
230 literature several more elegant, sophisticated but also more complex methods
231 are available to generate synthetic wave time series (e.g. Callaghan et al., 2008;
232 Antolínez et al., 2016; Jäger and Nápoles, 2017). Our forecast period is rela-
233 tively short and the average wave climate component for both the calibration
234 and the forecast period are comparable to the long term average. Indicating
235 that the wave climate behaves ergodic for the period of our interest, supporting
236 the approach followed.

237 *3.4. Quantification of model uncertainty*

238 The calibration uncertainty is estimated with GLUE (Beven and Binley,
 239 1992; Ruessink, 2005; Simmons et al., 2017) for the 2.5-year calibration period.
 240 GLUE was developed as a calibration method which, in contrast to traditional
 241 statistical inference, recognizes that the same result can be obtained with dif-
 242 ferent model settings and calls this ‘equifinality’. Equifinality is introduced
 243 because the model description of the real world is limited and thus contains
 244 errors of some extent. Therefore, a parameter set found by calibration can only
 245 be assumed to be a likely estimator. GLUE exploits this reasoning by search-
 246 ing within a large parameter space and appointing a non-zero likelihood to all
 247 parameter sets that have a prediction skill higher than a certain threshold.

248 The first step in GLUE is to decide on a likelihood measure and rejection
 249 criterion (Beven and Binley, 1992). In this study the Nash-Sutcliffe skill score
 250 (Nash and Sutcliffe, 1970) is used which divides the residual variance between
 251 model and observation by the variance in the observations as:

$$252 \quad NS = 1 - \frac{\sum_{i=1}^n (dV_i - dV'_i)^2}{\sum_{i=1}^n (dV_i - \bar{dV})^2} \quad (3)$$

253 in which dV and dV' are the observed and model predicted volume changes in
 254 between surveys, respectively, and n is the number of observations. NS is the
 255 skill score, a score of one represents a perfect model, whereas a negative score
 256 means that the mean square error (MSE) is larger than the observed variance.

257 In this paper all calibration parameters that result in a prediction with a
 258 score higher than zero are included, accepting predictions with a MSE equal or
 259 lower than the observed variance. Demanding a positive skill criterion guaran-
 260 tees that our model is behavioral, capturing the overall trend in the observations.

261 The second step is to decide which model parameters and input variables are
 262 considered uncertain. Here, we illustrate model uncertainty with the calibration
 263 parameter K .

264 The third step of the GLUE method is to decide on a prior distribution for

265 the uncertain parameter(s). In this case we choose a uniform distribution with
266 a wide range, $U(0 - 9.32)$, to minimize subjectivity of the procedure.

267 Finally, $M = 200$ equally spaced samples of K are drawn from the uniform
268 distribution and used to run the one-line model M times for the 2.5-year calibra-
269 tion period (Fig. 5, right side of blue dotted box), varying the K value for each
270 run while forcing the model with the observed waves of this period (orange line
271 in Fig. 4). The resulting posterior distribution of K will be a uniform distributed
272 PDF but with a reduced range. From this posterior distribution, $N = 12,000$
273 samples are drawn with a Monte Carlo procedure, and combined with the N
274 synthetic wave time series of 2.5 years to make a probabilistic forecast with the
275 one-line model.

276 Note that, by assuming K as the only stochastic variable and calibrating
277 to (uncorrected) field observations we do not limit ourselves to parameter un-
278 certainty only, but we include model inadequacies, numerical uncertainties and
279 observation errors in the posterior distribution of K .

280 3.5. Ranking Uncertainty Sources

281 The probabilistic procedure results in a distribution of predicted volume
282 change which varies in time. As a first step to achieve the objective of rank-
283 ing the relative contribution of both uncertainty sources, we perform a local
284 sensitivity analysis in which we compare the magnitude of the variance of the
285 volume change for the wave climate contribution or model uncertainty individ-
286 ually. That means that we pick two locations in the entire range of variables
287 K and w_{br} , the parameter space, at which we compare the variance of ΔV and
288 ΔV_{tot} . We do this for the points with maximum model skill ($Var(Y|K = 2.73)$)
289 and with an average wave climate contribution, $Var(Y|w_{br} = \bar{w}_{br})$ in which
290 $Y = (\Delta V, \Delta V_{tot})$.

291 The location with maximum model skill and average wave conditions is a
292 point of high interest in the parameter space, but conclusions based on this
293 local comparison are not necessarily true for the entire parameter space. With
294 a global sensitivity analysis (Saltelli et al., 2008) we quantify the fraction of

295 the variance that can be attributed to a certain input variable for each value
 296 in the parameter space. This is described by Sobols' indices which rank the
 297 contribution of model uncertainty and wave climate variability to the variance
 298 of total volume change. In contrast with a local sensitivity analysis, the global
 299 sensitivity analysis takes into account the complete range of the inputs, and
 300 attempts to apportion the output uncertainty to the uncertainty in the input
 301 factors (Jacques et al., 2006), and this can be done for every output time step.
 302 As a result the relative importance can be monitored over time.

303 The first order Sobol' indices describe the importance of each input variable
 304 ($X_i = (w_{br}, K)$) as the contribution of this variable to the total variance of
 305 output ΔV_{tot} , and can be calculated with:

$$306 \quad S_i = \frac{Var(E(\Delta V_{tot}|X_i))}{Var(\Delta V_{tot})} \quad (4)$$

307 $S_i = 1$ means that all the variance of output variable ΔV_{tot} can be attributed to
 308 input variable X_i , contrarily a $S_i = 0$ means that variability in input variable
 309 X_i does not translate to variance of ΔV_{tot} . Because our model (Eq. 2) is non-
 310 additive, i.e. is a product of two uncertain terms, both uncertainty sources also
 311 interact with each other. The interaction term, in case of two uncertain inputs,
 312 is given by:

$$313 \quad S_{12} = \frac{Var(E(\Delta V_{tot}|X_1, X_2))}{\Delta V_{tot}} - S_1 - S_2 \quad (5)$$

314 3.6. Probabilistic forecasts

315 Five sets of computations are examined, one calibration set and four differ-
 316 ent forecasts (Table 1). The calibration set is required to quantify the model
 317 uncertainty. The first forecast set includes the quantified distributions of both
 318 K and w_{br} . The second forecast includes only the distribution of w_{br} with fixed
 319 K as part of the local sensitivity analysis. Similarly, the third forecast includes
 320 only the distribution of K with fixed w_{br} . Finally, to examine the effect of a
 321 potential dependence between model uncertainty and wave climate variability
 322 on the total variance of our prediction, a set of computations is run in which K
 323 and w_{br} are correlated with $\rho = 0.5$, according to the findings and procedure of

Description	Calibration	Probabilistic Forecast	Wave climate component only	Model uncertainty only	Correlated Probabilistic Forecast
Run name		$w_{br} + K$	w_{br}	K	$w_{br} \& K$
Number of runs	400	12,000 ¹	12,000	12,000	12,000
Period	2012/12 - 2015/06	2015/06 - 2018/01	2015/06 - 2018/01	2015/06 - 2018/01	2015/06 - 2018/01
Wave conditions	Observed 2012/12 - 2015/06	Generated time series	Generated time series	$w_{br} = \bar{w}_{br}$	Generated time series
K	$U(0, 9.32)$	$U(2.18, 3.26)^2$	$K = 2.73^2$	$U(2.18, 3.26)^2$	$U(2.18, 3.26)^2$
Correlation ρ	0	0	0	0	0.5

Table 1: Model settings of different model runs.

324 Kroon et al. (2019). The marginal distributions of both variables remain equal
325 to the uncorrelated procedure, the only difference is that they are now partially
326 correlated. This means that in case the wave climate component is larger than
327 average in a sample, the probability of a K value larger than average increases.

328 4. Results

329 4.1. Uncertainty Quantification

330 As a first step of the probabilistic assessment, the uncertainty in the wave
331 climate component and the model uncertainty were quantified. The empirical
332 distribution of the wave climate component has a mean of $10 \text{ m}^2 \text{ s}^{1.5}$ and a stan-
333 dard deviation of $19 \text{ m}^2 \text{ s}^{1.5}$ and is highly asymmetrical with a large probability

¹For the global sensitivity analysis this number of runs is extended to 84,000.

²This distribution is the result of the uncertainty quantification procedure, presented in paragraph 4.1.

334 of lower than average wave climate components. The distribution of the wave
 335 climate component (w_{br}) of the generated wave time series perfectly resembles
 336 the empirical distribution of $w_{br,obs}$ of the 25 years of observed waves (Fig. 6).
 337 The PDF of all generated years (red dashed line) has no bias and deviates only
 338 locally (max. 4%) from the long term average observed distribution of w_{br} (black
 339 line). Not only the average generated series compare well to the observed series
 340 but also more energetic realizations of the wave climate. To exemplify this we
 341 compare observed and generated $w_{br,10}$ (green lines). In which $w_{br,10}$ is defined
 342 as the generated series or the (consecutive) 2.5-year observation period of which
 343 the average has 10% exceedence probability. Compared to the average values
 344 (black line), the generated time series with $w_{br,10}$ (green dashed line) has a lower
 345 probability of low values ($w_{br}/\bar{w}_{br} < 0.5$) and a higher probability of w_{br} values
 346 above average ($w_{br}/\bar{w}_{br} > 1$). This change in distribution is similar to the ob-
 347 served 2.5-year period (green line) with 10% exceedence. This realization of the
 348 wave climate with $w_{br,10}$ is also unbiased and deviations are local and limited
 349 to 20%. This means that our approach does not only represent the long-term
 350 average wave climate component well but also gives a realistic distribution of
 351 w_{br} for energetic realizations of the wave climate.

352 The model uncertainty has been quantified assessing the skill of the 400
 353 calibration computations with random $K \sim U(0 - 9.32)$. A comparison of the
 354 predicted and observed volume change between consecutive surveys (ΔV) for
 355 the calibration period indicates that the one-line model is able to predict the
 356 global observed trend, except for some outliers, Fig. 7. Next, based on the
 357 $NS > 0$ criterion, many of the prior calibration values are rejected, resulting in
 358 a significantly reduced posterior range of K to $U(2.18, 3.26)$, Fig. 8, while the
 359 maximum NS skill is found at $K = 2.73$. The range of K is reduced on both
 360 sides of the prior distribution, indicating that the range of the prior was chosen
 361 properly.

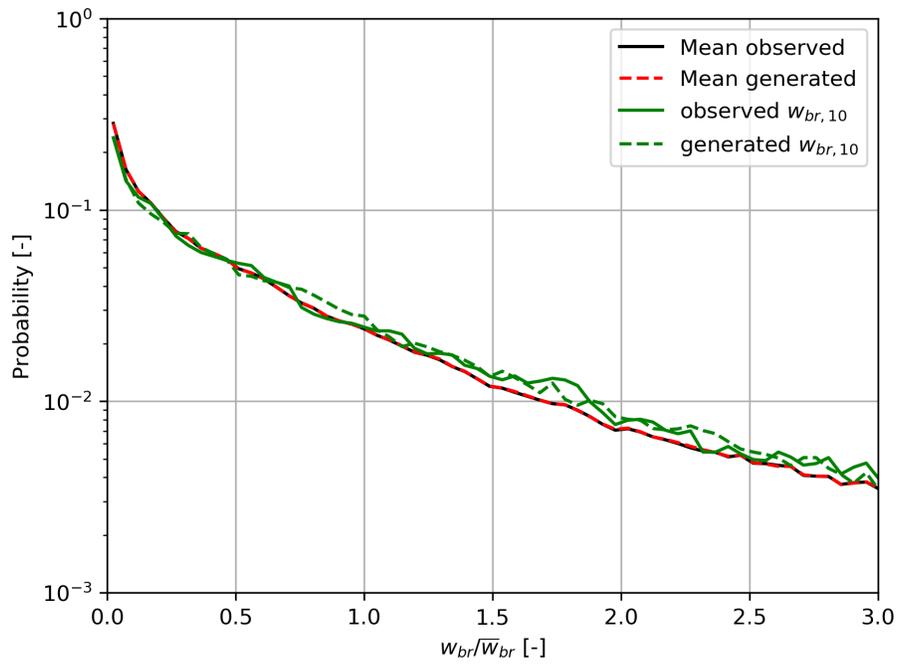


Figure 6: Probability density distribution of normalized wave climate component in Kamphuis formula. Observed (continuous lines) and generated (dashed lines) 2.5-year average (black/red) and 10% exceedence (green).

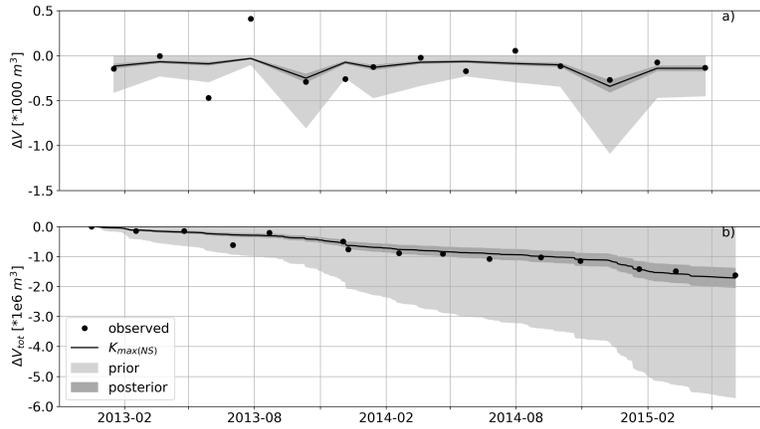


Figure 7: Volume change between consecutive surveys (a) and total volume change since June 2015 (b) for GLUE calibration procedure. The prior distribution (light grey area), the posterior distribution of all runs with $NS > 0$ (dark grey area), and the run with the highest skill score (black line) compared to observed volume change.

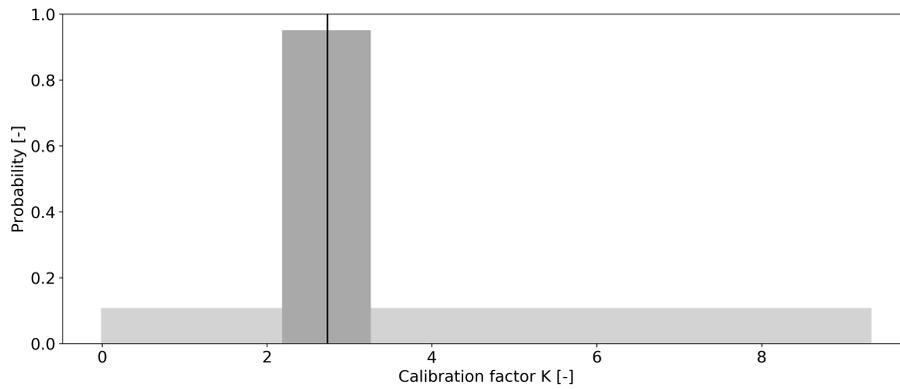


Figure 8: Probability density distribution of model calibration factor K , prior to the GLUE calibration procedure (light grey) and posterior (dark grey). The black line indicates $K = 2.73$, the value with the highest NS skill score.

362 *4.2. Uncertainty propagation*

363 This subsection presents the results of the probabilistic forecasts in which the
364 distributions of K and w_{br} , as derived in the previous section, are propagated
365 through the one-line model to come to a distribution of volume change. Four
366 different forecasts are examined (Table 1). Following the calibration of the
367 model, the adopted model settings are $K \sim U(2.18 - 2.36)$ and w_{br} similar to
368 the empirical distribution of $w_{br,obs}$.

369 The probabilistic forecast ($w_{br} + K$), predicts a loss of almost 1.000.000 m^3
370 in 2.5 years with a standard deviation of 15% (Fig. 9b). The observed volume
371 change between consecutive surveys shows a clear summer/winter pattern that
372 is reproduced by the probabilistic forecast (Fig. 9a). The width of the confi-
373 dence intervals, e.g. the distance between the 5% and the 95% percentile level
374 (Fig. 9a, light grey shade), is a measure for the variance of the distribution.
375 This forecasted variance is higher in winter than in summer. This is an effect of
376 the monthly bootstrapping procedure, which forces the model to have a smaller
377 variance in summer and a larger variance in winter, similar to the observed
378 wave climate. The model bias is negligible, but the variance is much lower than
379 observed. Only 50% of observations fall within the 90% confidence interval,
380 whereas this should be approximately 90%. Similarly only 8% of observed vol-
381 ume changes fall within the 50% confidence interval and no observations fall
382 within the 10% confidence interval (Table 2).

383 On the other hand, the total volume change is predicted very well by the
384 model (Fig. 9b). The model shows no bias in predicting the total volume change,
385 and the variance of the total volume change is more accurately represented.
386 Hence, 85% of the observations fall within the 90% confidence interval which
387 is very close to the expected 90%. Similarly, 70% and 15% of the observed
388 volume changes fall within the 50 and 10% confidence intervals, respectively
389 (Table 2). The total volume change and the corresponding confidence intervals
390 are predicted remarkably well considering the small number of observations.

391 Looking at the effects of K and w_{br} individually, we see that the conditional
392 variance of the volume change between consecutive surveys is significantly lower

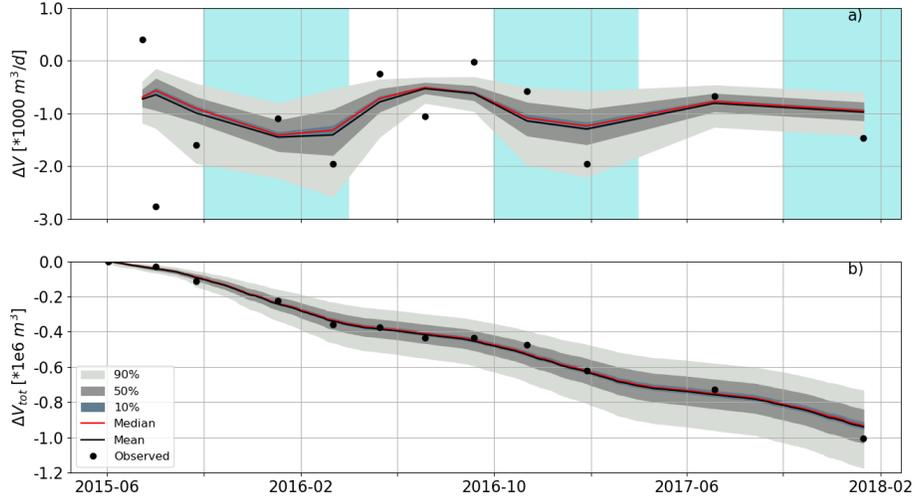


Figure 9: Predicted and observed volume change between consecutive surveys (a) and since June 2015 (b). The mean (red line), median (black line), and the 90, 50 and 10% confidence interval (light gray, dark gray and blue shaded areas) of the probabilistic forecasts are presented together with the observed volume change (black dots). Winter months October to April are indicated with the turquoise background.

393 when conditioned on the average wave climate component ($Var(\Delta V|w_{br} =$
394 $\bar{w}_{br})$), than conditioned on the model calibration parameter with the high-
395 est skill ($Var(\Delta V|K = 2.73)$) (Fig. 10b and f). However, the variance
396 of the total volume change conditioned on average wave climate component,
397 $V(\Delta V_{tot}|w_{br} = \bar{w}_{br})$, is increasing over time, whereas $V(\Delta V_{tot}|K = 2.73)$ in-
398 creases initially but becomes stable over time (Fig. 10d and h). As a result,
399 the variance of total volume change conditioned on $K = 2.73$ is, after 2.5 years
400 (Fig. 10d), approximately equal to the variance of the total volume change
401 conditioned on the average wave climate component (Fig. 10h), meaning that
402 the variance of total volume change is equally sensitive to both inputs at these
403 two locations in the parameter space.

404 Using Sobol's sensitivity index to quantify this change of relative importance
405 over time globally (Fig. 11), we see that the contribution of K to the total
406 variance of ΔV_{tot} is indeed only 20% at the start of the simulation. However,

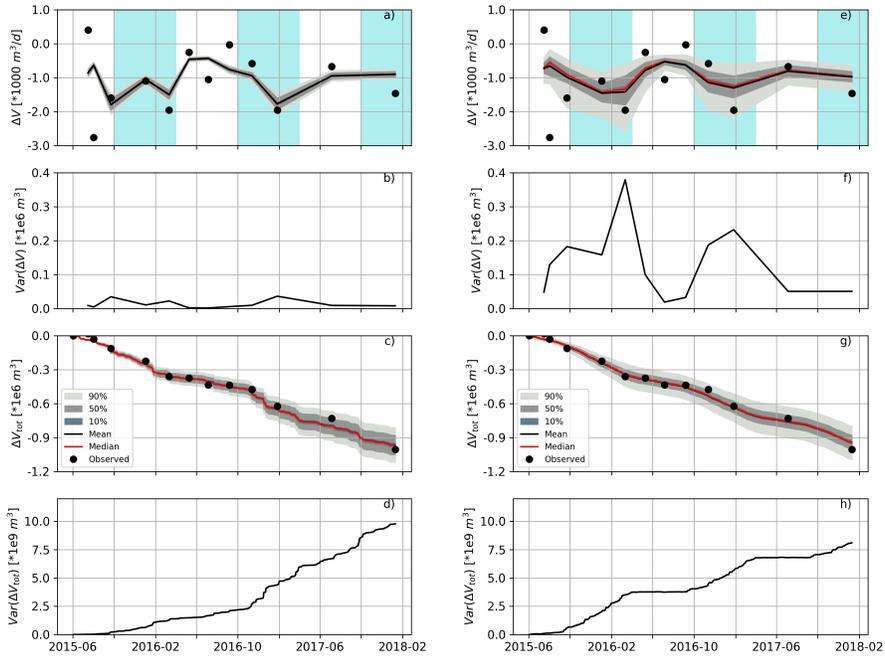


Figure 10: Comparison of predictions with model uncertainty (a-d) and wave climate variability (e-h) only . Predicted and observed volume change between consecutive surveys (a/e), variance of volume change between consecutive surveys (b/f), total volume change since June 2015 (c/g) and variance of total volume change (d/h) . The mean (red line), median (black line), and the 90, 50 and 10% confidence interval (light gray, dark gray and blue shaded areas) of the probabilistic forecasts are presented together with the observed volume change (black dots). Winter months October to April are indicated with the turquoise background.

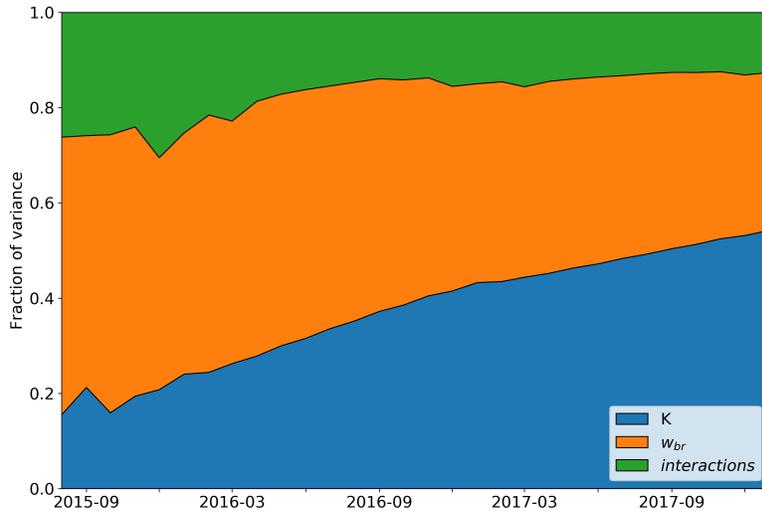


Figure 11: Fraction of the total variance of ΔV_{tot} , of model uncertainty K (blue), wave climate component w_{br} (orange) and interactions between both uncertainty sources (green).

407 by the end of the simulation this has increased significantly and amounts over
 408 50% of the total variance. w_{br} on the other hand constitutes 60% of the total
 409 variance at the start of the simulation but less than 40% after 2.5 years, due
 410 to the increasing contribution of model uncertainty to the total variance. In
 411 addition, both terms interact explaining another 15-20% of the variance. So, in
 412 the case of the sand engine, assessing the effect of wave climate variability only
 413 would give a significantly overconfident estimate which neglects more than half
 414 the variance.

415 Sobol's indices cannot be determined for correlated uncertainty sources.
 416 Therefore, the effect of a potential correlation between K and w_{br} is assessed
 417 by comparing the total variance of the uncorrelated runs (w_{br} and $w_{br} + K$)
 418 with the total variance as predicted by the correlated runs ($w_{br} \& K$). Positively
 419 correlated uncertainty sources increase the variance of both ΔV and ΔV_{tot} , Fig.
 420 12. Neglecting this correlation results in an additional underestimation of the

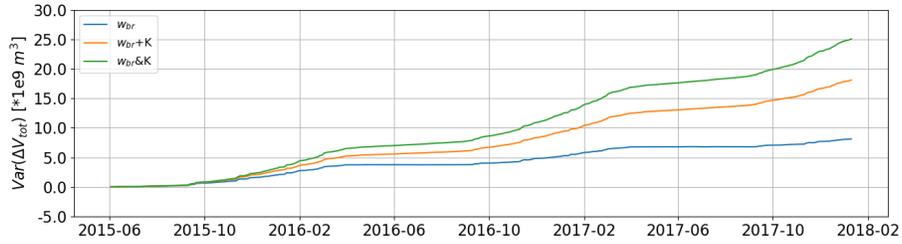


Figure 12: Variance of predicted volume change against time for ΔV (a) and ΔV_{tot} (b).

Confidence interval	ΔV	ΔV_{tot}
90 %	0.50	0.85
50 %	0.08	0.69
10 %	0.0	0.15

Table 2: Fraction of points within confidence interval.

421 variance by 40% after 2.5 years. So, not attributing for model uncertainty would
 422 at least underestimate the variance by 50% in a 2.5-year forecast, but in case of
 423 a positive correlation this will be significantly more.

424 5. Discussion

425 The probabilistic predictions show that the uncertainty in the volume change
 426 at the sand engine nourishment is considerable. We expect a loss of almost
 427 1.000.000 m^3 in 2.5 years with a standard deviation of 15% when including both
 428 wave climate variability and model uncertainty. Model uncertainty explains
 429 over 50% of the total variance after 2.5 years. These results stress that, for
 430 the assessment of large scale nourishments it is not only important to look at
 431 variations in wave forcing but also to account for uncertainty in the model(s)
 432 used. This conclusion is based on an assessment of a large scale nourishment,
 433 yet it is likely that these results are applicable to any sandy solution in the
 434 coastal zone.

435 Evidently, not in all cases the contribution of model uncertainty will be over
 436 50%. For instance, using a more sophisticated model or applying a sandy so-

437 lution in an environment with a very high variation in wave conditions could
438 reduce the relative importance of model uncertainty. Likewise, predicting a
439 more event driven parameter or process, such as depth of closure, storm re-
440 treat or spit breaching, could increase the relative importance of wave climate
441 variability. Also, after the design has been made and a sandy solution has been
442 implemented, the relative importance of model uncertainty in the prediction can
443 in theory be reduced by updating the model uncertainty with new observations
444 once they come available (Vitousek et al., 2017).

445 Contrarily, the relative importance of model uncertainty will likely increase
446 for smaller nourishments with a less pronounced signal, or in environments with
447 a very narrow distribution in wave forcing (e.g. swell dominated environment).
448 Thus, it is unlikely that in any case model uncertainty (beyond a monthly time
449 scale) can be considered negligible beforehand, without further analysis.

450 Looking at a slightly longer time scale, the decreasing relative importance of
451 wave climate variability justifies the established use of wave climate reduction in
452 morphological modeling (e.g. Benedet et al., 2016). This is also in line with the
453 findings of Luijendijk et al. (2019), who show that simulations with a reduced
454 wave climate and with brute force time series give a similar prediction of bulk
455 morphometrics such as total volume change after 5 years at the sand engine.

456 If we extend the time horizon further, other factors, such as sea level rise,
457 can become important contributors to uncertainty. Le Cozannet et al. (2019)
458 use a global sensitivity analysis to show that coastline recession is initially dom-
459 inated by seasonal, inter-annual and decadal variations, but that the relative
460 importance of model uncertainty increases quickly. Variations in sea level rise
461 scenarios only start to gain importance after half a decade. Although assessing
462 morphological effects of sea level rise, their conclusion is alike: model uncer-
463 tainty cannot be neglected.

464 Callaghan et al. (2013) predict beach erosion, a more event driven process,
465 with three different models. The envelope of their multi-model ensemble, is
466 70-150 % wider than the 95% confidence interval of each model individually.
467 Therewith indicating that in their case, model uncertainties contribute signifi-

468 cantly to the prediction uncertainty. For comparison, the 95% confidence inter-
469 val width of our prediction increases with 70% if we include model uncertainty
470 in the analysis.

471 The underestimation of the observed variance of monthly volume changes
472 (e.g. Fig. 9a) indicates that residual uncertainty remains. Our application of
473 the GLUE method with one free variable, focused on deriving a realistic estimate
474 of model uncertainty, but one can possibly give an improved representation
475 of the observed variance and exploit the full strength of GLUE by assuming
476 more variables to be stochastic. This could be done within the model (e.g.
477 the powers in the Kamphuis formula or the median grain size) but also by
478 including observation uncertainty or adding more processes in the model. So,
479 a straightforward next step is to differentiate between observation and model
480 uncertainty and applying a more advanced model.

481 In this article, we concentrated on determining the importance of intrinsic
482 versus epistemic uncertainty by distinguishing between wave climate variability
483 and model uncertainty. We found that assessing wave climate uncertainty only,
484 can result in significantly overconfident predictions. Still, in our analysis resid-
485 ual intrinsic and epistemic uncertainty remains, meaning that we might still
486 present an overconfident prediction. Nevertheless, these results clearly show
487 how important it is to be aware of the uncertainties in our models and to be
488 cautious with presenting (un)confidence intervals.

489 **6. Conclusion**

490 This paper includes both intrinsic and epistemic uncertainty in a probabilis-
491 tic framework, to investigate the relative importance of these uncertainties in
492 the evolution of a sandy solution. To this end, we assess a large scale nourish-
493 ment case with a one-line model in a probabilistic framework. In this framework,
494 transport and volume loss are considered to be a function of random wave forc-
495 ing (intrinsic uncertainty) and calibration settings (epistemic uncertainty). The
496 variance of both stochastic variables are based on observations using the Sand

497 Engine nourishment.

498 We show that confidence interval width and variance of predicted volume loss
499 increase when allowing for model uncertainty. The confidence interval width and
500 variance increase further (40%) if we not only recognize uncertainty in our model
501 but also include a correlation (of $\rho = 0.5$) between model parameter settings and
502 wave forcing. For the Sand Engine nourishment examined here, the contribution
503 of model uncertainty to the variance of total volume loss is of the same order
504 of magnitude as the contribution of wave climate variability after a 2.5-year
505 simulation period, indicating that accounting for wave climate variability only
506 will produce significant overconfidence in the results. Nevertheless, on a monthly
507 time scale the fraction of variance attributed to wave climate variability is three
508 times larger than that of model uncertainty, thus reducing the importance of
509 model uncertainty in predicting initial nourishment development.

510 For multi-year time scales, model uncertainty will become the dominant con-
511 tribution: more wave energy in one year is compensated by less wave energy
512 in another, whereas model uncertainty is a cumulative effect that grows with
513 each time step. Naturally, the relative importance of model uncertainty over
514 wave climate variability depends on the complexity and skill of the model. In
515 general, probabilistic frameworks rely on less complex models to reduce com-
516 putation time, thereby possibly increasing the relevance of model uncertainty
517 assessment within the framework.

518 These findings imply that for coastal modelling purposes a dual approach
519 should be considered, evaluating both epistemic and intrinsic uncertainties. Es-
520 pecially when forecasting large scale projects, with simplified models on a multi-
521 year time scale, the uncertainty in model settings may be the principal source
522 of uncertainty.

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