Combining data-driven and numerical modelling approaches to storm erosion prediction

Joshua A. Simmons, UNSW Sydney, j.simmons@unsw.edu.au
Kristen D. Splinter, UNSW Sydney, k.splinter@unsw.edu.au

INTRODUCTION

Physics-based numerical models play an important role in the estimation of storm erosion, particularly at beaches for which there is little historical data. However, the increasing availability of pre- and post-storm data for multiple events and at a number of beaches around the world has opened the possibility of using data-driven approaches for erosion prediction. Both physics-based and purely data-driven approaches have inherent strengths and weaknesses in their ability to predict storm-induced erosion. It is vital that coastal managers and modelers are aware of these trade-offs as well as methods to maximise the value from each modelling approach in an increasingly data-rich environment.

In this study, data from approximately 40 years of coastal monitoring at Narrabeen-Collaroy Beach (SE Australia) has been used to evaluate the individual performance of the numerical erosion models SBEACH and XBeach, and a data-driven modelling technique. The models are then combined using a simple weighting technique to provide a hybrid estimate of erosion.

METHODOLOGY

Storm events for the Sydney region were identified during the time period spanning 1979 and 2017. Storm identification was undertaken using a peaks-over-threshold method for the offshore significant wave height. Storm erosion was measured using monthly profile surveys at 5 locations along Narrabeen-Collaroy Beach between which there had been one or more storms. The storm erosion impact was quantified using the change in the 2 m contour, a proxy for the shoreline less sensitive to rapid post-storm accretion which may not be accounted for with monthly surveys, and the change in subaerial volume. After data cleaning, around 140 unique datapoints were identified for each of five survey transect locations spanning the Narrabeen embayment.

The numerical models SBEACH and XBeach were applied to the dataset using previously calibrated parameter values. A Neural Network machine learning algorithm was used as the data-driven modelling approach. A combined output of all three models was obtained using a learned best-fit weighting. Data were split into three equal sets: a training set for the machine learning model; a training set for the best-fit combined model; and a testing set of unseen data. The numerical, data-driven and combined modelling approaches were only compared based on their performance on the unseen portion of the data. A cross-validation process was carried out to randomise the selection of each of the three sets and get an indication of model performance across the entire dataset.

RESULTS

The models show a large variability in performance dependent on both the output variable being predicted and the magnitude of the measured impact. The numerical models tended to perform better for the more extreme storm events, with a tendency to overestimate small events. In general, this gives them a poor fit across the entire dataset which, due to the nature of erosion events, is dominated by moderate events interspersed with notably large storm events. The ML algorithm tended to perform more reliably across all types of storm events and output variables. However, the composition of the training dataset (as noted above) tends to affect the fit of the ML algorithm, leading to underprediction for more extreme and higher impact out-of-sample storm events.

The nature of the dataset and models as described above means that a weighted combination represents a more reliable prediction than any one individual model. The combined model shows around the same skill as the ML model across the entire dataset. As shown in Figure 1, the combined model performance is much greater than either the ML model or numerical models when evaluated over the top 10% of largest impact storm events in the test set. This is particularly crucial for coastal managers who are most interested in these higher impact events.

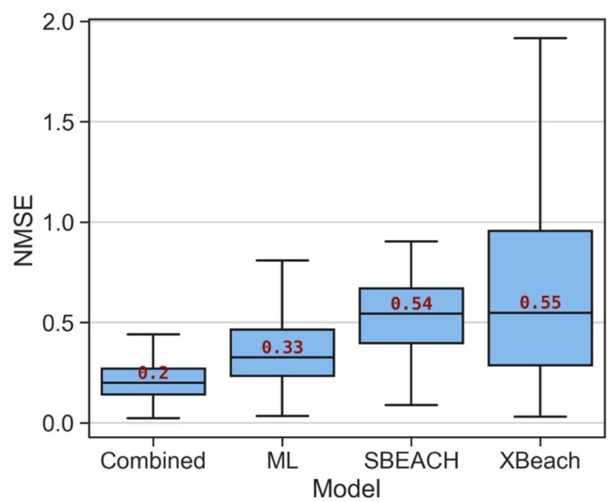

Figure 1 - Boxplots showing model performance through cross-validation when predicting subaerial eroded volume for the top 10% of largest impact storm events in the test set. Model performance is evaluated as the Normalised Mean Square Error (NMSE).