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Wave input reduction approach to compute the alongshore distribution of breaking wave conditions along the North Médoc coast

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Abstract:
This study introduces an input reduction (IR) methodology that we developed specifically to enhance computational efficiency in nearshore wave modeling for the complex area of the Nord Médoc coast, adjacent to one of the largest estuary in Europe (Gironde). This methodology combines simulated annealing optimization with wave modeling. We apply it to an extensive 15-year offshore wave time series obtained from MARC's WavevatchIII-based simulation and prediction system (LOPS). The IR effectiveness is assessed by comparing the original and simplified offshore wave time series, simulated with the spectral wave model SWAN, at three nearshore locations in our study zone. Results indicate a strong agreement nearshore between the original and simplified offshore wave time series, with mean absolute errors ranging from 8 to 20 cm for the significant wave height, 0.7 to 1 s for peak wave period and 1.2 to 3.8° for wave direction. Using an optimal number of 30 clusters, the simulated annealing optimization effectively clusters wave data. Further validation of this IR-method involves analyzing its impact on long-term sediment transport using a reduced complexity shoreline model (LX-shore). This study lays the groundwork for the set-up of the reduced-complexity shoreline model to be applied in this intricate hydro-morphodynamic zone.

Keywords:
Input reduction methodology, Simulated annealing, SWAN spectral wave model, Nearshore wave modeling, Wave forcing simplification.

1. Introduction

This work presents a study case on the Nord-Médoc coast, located in the southwest France adjacent to one of Europe's largest estuaries, the Gironde. Despite local efforts to mitigate erosion, this area is experiencing significant shoreline retreat, urgently requiring the development of a shoreline evolution model to address this issue. Shoreline evolution models can be used to hindcast and predict coastal changes, making them of strong interest for informed decision-making in coastal management strategies.

For long-term shoreline evolution predictions, traditional physically based models (e.g., X-Beach, ROELVINK *et al.*, 2009) are computationally demanding, particularly across wave-dominated coasts and spatial scales spanning kilometers (DALY *et al.*, 2014). Additionally, these process-based models tend to accumulate error over time, making them unsuitable for long-term simulations. In contrast, recent years have witnessed the emergence of reduced complexity shoreline models overcoming some of the limitations faced by traditional process-based models to tackle long periods (i.e. years, decades) and large domains. However, even though these models have proven to lead to more reliable long-term shoreline evolution (MURRAY, 2007), they are challenged in complex hydro-morphodynamic environments due to the oversimplification of wave transformation, which leads to a flawed description of the breaking wave conditions driving morphological changes. Recognizing this challenge, spectral wave modeling becomes necessary to resolve wave propagation in the nearshore and obtain more precise breaking wave parameters.

Our focus then turns to LX-shore, a reduced complexity shoreline model known for its effectiveness in long-term shoreline prediction (ROBINET *et al.,* 2018). LX-shore offers the advantage of being coupled with the spectral wave model SWAN (BOOIJ *et al.*, 1999), providing accurate wave nearshore resolution. Nevertheless, spectral wave modeling, particularly in complex hydro-morphological environments such as the Nord Médoc region can lead to excessive computational time. This contradicts the efficiency sought in reduced-complexity models, undermining one of their key advantages. To overcome this lock, this work presents an input reduction (IR) methodology aiming at reducing computational time while maintaining fine precision in nearshore wave conditions when modeling long-term wave propagation in the nearshore with SWAN. The ultimate goal of this IR-method is to provide reliable wave conditions to LX-shore for the prediction of long-term shoreline evolution in the Nord Médoc region. However, in this work, we focus on presenting the results of the IR-method, to demonstrate its effectiveness in accurately extracting breaking wave conditions.

2. Study site and input reduction methodology for nearshore modeling

2.1 <u>Study site and overall methodology</u>

The study area spans 15 km of sandy coastline along North Médoc, from Cape Grave to Cape Négade (Figure 1), located south of the Gironde estuary. This coastal region experiences rapid morphological changes, due to the interaction of external forces such as waves and tides, and internal dynamics within the estuaries. Figure 1 provides an overview of the study site bathymetry (based on SHOM, 2015, MNT Bathymétrique de façade Atlantique Projet Homonim, http://dx.doi.org/10.17183/MNT_ATL100m_HOMONIM_WGS84), illustrating its complexity. Waves approach mainly from westerly to northwesterly directions, with a monthly average significant wave height ranging from 1.1 to 2.4 m, indicating predominantly energetic wave regimes (CASTELLE *et al.,* 2017). Tides follow a semi-diurnal pattern, with a tidal range of 1.5 to 5.5 m, exerting strong influence on coastal currents.

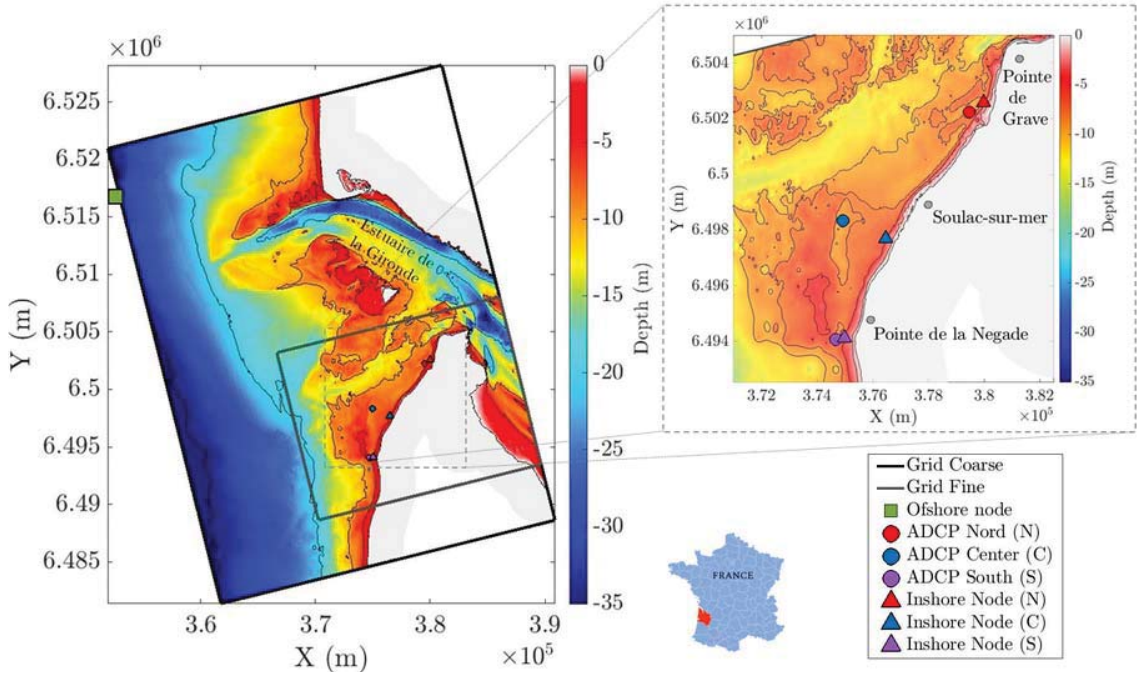

Figure 1. Bathymetry of the study zone illustrating the coarse and fine grid boundaries for the SWAN model. The offshore node, ADCP stations, and inshore nodes.

On the study area, we implemented SWAN models on two nested grids (Figure 1). We developed the IR-method to reduce the offshore time series limiting the number of wave conditions and thus reduce the number of simulations to do with SWAN to estimate nearshore wave conditions. For this purpose, this IR framework is applied to wave time series extracted from the MARC platform (https://marc.ifremer.fr) at our offshore forcing node of the SWAN model located at 35 m water depth (green box, Figure 1). The MARC wave time series comes from WAVEWATCH III (WW3; ARDHUIN *et al.,* 2010) simulations. Henceforth, we will refer to this offshore wave time series as our original offshore wave forcing. This time series covers the past 15 years (2008-2023) with an hourly time step. We simplify the wave forcing time series using an unsupervised classification method optimized by simulated annealing (KIRKPATRICK *et al.,* 1983). This process categorizes the offshore wave time series into a simplified dataset, maintaining representativeness of the wave forcing, where each cluster is distinguished by unique wave condition. These clusters are then propagated to nearshore using the SWAN model to further extract breaking wave conditions. These simulations enable the construction of a simplified yet comprehensive and representative dataset of wave climates, connecting offshore wave forcing with nearshore wave characteristics. Simplifying the wave forcing time series allows us to reduce the number of runs required with SWAN. However, a key question arises regarding the optimal number of clusters into which the time series can be reduced while still achieving the objective of serving as a representative input for long-term shoreline modeling. To address this question, the input reduction methodology involves: (i) the classification process to reduce offshore wave time series, and (ii) the propagation of wave clusters using SWAN spectral model extracting wave parameter near the breaking zone to evaluate the effectiveness of reducing the offshore time series, quantify associated errors, and determine the optimal number of clusters.

2.2 Classification process to reduce offshore wave time series

Various IR-methods are available for reducing offshore wave time series, including binning e.g., energy flux (BENEDET *et al.,* 2016), clustering e.g., simulated annealing, K-means (CAMUS *et al.,* 2011) and the equivalent wave approach (CHONWATTANA *et al.,* 2005). Despite their diversity, in this work, we adopt the approach of ABADIE *et al.,* (2006), that uses simulated annealing as the IR technique to establish boundary conditions for the SWAN model to compute breaking wave parameters. The IR-method is applied to reduce the 15-year original offshore wave time series (obtained at the offshore northern node of our study) into a limited number of wave conditions. The method is applied to the bulk wave features, i.e. significant wave height (Hs), peak wave period (Tp) and mean wave direction (Dir). Using these parameters, we define a total distance function (Equation 1) that sums the distances of each data point to their corresponding center class. The parameters are normalized with standard deviation (Hs_N, Tp_N, and Dir_N) to ensure equal weighting in the total distance function, written as,

$$DistTot = \sum_{ic=1}^{Nc} \sum_{i \in C} dist(x_i, Cg_{ic}) \quad (1)$$

$$dist = \sqrt{(Hs_N - Hs_C)^2 + (Tp_N - Tp_C)^2 + (Dir_N - Dir_C)^2} \quad (2)$$

where Nc is the number of class, C is any class in the data set, Cg_{ic} the center of gravity of the class ic, x_i any point within the class ic. This function serves to measure the quality of classification; therefore, the research of the class center becomes an optimization task aimed at minimizing the total distance function. Simulated annealing is introduced for this purpose, being an unsupervised optimization method known for its ability to avoid local minima and finding global optima result through iterative evaluation and acceptance of the total distance function values. Simulated annealing has demonstrated effectiveness in clustering optimization problems, outperforming other numerical methods (KIRKPATRICK *et al.,* 1983). However, the algorithm involves several parameters that require tuning to converge to an optimal solution. Through an extensive parametric study, we varied these parameters to optimize the number of class (Nc). Many simulations were conducted for Nc ranging from 8 to 100. To determine the most representative Nc, we first employed the elbow technique. This technique evaluates the total distance as a function of Nc, identifying an inflection point where the addition of more clusters does not significantly reduce the total distance, thereby preventing overfitting. While this technique typically provides an interval of optimal Nc rather than a clear inflection point, it serves to narrow down our choices. After narrowing down Nc, we delve deeper into the clustering results by employing a spectral wave model (SWAN).

2.3 Evaluation of offshore wave time series reduction with SWAN

We implemented a SWAN spectral model, featuring nested grids: a coarse grid covering 30 x 40.8 km with a regular spatial resolution of 100 m (shown in Figure1) and finer grid nearshore spanning 20 x 15 km with a regular spatial resolution of 20 m (shown in Figure 1). These grids have a 14° rotation to align the main offshore wave boundary of the coarse grid with the 35 m depth contour, allowing to force the model with homogeneous wave conditions on the offshore boundary. The bathymetry is the latest version uploaded from SHOM (Figure 1). The offshore boundary forcing is applied based on JONSWAP spectral formulation, employing constant forcing along the West, North and South boundaries. Tidal variation is incorporated using data from Port-Bloc tide gauge at Pointe de Grave (https://data.shom.fr), while currents and wind effects are initially excluded. A validation of the SWAN wave model is conducted prior to its implementation, aiming to assess the efficacy of simplifying the original offshore time series. This validation consists on comparing its results with in-situ measurements collected using three ADCPs (shown in Figure 1) during an intensive 5-week field experiment under low to medium wave energy conditions. Details regarding this field campaign are provided in VANDENHOVE *et al*. (JNGCGC 2024). Subsequently, the model is applied to compare the original and classified offshore wave time series, evaluating inshore wave parameters in a 5m depth (shown in Figure 1). This depth is chosen to approximate conditions near the breaking line, allowing to evaluate the efficacy of the simulated annealing clustering and quantify the errors.

3. Results

3.1 Simulated annealing: elbow method for optimal cluster number selection

Figure 2 shows the application of the elbow method, where the total distance resulting from simulated annealing optimization across varying Nc values is plotted. Although no clear inflection point is evident, an interval (Nc=15 to Nc=40) is observed, suggesting that the optimal value may lie within this range. Thus, we choose Nc=15, 30, and 40 to propagate both the original and these simplified wave forcing to nearshore.

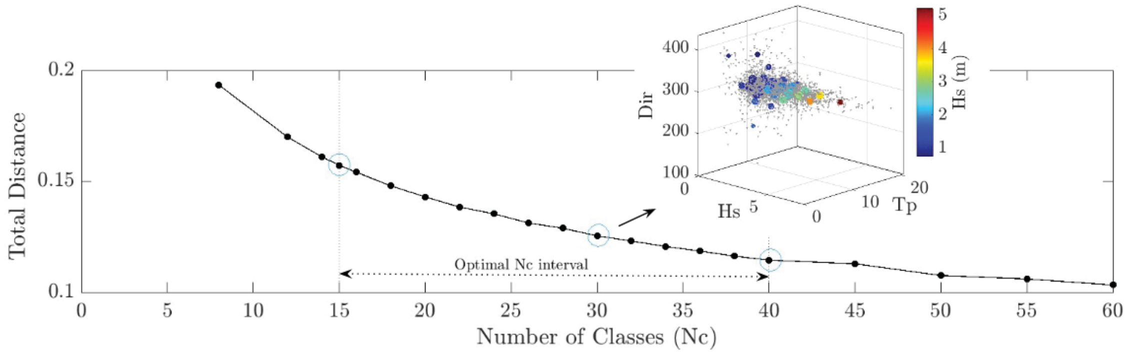

Figure 2. Elbow technique for cluster analysis and a 3D representation of the classification corresponding to Nc=30 (top right plot).

3.2 <u>Model validation with ADCP data</u>

We validated the SWAN model by comparing its results to field data collected during September 2022. The model is forced using original time series extracted at the northern offshore node (Figure 1) during this period. Figure 3 compares the evolution of Hs and Dir between the SWAN model results and the ADCP data.

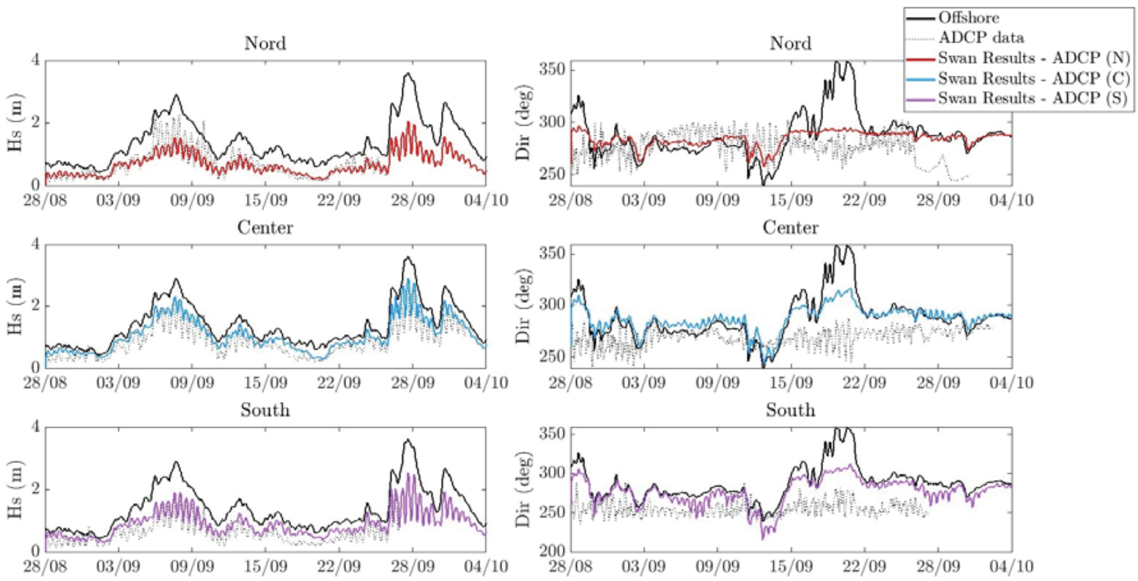

Figure 3. Comparison of observed and simulated wave at the 3 ADCP.

Despite spatial variations in estimation accuracy, the model generally performs well, with mean absolute errors ranging from 0.18 to 0.22 m for Hs, 2.5 to 5.8 s for Tp, and 12.2 to 24.3° Dir, with the largest errors observed in direction estimation. Therefore, it can be effectively used to evaluate the impact of the offshore simplified wave time series on nearshore parameters to obtain an optimal Nc.

3.3 Impact of simplified offshore wave forcing on nearshore wave parameters

We use the SWAN model to simulate the wave transformation for the original offshore wave time series in September 2022 and simplified wave time series reduced to Nc=15, 30 and 40. The results of these 4 simulations are compared at the 3 inshore nodes (depth 5m shown in Figure 1). The top plots in Figure 5 illustrate the evolution of Hs, Tp, and Dir at the offshore boundary for the original time series and its 30-classes reduced time series. The bottom plots in Figure 5 correspond to the SWAN results for the north inshore node (red triangle in Figure 1) comparing the results when forcing with the original offshore time series and simplified to 30 classes. Table 1 summarizes the mean absolute errors (MAE) between the original and the simplified wave forcing at the three inshore node locations (nord, center and south).

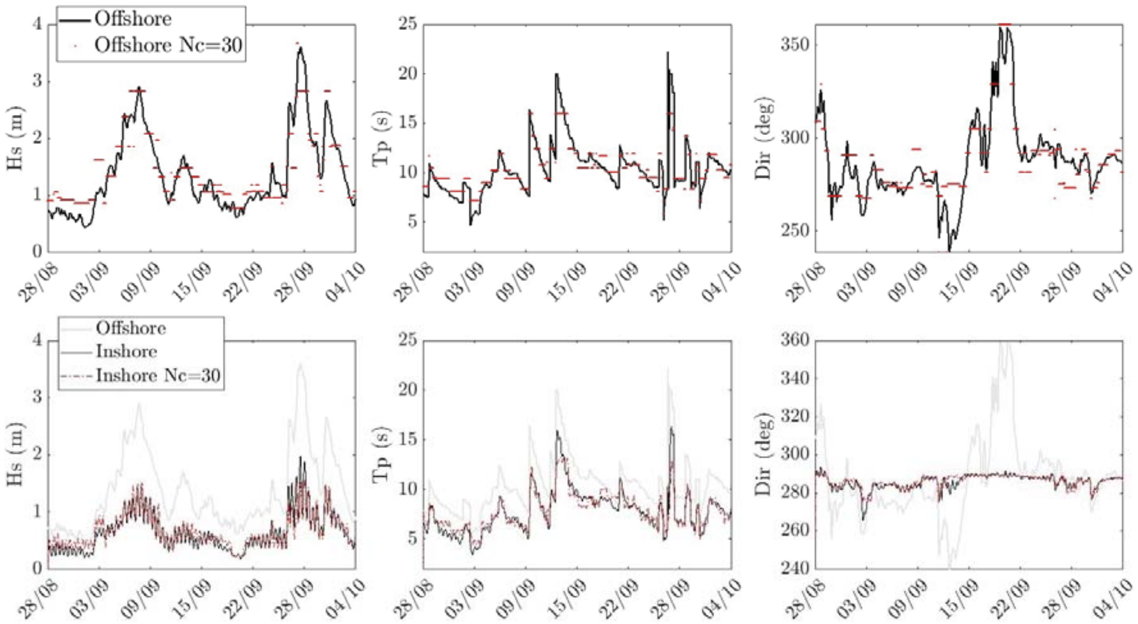

Figure 4. Comparison of original and simplified (Nc=30) offshore wave conditions at offshore boundary (top plots) and SWAN results at Nord inshore node (bottom plots).

Table 1. MAE at inshore locations using either original or simplified wave condition.

Inshore Node	Hs [m]			Tp [s]			Dir [°]		
	Nc15	Nc30	Nc40	Nc15	Nc30	Nc40	Nc15	Nc30	Nc40
Nord	0.126	0.090	0.086	1.056	0.758	0.790	1.462	1.186	1.217
Center	0.206	0.167	0.152	1.053	0.755	0.786	2.975	2.602	2.494
South	0.170	0.125	0.123	1.045	0.767	0.779	3.866	3.241	3.127

The mean absolute errors ranges from 8 to 20 cm for Hs, 0.7 to 1 s for Tp, and 1.2 to 3.8° for Dir. This suggests that this 15-year wave forcing dataset can effectively be condensed into a smaller number of classes such as 15 to 30 classes. Table 1 reveals a more significant reduction in errors from 15 to 30 classes compared to 30 to 40 classes, implying that Nc=30 may be an optimal choice balancing error reduction and computational time gain in SWAN simulations. These results also emphasize the effectiveness of the elbow method and of simulated annealing optimization for data clustering.

4. Discussion and conclusion

The comparison of the nearshore waves at the 3 inshore node locations extracted from SWAN simulations forced by either original or simplified offshore wave time series shows strong agreement. Indeed, it is important to note that while errors were analyzed separately, their impact on sediment transport is not linear. Moreover, WALTON & DEAN (1973) emphasized that only sea states inducing long-term shoreline changes should be considered for long-term morphodynamic studies. Therefore, further refinement may involve re-categorizing the number of classes to achieve a more significant reduction. This hydrodynamic analysis serves as an initial step, and validation of the IR-method must be conducted by analyzing the impact of the offshore wave forcing simplification on longshore sediment transport. This validation is going to be done by using the reduced complexity shoreline model LX-Shore.

Nevertheless, for the successful implementation of this reduced complexity model in this intricate study zone, it is necessary to establish the database linking offshore wave forcing for different water levels with wave parameters at the breaking zone. This database is going to be incorporate to LX-Shore with the purpose of reducing calculation time when modelling long-term shoreline evolution. Additionally, as accurate wave parameters at breaking zone are crucial, we plan further refinement of the SWAN spectral wave model as discrepancies were observed between model outputs and field data (ADCPs), indicating areas of improvement. These errors may come from simplifications in our SWAN modeling, such as neglecting currents or using constant friction values.

5. Acknowledgements

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