Author comments (AC) to reviewer 2 comments (RC2), manuscript Gomez de la Pena et al. “On the use of Convolutional Deep Learning to predict shoreline change” submitted to EGUsphere

Before addressing the comments, we would like to thank reviewer 2 for the time invested and comments made. All comments have been incorporated and the clarity of the manuscript has certainly improved.

RC2.1. While the manuscript provides sufficient details about the data and study site, it would greatly benefit from a figure that situates the reader in the study area and highlights the described elements. To enhance clarity, it is advisable to include a figure that portrays the study area's location, outlining the video camera system's position, the monitored coastline section, and the wave point utilized for forcing, among other pertinent features.

AC2.1. We realize that a study site figure would be of great benefit, and hence we have modified the manuscript and added a figure highlighting pertinent features (Figure 4):

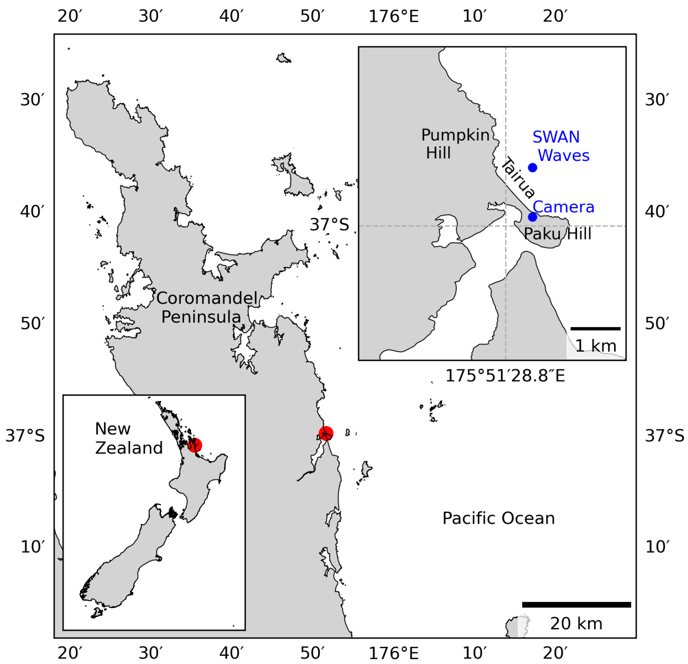

Figure 4. Location of Tairua on the Coromandel peninsula in the North Island of New Zealand. Blue dots represent the installed camera system and the SWAN wave bulk parameters location.

RC2.2 The shoreline position time series depicted in Montaño et al. (2020) displays more fluctuations compared to the one presented in Figure 4 of this manuscript. It would be valuable to clarify whether the time series corresponds to raw data or processed data, such as a moving average.

AC2.2. The reviewer is correct, we have modified the manuscript and clarified that we are applying a weekly moving average as done in Blossier et al. (2017), and Montaño et al. (2021), but not in Montaño et al. (2020) as the data in the above mentioned paper was provided in a raw format for the shoreline modeling competition (Shoreshop).

RC2.3. To enhance clarity, presenting the raw data as points rather than a continuous line in Figure 4 would enable readers to identify any potential gaps in the measurements.

AC2.3. We thank the reviewer for this comment, the figure has been modified and it does look better now:

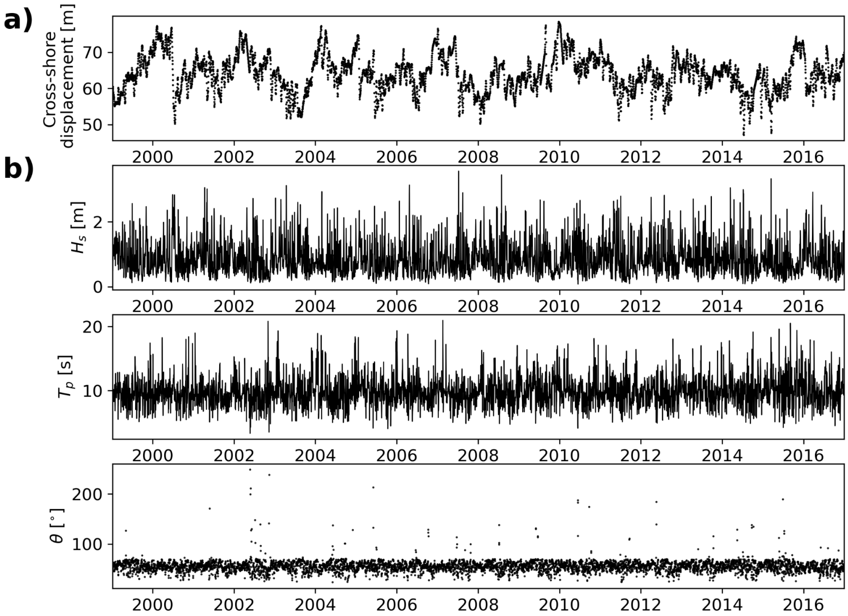

Figure 5. Shoreline (target) time series, weekly averaged (a) and (b) daily wave bulk parameters used as model inputs (Hs,Tp,θ) at Tairua.

In fact, we decided to also change Figure 7 of the preprint (since it shows measurements) following the advice of the reviewer.

C2.4. In the manuscript, it is recommended to specify the two distinct meanings of the term 'memory': one as memory cells or memory blocks in DL algorithms and the other as the 'memory decay function' employed in the ShoreFor model.

AC2.4. The reviewer is correct and we had not realized about the potential confusion that the term "memory" could lead to. We have added a description on ShoreFor and SPADS' coefficients. We have now clarified what ShoreFor's memory decay parameter describes and stated that it is a different concept than the "memory" concept used in LSTMs. The end of section 2.4 (Data) now reads:

To test the DL models, we use the time series previously presented in Montaño et al. (2021) generated with models SPADS (Montaño et al., 2021) and ShoreFor (Davidson et al., 2013); the coefficients for both SPADS and ShoreFor are determined in the models' calibration phase following optimization rules, no *a priori* information — besides wave model inputs and a shoreline target — is required.

The formulation of the equilibrium-based model ShoreFor (Davidson et al., 2013) used in Montaño et al. (2021) follows the modifications of Splinter et al. (2014) allowing for a general model with inter-site variability of model coefficients. The model contains two coefficients linked to wave-driven processes: (1) the memory decay parameter (ϕ) that describes the "memory" of a beach to previous wave conditions (notice this use of the concept "memory" is different than the one used in LSTMs) and (2) the rate parameter (c) that describes the sediment exchange efficiency between the beach face and surf zone. At Tairua, the memory parameter ϕ has been found to be around 220 days (Montaño et al., 2021).

The data-driven model SPADS (Montaño et al., 2021) uses non-stationary time series decomposition methods to reconstruct shoreline oscillations at specific time-scales (S_j) with statistically significant driver information (Y) . Coefficients c that best fit the relation $S_j = \sum_i^N c_i Y_i$ are optimized , where $N = 1, 2 ... i$ correspond to the number of drivers that are significant at the time scale considered, and the subindex j corresponds to the time scale of the shoreline being reconstructed.

RC2.5. Has the performance of the suggested approach been assessed considering different calibration period extensions? Is there a specific minimum timeframe or minimum quantity of data necessary for the application of this methodology?

AC2.5. We chose a fixed calibration period to allow a straightforward and reproducible comparison with Montaño et al. (2021) results. Although we have explored other training periods, we will describe this aspect of the calibration in a different publication that specifically addresses cross-validation.

We thank reviewer 2 for the detailed comments on typos and other minor corrections, they have all been addressed and will appear in the updated manuscript,

The Authors

REFERENCES

Blossier, B., Bryan, K. R., Daly, C. J., & Winter, C. (2017). Shore and bar cross-shore migration, rotation, and breathing processes at an embayed beach. Journal of Geophysical Research: Earth Surface, 122(10), 1745-1770.

Davidson, M. A., Splinter, K. D., & Turner, I. L. (2013). A simple equilibrium model for predicting shoreline change. Coastal Engineering, 73, 191-202.

Montaño, J., Coco, G., Antolínez, J. A., Beuzen, T., Bryan, K. R., Cagigal, L., ... & Vos, K. (2020). Blind testing of shoreline evolution models. Scientific reports, 10(1), 2137.

Montaño, J., Coco, G., Cagigal, L., Mendez, F., Rueda, A., Bryan, K. R., & Harley, M. D. (2021). A multiscale approach to shoreline prediction. Geophysical Research Letters, 48(1).