INPUT REDUCTION FOR LONG-TERM MORPHODYNAMIC SIMULATIONS

Dirk-Jan Walstra[1,2], Gerben Ruessink[3], Roderik Hoekstra[1], Pieter Koen Tonnon[1]

Abstract

Input reduction is imperative to long-term (> years) morphodynamic simulations to avoid excessive computation times. Here, we discuss the input-reduction framework for wave-dominated coastal settings introduced by Walstra et al. (2013). The framework comprised 4 steps, viz. (1) the selection of the duration of the original (full) time series of wave forcing, (2) the selection of the representative wave conditions, (3) the sequencing of these conditions, and (4) the time span after which the sequence is repeated. In step (2), the chronology of the original series is retained, while that is no longer the case in steps (3) and (4). The framework was applied to two different sites (Noordwijk, Netherlands and Hasaki, Japan) with multiple nearshore sandbars but contrasting long-term offshore-directed behavior: at Noordwijk the offshore migration is gradual and not coupled to individual storms, while at Hasaki the offshore migration is more episodic, and wave chronology appears to control long-term evolution. The performance of the model with reduced wave climates was referenced to a simulation with the actual (full) wave-forcing series. It was demonstrated that input reduction can dramatically affect long-term predictions, even to such an extent that the main characteristics of the offshore bar cycle are no longer reproduced. This was particularly the case at Hasaki, where all synthetic series that no longer capture the initial chronology (steps 3 and 4) lead to rather unrealistic long-term simulations. At Noordwijk, synthetic series can result in realistic behavior, provided that the time span after which the sequence is repeated is not too large; the reduction of this time span has the same positive effect on the simulation as increasing the number of selected conditions in step 2. It was further demonstrated that, although storms result in the largest morphological change, conditions with low to intermediate wave energy must be retained to obtain realistic long-term sandbar behavior. The input-reduction framework must be applied in an iterative fashion as to obtain a reduced wave climate that simulates long-term sandbar sufficiently accurately within an acceptable computation time. Given its potential huge impact on the actual simulation, we believe it is imperative to consider input reduction as an intrinsic part of model set-up, calibration and validation.

Key words: input reduction; morphodynamic modeling; process based modeling; cyclic bar behavior; Unibest-TC; morphodynamic upscaling

1. Introduction

Over the last decades process-based models have shown the capability to predict realistic evolution of coastal morphology in applications covering time scales ranging from years (e.g. Jones et al., 2007; Elias et al., 2006; Brown and Davies, 2009; Ruggiero et al., 2009; Tung et al., 2012; Walstra et al., 2012), decades (e.g. Lesser, 2009; Hibma et al., 2005) to centuries and even millenia (e.g. van der Wegen and Roelvink, 2008; Dastgheib et al., 2008). In such models morphology evolves because of the feedback between the hydrodynamics (waves and currents), sediment transport and the morphology itself. Most of these studies have considered a limited number of forcing conditions to avoid excessive computation times. The influence of the adopted input reduction method (i.e. derivation of a reduced set of representative conditions that accurately approximates the long-term morphological evolution, De Vriend et al., 1993) was usually not addressed. Input reduction tends to be based on the representation of a specific target such as the annual transports along a coast or through an inlet (e.g. Van Duin et al., 2004; Lesser, 2009), or on

[1]Deltares, Hydraulic Engineering, PO Box 177, 2600 MH, Delft, The Netherlands. Phone: + 31 (0)883358287, fax: +31 (0)883358582, email: DirkJan.Walstra@Deltares.nl, Roderik.Hoekstra@Deltares.nl, PieterKoen.Tonnon@Deltares.nl.

[2]Delft University of Technology, Faculty of Civil Engineering and Geosciences, Delft, The Netherlands.

[3]Utrecht University, Institute for Marine and Atmospheric Research, Department of Physical Geography, PO box 80115, 3508 TC Utrecht, The Netherlands, email: B.G.Ruessink@uu.nl.

the direct simplification of forcing times series whilst maintaining its relevant statistical properties (e.g. Southgate, 1995; Chesher and Miles, 1990; Brown and Davies, 2009). Clearly, any input reduction involves a number of choices, but their effect on the predicted morphological evolution is often not considered.

The ultimate evaluation of an applied input reduction method should be based on a comparison of the long-term predicted morphology using the reduced and the full set of conditions. Southgate (1995) was among the first to systematically study the effect of modified forcing by systematically varying the wave forcing time series in process-based profile model simulations covering a four month period, in this way focusing on wave chronology effects. Interestingly, he found that the order in which sequences with high waves were incorporated in the time series did not significantly affect the model predictions; whether this was also the case in a reduced wave climate was not investigated. Based on medium-term brute forcing simulations (i.e. simulations forced with measured time series) for an inlet system covering 5 years with various reduced wave and tidal climates, Lesser (2009) concluded that wave-climate reduction was the largest source of error. Curiously, Lesser (2009) found a cruder wave climate (i.e. based on less wave conditions) to yield the best results (i.e. closest to brute forcing prediction). Although Lesser’s (2009) study covered multiple years, the considered 5-year length was relatively short given the cycle duration inherent to such inlets of typically several decades to centuries. Input reduction aiming to reproduce coastal morphology on time scales similar to an inherent (quasi)-cyclic variation has not yet been performed and was the topic of Walstra et al. (2013).

This paper summarizes Walstra et al. (2013) in which the influence of input reduction on the wave-driven morphological evolution of nearshore sandbars on the time scale of years, i.e. on the time scale of their quasi-cyclic offshore-directed behavior was investigated. For this Walstra et al (2013) utilized the process-based cross-shore model Unibest-TC (Ruessink et al., 2007) on two sites (Noordwijk, The Netherlands and Hasaki, Japan) for which calibrated long-term brute force models are available (Walstra et al., 2012; Pape et al., 2010) that can act as a reference to evaluate the predictions using reduced wave forcing was utilized. We start off by introducing the input reduction framework (Section 2). The framework is then applied to both sites to evaluate the impact of the input reduction derived from morphological predictions generated by a range of reduced wave climates (Section 3). Section 4 discusses the results and the implications for long-term modeling. Finally, conclusions can be found in Section 5.

2. Approach to input reduction

2.1. *Concepts of Input reduction and implications for long-term modeling*

Two basic choices are available to derive the reduced set of forcing conditions that enable deterministic long-term predictions. The first option is to reconstruct (or aggregate) time series of measured wave forcing with a limited number of representative conditions to maintain the same pattern of wave chronology (e.g. Brown and Davies, 2009). The second option becomes available if wave chronology can be ignored, implying the selected representative conditions can be combined in ascending, descending or arbitrary order into a synthetic time series (e.g. Van Duin et al., 2004, Grunnet et al., 2004, 2005).

Besides chronology effects, the choice between reconstructed or synthetic time series is also governed by the morphological modeling approach. Brown and Davies (2009) utilized a model that simulates the morphology directly from the divergence in sediment transports originating from the hydrodynamic forcing. However, to increase the computational efficiency, a number of techniques have been developed which accelerate or upscale the morphology (Roelvink, 2006). The so-called “online” or “MorFac”-approach (Lesser et al., 2004 and Ranasinghe et al., 2011) is now one of the most commonly applied methods (e.g. Geleynse et al., 2010, 2011; Edmonds and Slingerland, 2010; van der Wegen and Roelvink, 2008; Dastgheib et al., 2008; Jones et al., 2007). This method directly scales the calculated depth change by a constant (MF) factor, so that after a simulation over a hydrodynamic period T we have in fact modeled the morphological changes over MF*T. Here we also use the MorFac-concept to illustrate the implications input reduction may have on the morphodynamic modeling approach.

Reconstructed time series are appropriate for simulations using a constant MF-value; however, the maximum allowable MF is typically governed by the high-energy events in the time series (Jones et al., 2007), as these induce the largest morphological response. For storm conditions, MF is typically set to 10-20, but for moderate conditions MF can be O(100) without affecting the quality of the predictions (Ranasinghe et al., 2011). Because moderate and low conditions occupy the majority of time, the application of a varying MF significantly reduces the computational time. However, the transition between conditions with a different MF requires the settling of all suspended sediment to the bed prior to the activation of the next condition followed by a spin-up to let the hydrodynamics (and sediment transports) re-adjust to the next condition before bed-updating can be re-activated in order to avoid mass balance errors. Therefore, a straightforward application of reconstructed time series with varying MF is typically less efficient than the application of a constant MF.

Synthetic time series do not require the selected conditions to be split up into short duration events. This can significantly reduce the number of transitions between conditions (NoT), therefore making synthetic time series more appropriate for varying MF applications. Application of synthetic time series (with reduced NoT) combined with varying MF has the potential to significantly increase the computational efficiency (typically, a varying MF -combined with a synthetic time series- reduces the computation time by at least a factor 2 compared to synthetic forcing with constant MF).

2.2. *Framework for input reduction*

Input reduction essentially aims at selecting a limited number of conditions with which the morphological prediction obtained with the original time series is accurately reproduced (de Vriend et al., 1993). Therefore, it is not the aim to reproduce or maintain the statistical properties of the full wave climate since an accurate reproduction of the coastal morphology is the primary objective. In Walstra et al. (2013) a framework is introduced in which all the issues related to input reduction are addressed in a number of analysis steps:

1. Selection of the input reduction period,
2. Selection of the representative wave conditions,
3. Sequencing of the selected conditions,
4. Determine the wave climate duration.

For reconstructed time series only steps 1 and 2 are relevant (e.g. sufficient for constant *MF* applications); all four steps need to be applied for synthetic time series (required for varying *MF* applications). The steps are briefly explained below, for all details is referred to Walstra et al. (2013).

Step 1. Selection of the reduction period.

The reduction period is defined as the length of the measured brute forcing time series that is used to reduce the input. The upper limit of the reduction period, T_R, is primarily governed by the time scales related to the inherent morphological (quasi)-cyclic variation. The annual time scale is typically the lower limit to ensure that the seasonal variations in the wave climate are included. In general T_R should be multiples of one year to avoid seasonal bias.

Step 2. Selection of the representative wave conditions.

The selection of the representative wave conditions is usually based on a weighted average of the frequency of occurrence aggregated over the observed wave conditions. The wave period can also be related to the wave height (if a strong correlation exists) to reduce the number of independent parameters (Roelvink and Reniers, 2011). The representative conditions are determined by grouping the observed wave conditions (i = 1, 2, .., n) enclosed by the bin boundaries (e.g. $F_{rep,j}$ is based on all wave conditions within each bin j, indicated by the squares in Fig. 1b). The representative wave condition $F_{rep,j}$ is weighted with the cumulative frequency of occurrence, $f_{rep,j} = \sum_{i=1}^{n} f_i$.

To account for non-linear effects (i.e. the non-linear dependence of sediment transport on wave height), the representative root-mean-square wave height, H_{rms}, conditions can also by including a power or incorporating a sediment transport formula (see e.g. Roelvink and Reniers, 2011).

Both equidistant (i.e. constant bin-size) and non-equidistant binning (varying bin-size) of the wave conditions were considered. In the non-equidistant binning method, bin sizes are chosen such that weights of the representative conditions are approximately similar (Benedet et al., 2013).

The difference between equidistant and non-equidistant binning is illustrated in Fig. 1. Equidistant binning, in Fig. 1b with intervals of 1 m and 30º for H_{rms} and θ (the offshore incident wave angle with respect to the shore-normal), respectively, results in non-equal representative weights $f_{rep,j}$ (indicated by the colors of the bins). By varying the bin sizes such that the representative weights are approximately equal (notice the more evenly distributed weighting colors in Fig. 1c compared to Fig. 1b), small bin sizes result for levels where wave conditions are frequent (and vice versa). Notice, furthermore, that the representative wave conditions (indicated by the red circles) are not in the bin centers as the wave selected wave conditions are not evenly distributed over the bins. The reconstructed time series are rebuilt observed time series in which each observation is converted to the representative condition of the bin that it falls within.

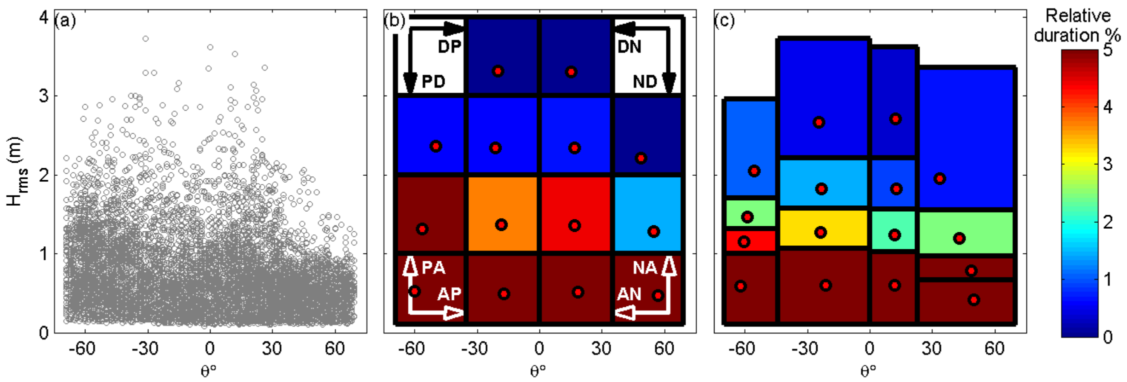

Figure 1. Comparison of (b) equidistant and (c) non-equidistant binning based on (a) the measured conditions; colors indicate the relative duration; red circles represent the representative wave conditions (source: Walstra et al., 2013).

Step 3. Sequencing of the selected conditions.

As the morphological response to time-varying forcing is usually non-linear, the sequence in which the wave conditions are imposed potentially influences or may even dominate long-term predictions. In the case of synthetic time series it is therefore essential to investigate to what extent wave chronology influences the long-term morphological evolution. This is also related to step 1 as chronology effects smaller than the reduction period are destroyed in synthetic time series (e.g. seasonal fluctuations are removed in synthetic time series based on T_R=1 yr). Therefore, a range of predictions resulting from synthetic time series with different sequencing options are evaluated in Section 3. To that end, a reduced wave climate resulting from step 2 is systematically and randomly sequenced into a number of synthetic forcing time series. The systematically sequenced time series are constructed by arranging the representative wave conditions in ascending or descending H_{rms} and arranging θ in positive or negative directions. This results in 8 possible combinations (schematically shown in Fig. 1b), the wave height sequence is indicated by A (ascending) and D (descending) whereas the wave direction sequence is indicated by P (positive direction) and N (negative direction). For example wave sequence DP implies that first the wave heights are sequenced by starting at the top row and than ordering θ within this row from left to right, whereas for wave sequence PD the conditions are sequenced by starting at the left column and subsequently ordering H_{rms} within this column from top to bottom. Furthermore, five randomly sequenced time series are considered in Section 3.

Step 4. Determine the wave climate duration.

The wave climate duration, T_{wc}, is defined as the length of the synthetic time series containing all the selected conditions. As was highlighted in Section 2.1, the computational efficiency increases significantly if the synthetic time series can be lengthened and coupled to increased *MF* as this reduces *NoT*. However, T_{wc} can affect the morphological prediction as the morphological response depends on both the magnitude and the duration of the forcing. For example, increasing T_{wc} could result in an over-estimated storm response for infrequent storm events (or vice versa). Conceptually, this imposes both upper and lower limits to T_{wc}. An indication of the lower limit is estimated by applying the randomized time series approach (Southgate, 1995). It is determined by evaluating morphodynamic simulations forced with time series in which the observed conditions are randomly re-arranged. These random time series are generated by splitting the observed time series into a number of segments of constant length, and randomly re-ordering these segments. T_{wc} is compared to the segment length by considering the condition with the lowest frequency of occurrence of the reduced wave climate: $f_{rep,\min} * T_{wc}$ The lower limit of T_{wc} is based on the shortest segment length for which still an acceptable prediction (skill) results. The upper limit of T_{wc} is iteratively established by evaluating the morphological predictions resulting from synthetic time series composed with a range of T_{wc} (i.e. evaluation of multiple synthetic time series in which N_R is varied).

Conceptually, a limited reduction in the number of wave conditions (step 2) makes the sequencing of the conditions (step 3) less critical and vice versa and also affects the optimal climate duration (step 4). Because cyclic morphodynamic sandbar behavior is governed by the interplay between episodic storms and prolonged calm periods (e.g. Walstra et al., 2012), it is essential that a reduced wave climate preserves the associated response mechanisms. It is especially challenging to preserve the storm response in a reduced wave climate due to its intermittent character. Above considerations and the non-linear response of the coastal morphology to the magnitude and duration of the forcing are of major importance in all input reduction steps and therefore inhibit a straightforward step by step application of the input reduction framework. Instead, it is envisaged that the input reduction steps should be repeated a number of times to establish an optimal wave climate. The optimal wave climate implies a minimization of *NoT* which is determined by the number of conditions (*NoC*) from step 2 and T_{wc} (identified by N_R, the number of times the sequence is repeated) from step 4 as

$$NoT = NoC * N_R - 1. \tag{1}$$

To evaluate the effect of input reduction the resulting model predictions (z_{red}) were compared with the reduced wave forcing to the model prediction based on the brute forcing time series (z_{full}). Following Lesser (2009) and Ranasinghe et al. (2011) the performance of the reduced set of wave conditions was defined by using a cumulative skill score *R* (Ruessink et al., 2007). An *R* of 1 implies a perfect match in predicted morphological evolution between the reduced and full set of wave conditions. An *R* less than 1 indicates a difference between both simulations.

2.3. *Test cases*

The input reduction framework was applied on two sites (Noordwijk, The Netherlands and the Hasaki Oceanographic Research Station (HORS), Japan) for which calibrated long-term brute force predictions were available (Walstra et al., 2012; Pape et al., 2010) that act as a reference to evaluate $z_{red}(x,t)$ found by the reduced wave climates. In both studies the calibrated model predictions compared favorably to the observed morphological evolution. To enable a consistent comparison the same model (Unibest-TC, Ruessink et al., 2007) as in the brute force predictions using identical model settings without morphodynamic upscaling (i.e. *MF* = 1) was applied. The brute forcing for Noordwijk contains 3 hourly observations for wave height, period and direction, whereas for Hasaki daily observations of wave height and period were available. However, no wave direction was measured at Hasaki; therefore Pape et al. (2010) used a constant direction of 30º relative to the coast normal which was also applied in the present study in both the brute forcing and the reduced wave climates.

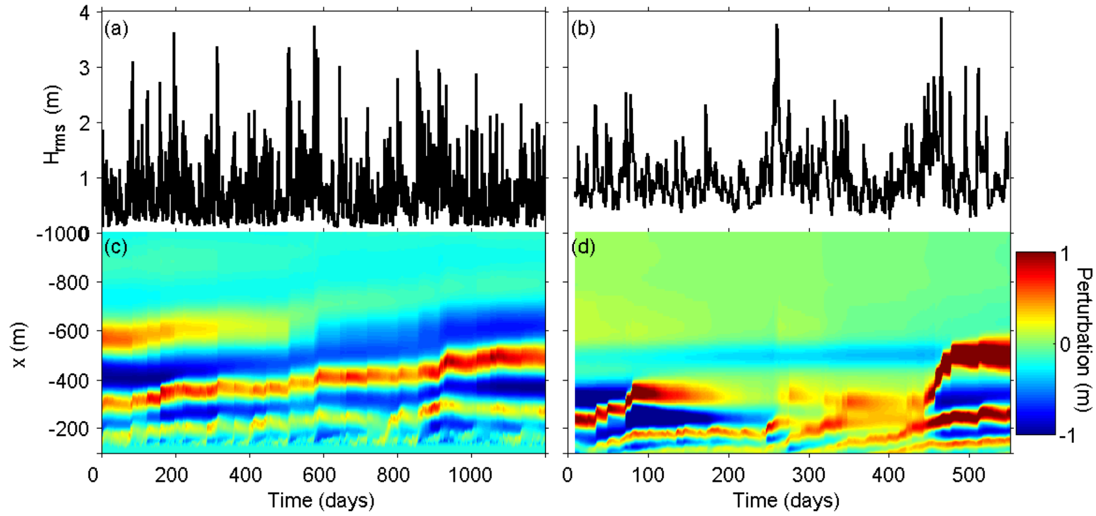

Figure 2. Time series of (a,b) offshore root-mean-square wave height H_{rms} and (c,d) time stacks of brute forcing based predictions of the profile perturbations (i.e. deviations from the time mean profile) at Noordwijk (left) and Hasaki (right). In (c,d) warm colors correspond to sandbars, cold colors to troughs (source: Walstra et al., 2013).

Both Noordwijk and Hasaki are characterized by a double sandbar system that propagates offshore on the time scale of years (Wijnberg and Terwindt, 1995; Kuriyama et al., 2008). At Noordwijk the cycle from bar inception in the swash zone to bar decay in the outer surf zone region takes about 3 - 4 years (Figures 2a,c). There appears to be no direct link between specific wave events and the bar cycle duration, see also Ruessink et al. (2009). Storms cause a noticeable offshore migration, but the magnitude of the response is small relative to the width of the barred part of the cross-shore profile. The bars at Hasaki exhibit similar behavior, but with a cycle period in the range of 1 to 4 years it is substantially more variable than at Noordwijk (Figures 2b,d). This is primarily caused by the fact that outer-bar decay (i.e. the end of a cycle) usually sets in after a storm event (Kuriyama et al., 2008; Pape et al., 2010). From Figures 2b,d it can be seen that two distinct bar cycles were present in the considered period. After about 200 days the initial outer-bar decayed followed by a period of about 250 days during which a new bar developed whilst gradually moving offshore. After 450 days a stormy period caused the outer bar to migrate beyond the location where the previous bar decayed. Following Ruessink et al. (2009), bar dynamics at Hasaki was classified as episodic net offshore migration (NOM) and the Noordwijk bar dynamics as inter-annual NOM. The contrasting sensitivity to individual wave events and hence chronology was the main motivation to include both sites in Walstra et al. (2013).

3. Application

3.1. *Steps 1 and 2 (reduction period and selection of wave conditions)*

Based on the observed cycle periods ~4 years at Noordwijk and ~1.5 years at Hasaki were used as the reduction periods. This corresponds to the length of the time series in the brute force simulations for both sites.

For Noordwijk, representative H_{rms}, T_p and θ were determined by considering equidistant bins for all combinations of 2, 4, 8 and 16 H_{rms}-bins (respectively ΔH_{rms} = 2, 1, 0.5 and 0.25 m) with 2, 4, 7 and 14 θ-bins (respectively Δθ= 70°, 35°, 20° and 10°). Two non-equidistant wave climates were also evaluated: 4 and 8 H_{rms}-bins combined with 4 non-equidistant θ-bins. All the reduced wave climates were subsequently converted to reconstructed time series. Correlating the reconstructed and observed H_{rms}, T_p and θ time series showed that ΔH_{rms}=2.0 m resulted in a significantly reduced correlation, r, compared to ΔH_{rms}=1.0 m. For θ, r seemed to be fairly insensitive to bin size. The non-equidistant binning resulted in a comparable r

for both 4 and 8 H_{rms}-bins.

Above certain bin size thresholds the model performance appeared to be rather insensitive to the chosen bin sizes. The skill R was high for all combinations of $\Delta H_{rms} \leq 1$ m and $\Delta\theta \leq 35°$. For $\Delta H_{rms}=2.0$ m the final profile did not contain any bars and the inter-tidal area had accreted unrealistically. While $\Delta H_{rms}=0.25$ and 0.5 m resulted in near perfect agreement with the reference run ($R=0.99$), $\Delta H_{rms}=1.0$ m maintained the bars, but slightly underestimated offshore bar migration ($R=0.92$). Varying $\Delta\theta$ hardly influenced the predictions for $\Delta\theta \leq 35°$, but with $\Delta\theta=70°$ the outer bar migrated too far offshore. The temporal evolution of the R-values revealed that the model performance was high throughout the simulation period for $\Delta H_{rms}<1$m. The largest bin size ($\Delta H_{rms}=2$ m and $\Delta\theta=70°$) had considerably lower R throughout the simulation. For $\Delta H_{rms}=2$ m and $\Delta\theta=70°$ R was low irrespective of the bin size for $\Delta\theta$ and ΔH_{rms}, respectively. Non-equidistant binning only improved R for 4 H_{rms}-bins, while for 8 H_{rms}-bins R was high for both types of binning.

For Hasaki 4 and 8 H_{rms} equidistant and non-equidistant bins were considered, respectively. The correlation between the reconstructed H_{rms} time series and the observations was approximately similar to Noordwijk. On the whole, R for Hasaki was lower compared to Noordwijk. With all reconstructed time series the model underestimated the offshore bar migration after 420 days (Fig. 2d) causing the overall low R.

3.2. *Steps 3 and 4: sequencing and duration of the reduced wave climate*

The construction of a synthetic time series is governed by the sequence in which the conditions (step 3) are imposed as well as by the duration of the wave climate (step 4). In this section both steps are jointly investigated for a number of the reduced wave climates derived in step 2 for Noordwijk and Hasaki.

First, the randomized waves approach (Southgate, 1995) to establish the lower limit of T_{wc} was applied. This involves the application of re-ordered time series which are generated by splitting up the observed time series into segments of constant length and than randomly re-ordering these segments. For Noordwijk, time series based on segment lengths of 3 hrs, 12 hrs, 1, 2, 7, 28 and 92 days were considered. For Hasaki the segment lengths of 1 day and larger were applied due to the 1-day resolution of the observations. For each segment length 5 randomly sequenced time series are imposed on the model. The lower limit of T_{wc} was therefore defined as the minimum segment length at which the model outcomes become insensitive and are in good agreement with the brute force simulations.

For Noordwijk the model predictions for 3-hour segments length all deviated from the reference run results (Fig. 3). In contrast, model predictions resulting from the 28 days segment length in general agreed well with the reference run. On the whole, a segment length of 12 hours caused the predictions to agree fairly well with the reference run ($R>0.8$, see Fig. 3); model performance was found to be relatively insensitive to longer segment lengths. For Hasaki the performance of the considered segment lengths was comparable but with a considerable scatter (Fig. 3). Compared to Noordwijk, the overall performance was significantly lower for all segment lengths. The most detailed considered representative wave climates result in lower limits for T_{wc} of about 10 to 20 days (assuming the minimum segment lengths of 12 hrs and 1 day equals $f_{rep,\min} * T_{wc}$, for Noordwijk and Hasaki respectively).

Conceptually, the model performance using reconstructed time series constitutes the best possible performance given a reduced set of input conditions and therefore acts as the upper performance limit for synthetic time series. The randomized time series approach therefore acts as an indicator to what extent synthetic time series are an appropriate way to simulate long-term profile evolution (tested in the next section). Consequently, an accurate reproduction of the brute forcing prediction based on synthetic time series may be achievable for Noordwijk, while this is unlikely for Hasaki. In stead, for the latter focus could be on more aggregated bar cycle characteristics such as averaged cycle period and the transient bar amplitude response which are still predicted using the randomized time series; therefore, the efficacy of synthetic time series was also considered for Hasaki.

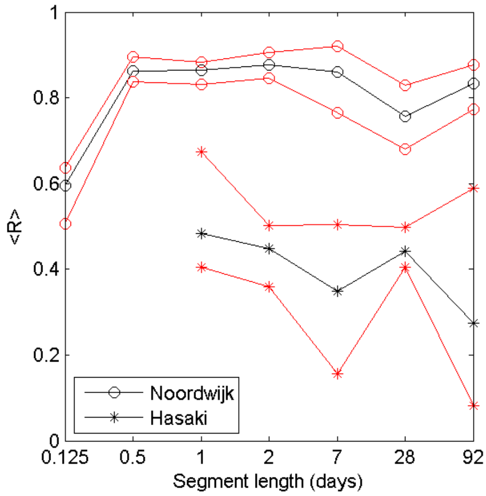

Figure 3. Skill *R* (black) averaged over the 5 random simulations as a function of the segment length, red lines are the maximum and minimum *R* (source: Walstra et al., 2013).

The Noordwijk case was used to jointly investigate the influence of sequencing and varying T_{wc} for the $8x4_{EQ}$ wave climate (i.e wave climate resulting from equidistant binning of the observed H_{rms} and θ into 8 and 4 bins, respectively). To that end, the model performance for six wave climate durations (T_{wc} =1205, 603, 402, 301, 241, 114 days which implies the conditions in the reduced wave climate are repeated 1, 2, 3, 4, 5 and 9 times, respectively) combined with all the sequencing options is summarized in Fig. 1. Interestingly, a wave climate duration equal to the reduction period (i.e. T_{wc}=1205 days) resulted in negative *R* for most of the sequencing options, while T_{wc} < 401 days only marginally increased *R*. For all synthetic time series, *R* increased for shorter wave climate durations. This is due to the reduced duration of the individual conditions and the repetition of the wave conditions, causing a better resemblance to the brute forcing time series. It was found that systematic sequencing of wave conditions consistently resulted in lower skills compared to the randomly ordered time series. Only for the lowest considered climate duration (T_{wc} = 114 days) all sequences (systematic and random) converged to a comparable skill.

3.3. *Influence of bin size and binning method on synthetic time series*

In Walstra et al. (2013) the analysis from the previous section was extended to also include the 4x4 and 8x4 wave climates for Noordwijk and the 4x1 and 8x1wave climates for Hasaki considering both equidistant (EQ) and non-equidistant binning (NEQ). At Noordwijk the use of the more detailed 8x4 wave climates generally improved *R* (Figure 4). Non-equidistant binning had a similar or larger positive impact on R for most of the 4x4 based synthetic time series; compare *R* for 4x4EQ and 4x4NEQ in Figures 4a,b. For the 8x4 wave climates, non-equidistant binning improved results to a lesser extent. In general, *R* converged at about 0.85 for all wave climates with T_{wc}=114 days. The influence of *N* (number of conditions in the reduced wave climate) is limited for non-equidistant binning (i.e. compare *R* of $4x4_{NEQ}$ with $8x4_{NEQ}$ wave climates). For the equidistant binning method, the influence of *N* is somewhat larger.

The large influence of the sequencing found at Hasaki (not shown) was caused by the fact that the morphological response strongly depends on the phase of the bar cycle at the time of high wave events.

For both sites it can be concluded that sequencing, the aggregation level (i.e. number of conditions in the reduced wave climate) and the binning method (equidistant vs non-equidistant) are less critical for low T_{wc} as $\langle R \rangle$ and s_R converge to minimal values. For larger T_{wc} both input reduction parameters are of similar importance.

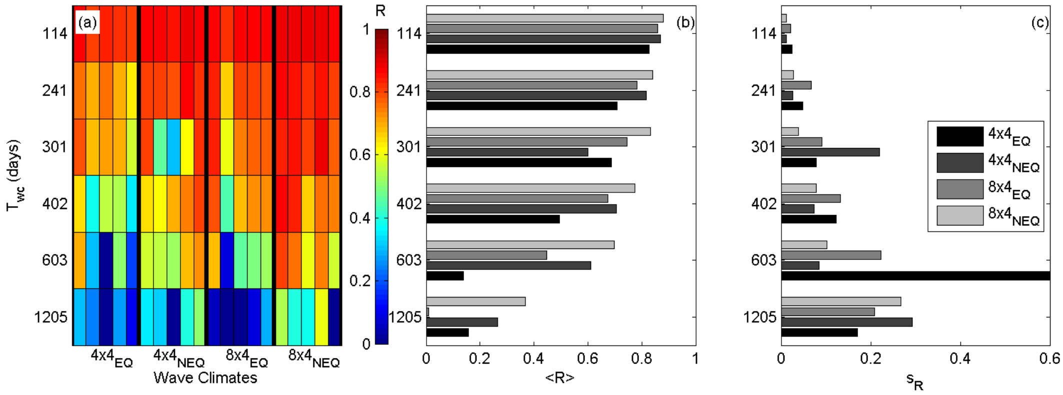

Figure 4. Model performance at Noordwijk for the reduced wave climates: a) skill *R* resulting from the 5 randomly sequenced synthetic time series; b) and c) shows average *R* and its standard deviation s_R, respectively (source: Walstra et al., 2013).

4. Discussion

The influence of T_{wc} was illustrated by comparing time stacks of the profile perturbations for Noordwijk and Hasaki for all six considered T_{wc} with the brute force predictions (Figs. 5 and 6). At Noordwijk the outer and middle bars characteristics were already fairly well reproduced with T_{wc} =602 days (Fig. 5b). However, the inner bars (*x*=-400 m) only started to converge for $T_{wc} \leq 401$ days (Fig. 5c-f). On the bar cycle time scale, the middle and inner bars were coupled to the dynamics of the outer bars. However, near the water line (*x*>-200 m) bar generation, decay and/or merging with the inner bar occurred at a much higher frequency as it was directly coupled to the wave forcing. At Hasaki T_{wc} had an even large influence, for $T_{wc} \geq 277$ days (Fig. 6a,b) the initial outer bar rapidly decayed which was the onset for strong bar growth and offshore migration of the former inner bar. With shorter T_{wc} (Fig. 6c-f) the offshore migration and bar growth of the inner bar was less pronounced. As a result this bar only gradually moved offshore and slowly decayed for the remainder of the simulation. Although the predictions converge for Hasaki, the model failed to reproduce the bar characteristics of the brute force prediction for all the considered wave climates. The predicted gradual offshore migration, decay and merging of the inner and outer bars contrast with the episodic nature of the bar dynamics in the brute forcing prediction. Therefore, input reduction at Hasaki is only feasible by applying reconstructed time series. The morphological response to extreme wave events is so strong that this will be an important aspect for the interpretation of the model predictions. This could be addressed by considering a number of reconstructed time series for different time periods to obtain further insight in the variability in the model predictions.

The considered wave climates were relatively detailed (16 to 32 wave conditions) compared to commonly applied wave climates in multi-annual morphodynamic simulations (typically about 10 wave conditions, see, for example van Duin et al., 2004 and Grunnet et al., 2004). This further reduction was partly achieved by ignoring the low to moderate wave conditions. To test whether exclusion of low conditions is justified H_{rms}<1 m wave conditions were excluded from the $8x4_{EQ}$ and $8x4_{NEQ}$ wave climates for all wave climate durations for the Noordwijk case. This resulted in significantly increased bar amplitudes and enhanced offshore bar migration, causing negative skill for all considered wave climates and T_{wc}. It proves that, although storms strongly influence profile evolution, the interplay between such episodic events and prolonged periods of low to moderate waves cannot be ignored.

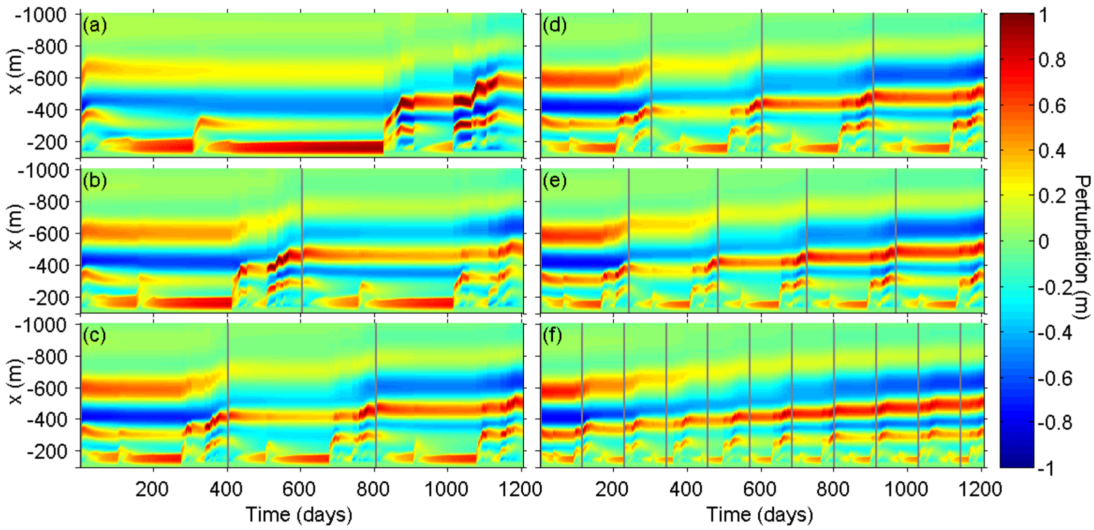

Figure 5. Time stack of the predicted profile perturbations at Noordwijk for the $4x4_{EQ}$ wave climate with randomized time series (R3) with T_{wc}= (a) 1205, (b) 602, (c) 401, (d) 301, (e) 241 and (f) 114 days. T_{wc} is indicated by the vertical grey lines (source: Walstra et al., 2013).

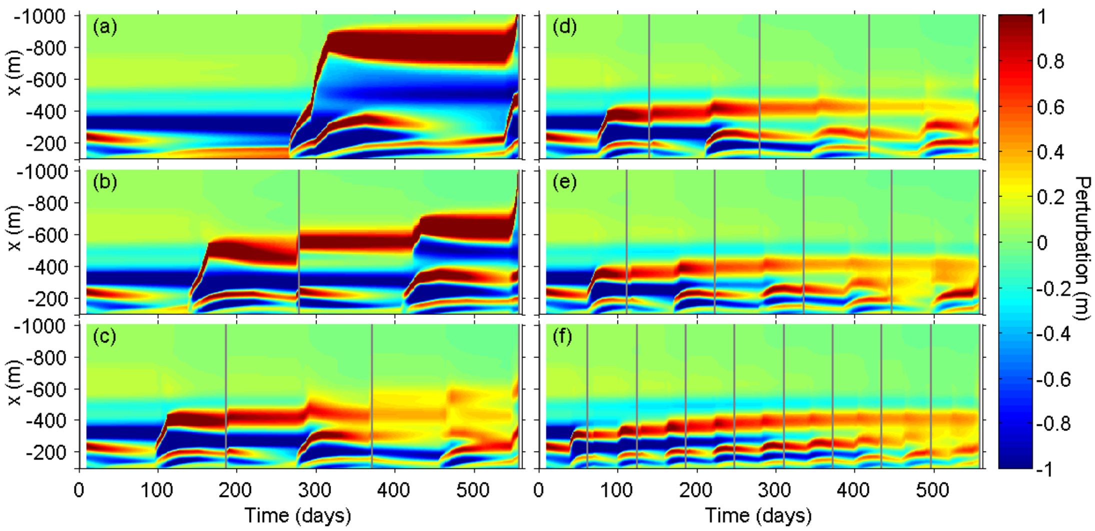

Figure 6 Time stack of the predicted profile perturbations at Hasaki for the $4x4_{EQ}$ wave climate with randomized time series (R3) with T_{wc}= (a) 555, (b) 278, (c) 185, (d) 139, (e) 111 and (f) 62 days. T_{wc} is indicated by the vertical grey lines (source: Walstra et al., 2013).

Because the computational efficiency of a reduced wave climate is governed by *NoT*, this parameter should be used as the primary selection criterion. Therefore, the considered wave climates were evaluated for Noordwijk by comparing R averaged over the 5 random simulations as a function of *NoT* (Fig. 7). It is evident that the number of conditions and binning method (step 2) were of similar importance as the wave climate duration (step 4). Although, the $4x4_{NEQ}$ wave climate was the optimal climate (largest R for a given *NoT*), the $8x4_{NEQ}$ wave climate resulted in a comparable model performance with a nearly similar efficiency. Given the comparable performance of the $4x4_{NEQ}$ and $8x4_{NEQ}$ wave climates, a final selection could also be based on a more detailed inspection of the predictions and other aspects such as robustness of the predictions. For example, the standard deviation s_R shown in Figure 4c is mostly lower for $8x4_{NEQ}$, suggesting that it is to be preferred over $4x4_{NEQ}$.

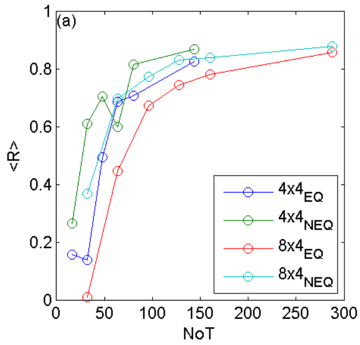

Figure 7. Averaged skill *R* for a) the complete profile, b) the upper part of the profile (*x*=[-400m:-100m]) and c) the lower part of the profile (*x*=[-1000m:-400m]) as a function of the number of condition transitions (*NoT*) in the synthetic time series at Noordwijk (source: Walstra et al., 2013).

5. Conclusions

Input reduction can have a major impact on model simulations, even to such an extent that major characteristics of cyclic behavior of sub tidal sandbars are no longer reproduced. This is particularly true when long-term evolution is steered by episodic storm events, such as at Hasaki. Therefore, the characteristics of the bar cycle response (e.g. episodic or inter-annual net offshore migration of bars) should be accounted for when applying input reduction. Synthetic time series of wave conditions are only appropriate if the bar-cycle dynamics are not directly linked to individual storm events. If such a coupling does exist, reconstructed time series that retain the original chronology should be applied (also implying that constant *MF*-values should be used in case morphodynamic upscaling is utilized). The effect of input reduction is not steered by a single choice. In the presented applications, the aggregation level, the binning methods and the wave climate duration T_{wc} affected skill to a similar degree. Since the efficiency of long-term process-based morphodynamic models (with varying *MF*) is governed by the number of transitions *NoT*, the optimal wave climate should also consider T_{wc}. This could result in the selection of an optimal reduced wave climate containing a larger number of conditions but with a longer T_{wc}. Given its potentially major influence, the type of input reduction, including associated choices, should be well-motivated and investigated. In other words, it should be an intrinsic part of model set-up, calibration and validation procedures.

References

Benedet, L., Dobrochinski, J., Ranasinghe, R., Klein, A., Walstra, D.J.R., 2013. Wave climate schematization for morphological modeling of open ocean beaches: analysis of methods and application to the Delray Beach case study. To be submitted to *Coastal Engineering*.

Brown, J.M. and Davies, A.G., 2009. Methods for medium-term prediction of the net sediment transport by waves and currents in complex coastal regions. *Continental Shelf Research* (29), pp 1502-1514. doi:10.1016/j.csr.2009.03.018.

Chesher, T.J. and Miles, G.V., 1990. The concept of a single representative wave for use in numerical models of long term sediment transport predictions. *Proc. 2nd intl. conf. on hydraulic and environmental modelling of coastal, estuarine and rivers waters*. Eds. Falconer, R.A., Chandler-Wilde, S.N. and Liu, S.Q.

Dastgheib, A., Roelvink, J.A. and Wang, Z.B., 2008. Long-term process-based morphological modeling of the Marsdiep Tidal Basin. *Marine Geology* 256 (1-4), pp 90-100. doi:10.1016/j.margeo.2008.10.003.

De Vriend, H.J., Capobianco, M., Chesher, T., de Swart, H.J., Latteux, B. and Stive, M.J.F., 1993. Approaches to long-term modelling of coastal morphology: a review. *Coastal Engineering* 21, 225-26. doi:10.1016/0378-3839(93)90051-9.

Edmonds, D.A., Slingerland, R.L., 2010. Significant effect of sediment cohesion on delta morphology. *Nature Geoscience* 3, 105–109. doi:10.1038/ngeo730

Elias, E.P.L., Cleveringa, J., Buijsman, M.C., Roelvink, J.A., Stive, M.J.F., 2006. Field and model data analysis of sand transport patterns in Texel tidal inlet. *Coastal Engineering* 53(5–6), pp 505–529. doi:

10.1016/j.coastaleng.2005.11.006.
Geleynse, N., Storms, J.E.A., Stive, M.J.F., Jagers, H.R.A., Walstra, D.J.R., 2010. Modeling of a mixed load fluvio-deltaic system. *Geophysical Research Letters*, Vol. 37, L05402, doi:10.1029/2009GL042000.
Geleynse, N., Storms, J.E.A., Walstra, D.J.R., Jagers, H.R.A., Wang, Z.B., and Stive, M.J.F. 2011. Controls on river delta formation; insights from numerical modeling, *Earth and Planetary Science Letters*, Vol 302, pp 217–226, doi: 10.1016/j.epsl.2010.12.013.
Grunnet, N.M., Walstra, D.J.R., Ruessink, B.G., 2004. Process-based modelling of a shoreface nourishment. *Coastal Engineering* 51 (7), 581–607. doi:10.1016/j.coastaleng.2004.07.016.
Grunnet, N.M., Ruessink, B.G., Walstra, D.J.R, 2005. The influence of tides, wind and waves on the redistribution of nourished sediment at Terschelling, The Netherlands. *Coastal Engineering* 52, 617–631. doi:10.1016/j.coastaleng.2005.04.001.
Hibma, A.; de Vriend, H.J.; Stive, M.J.F., 2005. Numerical modelling of shoal pattern formation in well-mixed elongated estuaries, *Estuarine Coastal and Shelf Science*, Vol. 57 (5-6), pp 981-991. doi:10.1016/S0272-7714(03)00004-0.
Jones, O.P., Petersen, O.S., Kofoed-Hansen, H., 2007. Modelling of complex coastal environments: Some considerations for best practice. *Coastal Engineering* 54, 717–733. doi:10.1016/j.coastaleng.2007.02.004.
Kuriyama, Y., Ito, Y., Yanagishima, S., 2008. Medium-term variations of bar properties and their linkages with environmental factors at Hasaki, Japan. *Marine Geology*, Vol. 248 (1-2), pp1-10. doi: 10.1016/j.margeo.2007.10.006.
Lesser, G.R., Roelvink, J.A., van Kester, J.A.T.M., Stelling, G.S., 2004. Development and validation of a three-dimensional morphological model. Coastal Engineering 51 (8-9), 883-915. doi:10.1016/j.coastaleng.2004.07.014.
Lesser, G.R., 2009. An approach to medium-term coastal morphological modeling. *Phd-thesis*, Delft University of Technology, CRC Press/Balkema. ISBN 978-0-415-55668-2.
Pape, L., Kuriyama, Y., Ruessink, B.G., 2010. Models and scales for nearshore sandbar behavior. *Journal of Geophysical Research — Earth Surface* 115, F03043. doi:10.1029/2009JF001644.
Ranasinghe, R., Swinkels, C., Luijendijk, A., Roelvink, J.A., Bosboom, J., Stive, M.J.F., Walstra, D.J.R, 2011. Morphodynamic upscaling with the MorFac approach: dependencies and sensitivities. *Coastal Engineering* 58, 806–811, doi:10.1016/j.coastaleng.2011.03.010.
Roelvink, J.A., 2006. Coastal morphodynamic evolution techniques. *Coastal Engineering* 53, 277–287. doi:10.1016/j.coastaleng.2005.10.015.
Roelvink, J.A., Reniers, A.J.H.M., 2011. A guide to modelling coastal morphology. Advances in Coastal and Ocean Engineering. World Scientific Pub. Co. Inc.
Ruessink, B.G., Kuriyama, Y., Reniers, A.J.H.M., Roelvink, J.A., Walstra, D.J.R., 2007. Modeling cross-shore sandbar behavior on the timescale of weeks. *Journal of Geophysical Research-Earth Surface* 112 (F3), 1–15. doi:10.1029/2006JF000730.
Ruessink, B.G., Pape, L. and Turner, I.L., 2009. Daily to interannual cross-shore sandbar migration: observations from a multiple sandbar system. Continental Shelf Research, 29, 1663-1677. doi:10.1016/j.csr.2009.05.011.
Ruggiero, P.,Walstra, D.J.R., Gelfenbaum, G., van Ormondt, M., 2009. Seasonal-scale nearshore morphological evolution: field observations and numerical modeling. *Coastal Engineering* 56 (11–12), 1153–1172. doi:10.1016/j.coastaleng.2009.08.003.
Southgate, H., 1995. The effects of wave chronology on medium and long term coastal morphology. *Coastal Engineering* 26, 251-270. doi:10.1016/0378-3839(95)00028-3
Tung, T.T., van der Kreeke, J., Stive, M.J.F., Walstra, D.J.R, 2012. Cross-sectional stability of tidal inlets: A comparison between numerical and empirical approaches. *Coastal Engineering* 60, 21–29. doi:10.1016/j.coastaleng.2011.08.005.
Van der Wegen, M., Roelvink, J.A., 2008. Long-term morphodynamic evolution of a tidal embayment using a two-dimensional, process-based model. *Journal of Geophysical Research-Oceans* 113 (C3016). Doi:10.1029/2006JC003983.
Van Duin, M.J.P.,Wiersma, N.R.,Walstra, D.J.R., van Rijn, L.C., Stive, M.J.F., 2004. Nourishing the shoreface: observations and hindcasting of the Egmond case, The Netherlands. *Coastal Engineering* 51 (8–9), 813–837. doi:10.1016/j.coastaleng.2004.07.011.
Walstra, D.J.R., Reniers, A.J.HM., Ranasinghe, R., Roelvink, J.A., Ruessink, B.G., 2012. On bar growth and decay during interannual net offshore migration. *Coastal Engineering* 60, 190-200. doi:10.1016/j.coastaleng.2011.10.002.
Walstra, D.J.R., Hoekstra, R., Tonnon, P.K., Ruessink, B.G., 2013. Input reduction for long-term morphodynamic simulations in wave-dominated coastal settings. *Coastal Engineering* 77, 57-70. doi:10.1016/j.coastaleng.2013.02.001
Wijnberg, K.M., Terwindt, J.H.J., 1995. Extracting decadal morphological behavior from high-resolution, long-term bathymetric surveys along the Holland coast using eigen function analysis. *Marine Geology* 126 (1–4), 301–330. doi: 10.1016/0025-3227(95)00084-C.