

NON-STATIONARY PARAMETERS ON EQUILIBRIUM-BASED SHORELINE EVOLUTION MODELS

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INTRODUCTION

Equilibrium-Based Shoreline Evolution Models (EBSEM) are computationally efficient tools for simulating beach response to environmental conditions, such as hydrodynamic forcings. Thus, they are valuable to understand the footprint of longshore and cross-shore sediment transport processes on shoreline rotation and breathing at several temporal scales. Despite its simplicity, EBSEM are parametric models that rely on calibration. Existing EBSEM applications in literature have traditionally used constant in time and space calibration parameters to forcing conditions, which restricts their ability to capture shoreline change signals to changing morphodynamic behavior. Therefore, calibrating these models with non-stationary parameters might be crucial to enhance predictability of multi-timescale shoreline variations (Antolínez et al. 2019).

The conventional approach to calibrating EBSEM involves brute force approach and optimization methods like simulated annealing. Recently, data assimilation techniques such as Ensemble Kalman Filters were used to accommodate nonstationary beach responses within model parameters, as proposed by Ibaceta et al. (2022).

Another promising approach, in recent years, has been the implementation of Machine Learning Data Driven Models (MLDDM). These models have been shown as promising algorithms to identify nonlinear responses on shoreline variability to wave, sea level, wind and other climatic forcing (Gomez-de la Pena et al. 2023). Nonetheless, accuracy of predictions generated by such models is closely tied to the availability of (training) observational data, and it's crucial to exercise caution to prevent over or under-fitting issues.

To date, no hybrid technique integrating MLDDM and EBSEM to improve the quality of shoreline modeling has been developed. This study presents an innovative calibration method that is adaptable to EBSEMs. It considers non-stationary model parameters to capture data signals variations over the time, improving shoreline modelling by this typology of models.

METHODS

The method for calibrating EBSEMs proposed in this study is structured in three sequential steps shown in Figure 1:

1) Assess spatio-temporal variability on environmental forcing. It's essential to consider the information contained in the data. The application of the method is conditioned to the frequency and amount of data available on the shoreline signal, since the variability of the parameters is

conditioned to multiple time scales.

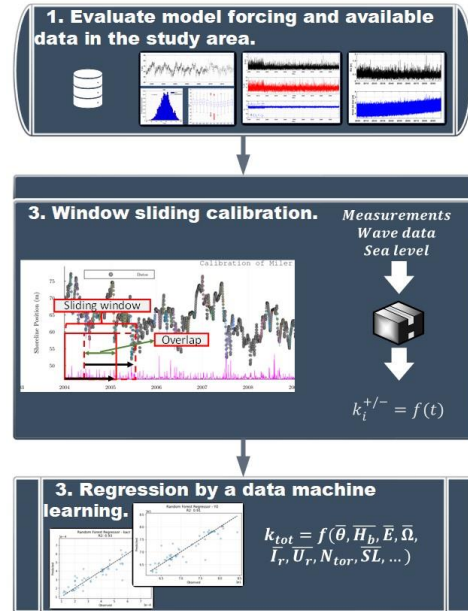


Figure 1 - Proposed framework flowchart.

2) Window sliding based calibration: the first step seeks for incorporating the influence of beach memory in model calibration. Length of time windows can be achieved through established time or frequency domain analysis, such as harmonical, wavelet or fourier transforms. Next, using the Borg Multiobjective Evolutionary Algorithm (BorgMOEA) (Hadka and Reed 2013), The calibration is performed such as beach response for each time segment is optimal. We use a set of statistical performance indicators as objectives for the optimization function. They are the Root Mean Square Error (RMSE), Mielke correlation coefficient (λ_M), and Brier Skill Score (BSS). However, others could be applied.

3) Machine learning-based regression: Using the calibrated coefficients time-series, a machine learning model is trained to find the relationship between them and the forcing variations over the time. The underlying assumption here is that the changes observed in these parameters are linked to periodic fluctuations in the mean values of hydromorphological variables significantly connected to coastal sediment transport. These key variables include wave power (P), Dean's parameter (Ω), Iribarren number (I_r), wave skewness (S_K), number of storms (N_S), wave propagation angle (θ_p) and mean sea level (MSL).

Therefore, a multivariate regression is performed in order to generate a predictive model for the EBSEM parameters.

APPLICATION

As an illustrative example, the cross-shore model developed by Miller and Dean (2004) was used. This is one of the earliest models of its kind and a well-established choice in the literature.

To assess the methodology's performance, the publicly accessible data from Tairua Beach, New Zealand, made available by the University of Auckland was acquired. This dataset encompasses time series data for shoreline positions and wave forcing. The shoreline data were obtained from a video-camera system, with an average frequency of one measurement every 16 hours, spanning from 2000 to 2017. Therefore, it enables to capture timescales greater than 1.4 days.

Considering the 17 years of data, the first 10 years (between the beginning of 2000 and the end of 2010) were used to calibrate the model, and then the following years until the beginning of 2017 were used to validate the prediction of the evolution model. Figure 2 shows the standard calibration using the entire calibration period and the one utilizing the proposed methodology. In this case study, several ML algorithms were tested and the Ensemble Random Forest exhibited superior ability in capturing fluctuations of the parameters.

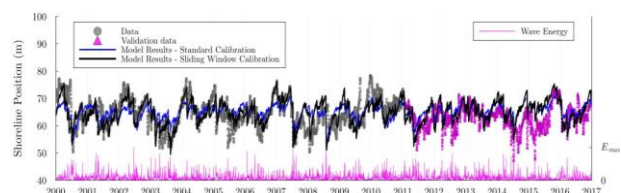


Figure 2 - Application of the proposed method on Tairua Beach, New Zealand

The quantitative statistics of λ_M and RMSE for the calibration and validated periods using the two calibration techniques described are presented in Table 1.

Table 1 - Mielke correlation coefficient and root mean square error between the observed and modeled shoreline positions at Tairua Beach

Period	Metric	Standard calibration	Proposed methodology
Calibration	λ_M	0.38	0.58
	RMSE	4.58 m	4.38 m
Validation	λ_M	0.30	0.40
	RMSE	5.25 m	5.03 m

The assessment of calibration quality involved the utilization of RMSE and λ_M metrics. The proposed methodology yielded a 4% enhancement in RMSE for both calibration and validation periods. Furthermore,

there was a substantial 53% improvement in λ_M for the calibration period and a 33% improvement for the validation period.

CONCLUSIONS

To showcase its effectiveness, the approach was implemented using the model proposed by Miller and Dean (2004) at Tairua Beach, New Zealand. The results revealed a significant improvement in the model's predictive accuracy when incorporating time-varying parameters. This innovative methodology is versatile and can be seamlessly integrated into any EBSEM, whether for cross-shore, longshore or integrated sediment transport processes. Finally, it's worth mentioning that further analysis considering different machine learning techniques are being explored in order to better predict parameters variations.

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