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Wave Input-Reduction for Shoreline Modelling of a High-Energy Environment with Complex Geological Settings

Ivana Mingo¹(✉), Arthur Robinet², Vincent Marieu¹, Bruno Castelle¹, Idier Deborah³, Vincent Mazairaud⁴, and Alexandre Nicolae Lerma²

¹ Université de Bordeaux, CNRS, UMR EPOC 5805, Pessac, France
ivana.mingo@u-bordeaux.fr

² Bureau de Recherches Géologiques Et Minières, Pessac, France

³ Bureau de Recherches Géologiques Et Minières, Orléans, France

⁴ Communauté de Communes Médoc Atlantique, Soulac-Sur-Mer, France

Abstract. The long-term (decades) evolution of shoreline change along coastline (O(15)Km) with complex offshore wave transformation challenges both, state of the art process-based morphodynamics and reduce-complexity shoreline models. A major limitation is the computational time required to simulate the detailed spatiotemporal evolution of the wave field, particularly in regions where offshore wave refraction induces localized energy focusing. This study focuses on a 15-km sandy coast on the North Medoc, southwestern France, characterized by high-energy, macro-tidal conditions, severe erosion, and complex offshore bathymetry. Effective coastal management strategies for the coming decades require the implementation of a reduced-complexity (RC) shoreline model. However, oversimplification of wave transformations in such a complex hydro-morphodynamic environment can result in flawed predictions of alongshore wave-breaking parameters and, consequently, shoreline change. Thus, a full wave propagation model is required, but computational time reduction techniques must be implemented to minimize computational cost. To address these challenges, this study introduces an easy-to-apply input reduction (IR) methodology that integrates offshore wave clustering to reduce computational costs when modeling long-term shoreline change within RC shoreline models.

Keywords: Shoreline change · input reduction · wave clustering · longshore sediment flux · reduced complexity models · computational efficiency

1 Context and Challenges in the Study Area

This work presents a case study on the North Médoc coast, a 15-km stretch of sandy coastline in the southwest of France, located adjacent to the Gironde Estuary. The North Médoc coast undergoes rapid morphological changes driven by the interplay of external forces such as waves and tides, and internal estuarine dynamics. This high-energy meso- to macrotidal environment, situated near one of the largest estuary mouths in

Europe, features a complex offshore bathymetry, rocky outcrops, and shallow banks that significantly influence wave transformation processes. Figure 1 illustrates the location and its bathymetry (SHOM, 2015: *MNT bathymétrie de façade Atlantique – Projet Homonim*), highlighting its geological complexity. Chronic erosion severely impacts parts of the region, with shoreline retreat rates reaching up to 5 m per year despite local mitigation efforts. This issue underscores the urgent need for a reliable shoreline change model capable of predicting long-term evolution to support decision-making and management strategies.

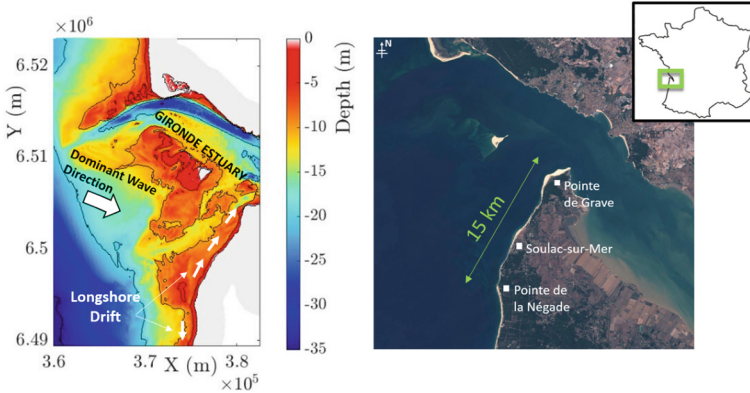


Fig. 1. Location and bathymetry of the North Médoc, illustrating its geological complexity.

Modeling long-term shoreline evolution in such a dynamic and complex setting poses significant challenges. Spatially, there is a need to achieve high resolution at the scale of individual beaches—on the order of meters—due to the presence of numerous coastal structures and zones of interest within the broader 15-km study area. Temporally, it is essential to capture long-term evolution over decades while resolving seasonal variations driven by significant winter storms. This dual requirement for fine spatial and temporal resolution over a large and intricate region challenges both state-of-the-art process-based and reduced-complexity (RC) shoreline change models.

Traditional process-based models, e.g., XBeach, [1] are computationally demanding, particularly when applied to spatial domains spanning several kilometers [2]. Additionally, they tend to accumulate errors over time, making them unsuitable for long-term simulations. In contrast, RC models have proven more reliable for long-term shoreline evolution [3]. However, their excessive simplifications in wave transformation modeling can result in inaccurate alongshore distributions of breaking wave parameters, ultimately leading to flawed shoreline change predictions. To address these challenges, a full wave propagation model is required, complemented by computational time reduction techniques to manage the associated computational costs. Various input reduction (IR) methods exist to simplify offshore wave time series, including hybrid downscaling [4], binwaves [5], and clustering [6]. Each method offers unique advantages and limitations. In this study, we compare two clustering techniques—Simulated Annealing [7] and K-means [8]—and focus on validating these reduction techniques by evaluating the

impact of the simplified offshore wave field on the longshore sediment flux, which is a key driver of long-term shoreline change evolution in our study area.

2 Input Reduction Methodology

The input reduction (IR) methodology simplifies a recent 15-year offshore wave time series (2008 - 2023) using two unsupervised clustering techniques: Simulated Annealing (SA) [7] and K-means [8]. These techniques group the original time series into clusters based on offshore wave bulk parameters—wave height (H_s), wave period (T_p), and mean direction (Dir)—to create a reduced yet representative dataset of unique wave conditions (H_s , T_p , and Dir) for each cluster. For this purpose, the offshore wave time series was extracted at a 35 m water depth from a high accuracy wave modelling system. Henceforth, the original offshore wave time series is referred to as the “full forcing,” while the clustered wave time series is referred to as the “simplified forcing”.

The analysis of relative errors induced by wave climate simplification through clustering is performed at two-time scales: a long-term scale (15 years) and a short-term scale (1 year). The objective is to determine the optimal number of clusters (N_c) that accurately represent the diversity of offshore wave conditions for long-term shoreline change simulations. This is achieved by comparing the longshore sediment flux (QL) computed from the simplified forcing with reference values derived from the full forcing and assessing the associated errors at both time scales. Three error metrics are introduced to quantify these differences:

1. **Diffusion Error Coefficient (DEC):** Reflects the deviation in the diffusion capacity of longshore sediment transport.

$$DEC_{QL} = \frac{(\sum |QL_{NC}| - \sum |QL_0|)}{\sum |QL_0|} * 100 \quad (1)$$

2. **Accumulation Error (AE):** Quantifies the change in the total accumulation capacity of longshore sediment flux.

$$AE_{QL} = \frac{\sum QL_{NC}}{\sum QL_0} \quad (2)$$

3. **Mean Absolute Percentage Error (MAPE):** a statistical indicator that evaluates the discretization of the full wave forcing.

$$MAPE_{QL} = \frac{1}{n} \sum_{i=1}^n \left| \frac{QL_{0i} - QL_{NCi}}{QL_{0i}} \right| * 100 \quad (3)$$

Here QL_0 represents the longshore sediment flux associated with the full forcing, QL_{NC} is derived from simplified forcing, and n is the total number of wave conditions.

The transformation of the wave field to nearshore, needed to compute breaking wave conditions, is conducted differently at each time scale. For the long-term analysis, Larson’s empirical formulation [9] is applied over the entire 15-year period. This approach enables calculations for a broad range of shoreline orientations (θ_c) from 250° to 360° ,

covering the full extent of the study area, while varying the number of clusters (N_c) from 1 to 200. In contrast, the short-term analysis employs a SWAN spectral wave model to propagate both the full and simplified wave fields to the nearshore. This approach incorporates more detailed physical processes, such as wave refraction, enabling a more realistic simulation of wave transformation. In both the long- and short-term analyses, QL is calculated using the CERC formulation [10].

The long-term analysis, using Larson’s empirical formulation, facilitates broad parameter variation by enabling a comprehensive exploration of shoreline orientations (θ_c) and cluster numbers (N_c), making it suitable for assessing relative errors across a wide range. However, the short-term analysis is more constrained due to the high computational cost of the SWAN model, which limits the range of θ_c and N_c that can be explored. The short-term approach serves primarily to validate and quantify the errors derived from the long-term analysis. This validation is conducted for two distinct one-year periods: 2013–2014, which included several extreme events, and 2022–2023, which represented more typical wave conditions.

3 Results of the IR-Methodology

The results of the long-term empirical scenario using K-means as the clustering technique are presented in Figs. 2 and 3. Simulated Annealing (SA) yielded similar results and patterns. Figure 2 illustrates the errors in QL within the $N_c - \theta_c$ space, represented in a colormap for the two error indicators: Accumulation Error (AE, Fig. 2a) and Diffusion Error Coefficient (DEC, Fig. 2b).

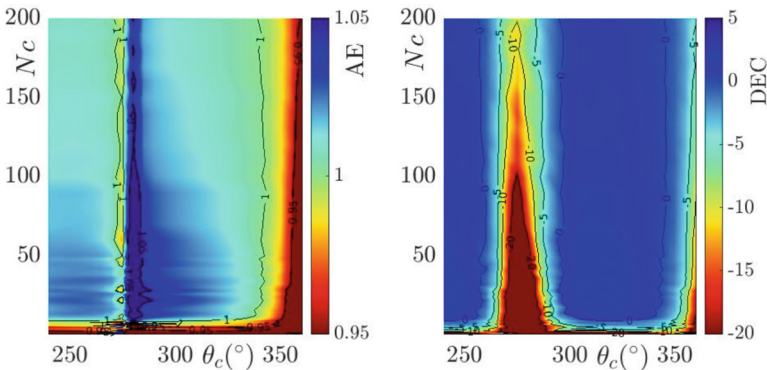


Fig. 2. 2D plot of QL errors in the $N_c - \theta_c$ space from the long-term analysis (15 years) for both indicators: Accumulation Capacity Error (left) and Diffusion Error Coefficient (right).

A notable peak of error is observed between shoreline orientations 270° and 290° , corresponding to the dominant wave direction, where the waves are normal to the coast, resulting in minimal QL . For $N_c > 20$, both indicators show low relative errors, generally less than 5% for coastline orientations outside the dominant wave direction range. Within the dominant wave direction range (270° – 290°), errors vary: for DEC, the error remains

around 20% for $N_c = 20$ to $N_c = 100$, decreasing to 10% for $N_c > 100$. For AE, the error remains consistently at 5% across all N_c .

Relative errors calculated using the MAPE indicator from the long-term scenario are shown in Fig. 3. Unlike the 2D representation used for the other indicators (AE and DEC), this figure focuses on three specific shoreline orientations: 270° , 280° , and 300° . This representation was chosen for its clarity in depicting key trends, making it easier to interpret. These orientations correspond to the southern, central, and northern points of the study area—Pointe de La Négade, Soulac-sur-Mer, and Pointe de Grave, respectively, as illustrated in Fig. 1. The trends observed for these points are consistent across all analyzed shoreline orientations. An inflection point is observed around $N_c = 60$, beyond which further increases in N_c result in no significant improvement, with MAPE error stabilizing.

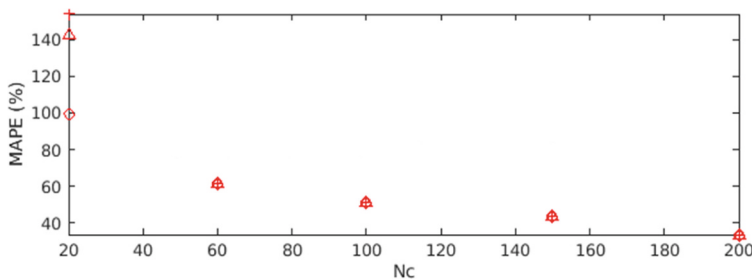


Fig. 3. MAPE errors from the long-term analysis (15 years) as a function of N_c for three specific coastline orientations: 270° (red circles), 280° (triangles), and 300° (crosses), corresponding to the southern, central, and northern points of the study area, respectively.

Finally, SWAN simulations validated the long-term analysis and quantified the relative errors. For example, for the long-term simulation when $N_c = 60$, using K-means as a clustering technique, the MAPE relative error was 60% (Fig. 3). This relative error, according to the SWAN simulations for the same case ($N_c = 60$ and K-means) in the year 2013–2014, corresponds to a mean absolute error of approximately 100 m³/year in the longshore sediment flux.

4 Conclusion and Perspectives

This study presents a simple and universally applicable IR-approach focused on optimizing the computational cost of long-term shoreline change predictions by analyzing errors induced in longshore sediment flux. The IR approach identifies an optimal number of clusters (N_c) that effectively reduces errors in longshore sediment flux (QL), while maintaining an accurate representation of the diversity in offshore wave climates.

The results demonstrate that reducing the 15-year offshore wave time series to $N_c > 20$ clusters results in errors of less 5% for the Accumulation Error (AE) indicator, while the Diffusion Error Coefficient (DEC) shows errors under 5% in zones where the coastline aligns with the dominant wave direction. However, outside this alignment,

errors increase up to 20%. The acceptability of these errors ultimately depends on the precision required for the specific shoreline change modeling application.

Additionally, the MAPE analysis shows that increasing N_c to around 60 significantly reduces the MAPE error, suggesting that this is the optimal number of clusters for most scenarios. However, the acceptable error threshold remains case-dependent. To address this variability and validate the relative errors calculated from the long-term empirical scenarios, the SWAN spectral model was employed to quantify errors in shorter-term periods, such as one year.

This methodology enables the assessment of clustering techniques and the refinement of the errors induced for long-term shoreline modeling applications, in regions dominated by longshore processes. The approach is versatile and can be adapted to various time scales and specific requirements. Future work will focus on implementing this IR approach within a RC model in the intricate environment of the Nord Médoc for long-term shoreline change modeling.

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