PREDICTING SHORELINE EVOLUTION IN A CHANGING WAVE CLIMATE

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INTRODUCTION

Reliable predictions of shoreline evolution at a range of time scales both now and by end of the century are required for assessing coastal vulnerability in a changing climate. This is particularly important given the possible changes in regional wave climates and/or ocean water levels due to climate variability. To this end, much work has gone into the development of simple and efficient semi-empirical shoreline models that can be used to predict shoreline evolution over time scales ranging from seasonal to multi-decadal. Semi-empirical shoreline models are simplified representations of the complex sediment transport processes occurring between the shoreface and beach face, and thus inherit uncertainties from the imprecise representation of physical processes in the model structure. This misspecification of physical processes is typically addressed via model calibration, whereby a set of stationary (or time-invariant) model parameters are optimized during a period of observed forcing for a specific set of shoreline data. However, recent research suggests that the calibration period may introduce biases associated with the particular time period and/or duration of the selected wave and shoreline dataset (Montaño et al., 2020).

An alternative is to use time-varying model parameters to improve model predictability at interannual timescales. Kalman filter techniques offer a framework to detect time-varying (or non-stationary) model parameters by adjusting them as shoreline observations become available. Ibaceta et al. (2020) implemented a dual state parameter Ensemble Kalman Filter (EnKF) within the shoreline evolution model *ShoreFor* (Davidson et al., 2013), and showed that this methodology is suitable to detect parameter changes that best hindcasted observed shoreline evolution. Additionally, they demonstrated that this observed parameter non-stationarity could be linked to the changing characteristics of the underlying wave forcing. The application of this methodology over long-term datasets now enables the parametrization and physical interpretation of the model parameters as a function of the multi-year variability in wave forcing, allowing for enhanced shoreline predictions out of the selected training period.

METHODS AND RESULTS

A multi-decadal (28-year) dataset of satellite-derived shorelines observations at the Gold Coast, Australia was used to predict shoreline changes considering non-stationary parameters. The EnKF technique presented in Ibaceta et al. (2020) was first applied to half of the data to explore time-variability in model parameters. Then, correlation analysis between parameters and wave climate covariates identified the variables and time scales of change related to the observed parameter non-stationarity. Correlation analysis revealed that all three cross-shore associated parameters of the *ShoreFor* model were strongly correlated with the dimensionless fall velocity at 5-year running average windows $\overline{(\Omega)}$. By expressing this time-variability using simple linear regressions, an enhanced *ShoreFor* model considering parameter non-stationarity outperformed the 28-year predictions of a more conventional stationary approach based on time-invariant parameters ($RMSE_{non\text{-}stationary}$ = 11.1 m; $RMSE_{stationary}$ = 254.3 m) (Figure 1).

Results from this work emphasize the need for shoreline models that can adjust to changes in the underlying wave-forcing and coupled shoreline response. This contribution is the first effort to reduce the uncertainty associated with the misspecification of physical drivers within semi-empirical shoreline change models and provides an important step to achieve reliable multi-decadal shoreline projections in a changing wave climate.

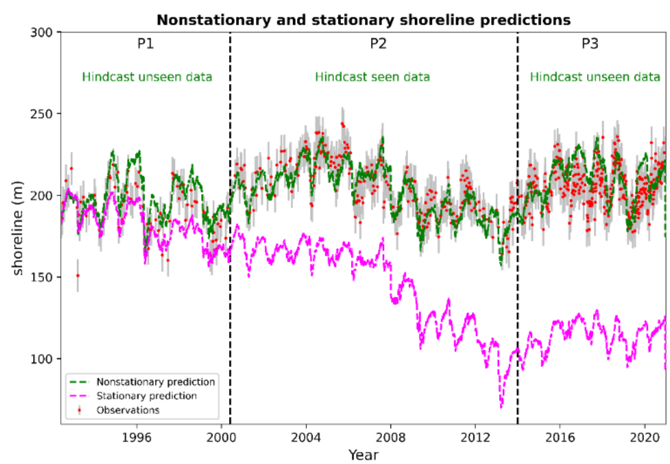

Figure 1 - *ShoreFor* shoreline predictions using non-stationary (green line) and stationary (magenta) parameters

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