

# PREDICTING SHORELINE CHANGE WITH DEEP LEARNING: CASE STUDIES FROM THE EAST AND WEST COASTS OF THE U.S.

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## INTRODUCTION

As the coastal population continues to expand, the risk of experiencing social and economic losses due to the effects of a changing climate also increases. Although considerable advances have been achieved in terms of developing numerical process-based models for shoreline change, ensuring reliable predictions remains a formidable task. We propose an innovative approach by implementing Convolutional Neural Networks (CNNs) to predict the evolution of shorelines in response to wave forcings. While the use of these data-driven model frameworks in coastal research is still in its early stages, it holds promise in capturing the strong autocorrelation and memory/storage effects involved in shoreline evolution and may therefore offer a viable alternative to process-based models, at least in some locations. Our models were put to the test at two distinct beach locations: Ocean Beach in California, characterized by its seasonal patterns, and Duck in North Carolina, which lacks a strong seasonal signal. We offer an assessment of the models' performance through the use of absolute-value error metrics. The findings presented shed light on the potential of Deep Learning in forecasting shoreline change.

## DATA AND MODEL

The models are implemented for two well-monitored beaches: Ocean Beach, California, and Duck, North Carolina. For Ocean Beach a mix of satellite-derived (obtained with CoastSat developed by Vos et al. 2019) and in-situ (Barnard et al., 2012; Hansen & Barnard, 2010) shoreline change data is used; the combined dataset extends for ~26 years (from 1995-2020). It has been previously showed in Vitousek et al. (2023) that satellite-derived shorelines have a low error at Ocean Beach.

For Duck Beach, monthly in-situ data (Pianca et al. 2015) is used. The dataset extends for ~31 years (from 1990 to 2023, with a gap of 3 years between the 2013-2015 period). Multiple cross-shore transects are available, although we here illustrate performance in selected transects. For both sites we tested a series of model inputs in order to obtain the best performance (see Table 1). For Ocean Beach, wave related inputs were obtained from the Coastal Data Information Program hindcast (O'Reilly et al. 2016). For Duck Beach, in-situ wave data is

taken from the U.S. Army Corps of Engineers Field Research Facility 8m pressure gauge array. Climate-index data was obtained from the Climate Prediction Center, NOAA, for both study sites.

We used an array of 10 CNNs, where the configurations used were the best performing ones previously tested in another study site (Gomez-de la Pena et al. 2023). We left the last 5 years of both datasets to provide an unbiased test of our models.

Table 1. Model inputs for Ocean and Duck beaches.

	Model inputs
Ocean Beach	Hs, Tp, Wave Direction, Hs max, time elapsed since Hs max, Mean wave energy, Multivariate ENSO Index (version 2)
Duck	Hs, Tp, Wave Direction, Hs max, time elapsed since Hs max, Mean wave energy, North Atlantic Oscillation index

## RESULTS AND CONCLUSIONS

We consider a model's performance competitive when its RMSE is similar to or smaller than the observed standard deviation, and when the modeled time series closely matches the observations in the time series plot. CNNs were successful in reproducing the observed behavior in the equilibrium dominated site Ocean Beach (see Figure 1). Model performance at Duck Beach was lower, although competitive performance was detected within periods of the test window (see Figure 2).

CNN average performance in Ocean Beach was  $RMSE=23.46$  m, while the standard deviation of the observations was 26.38 m. Out of the model input combinations, Hs and wave direction showed to be the combination that increased performance the most. This might be explained due to the high correlation in winter between Hs and Tp at the study site, making the information between these two variables redundant and decreasing model performance if included.

CNN average performance for Duck was of  $RMSE=9.85$  m, while the standard deviation of the observations was 5.69 m. For Duck beach, the model input combinations that showed the best performance were the joint use of Hs, Tp and wave

direction.

These findings support the use of CNNs as an appropriate tool for coastal time-series prediction, particularly to simulate shoreline variability, although further work is needed to improve prediction accuracy in sites where the wave-equilibrium is not met. Future work involves incorporating additional metrics and graphical results to comprehensively evaluate model performance across multiple transects and test time windows.

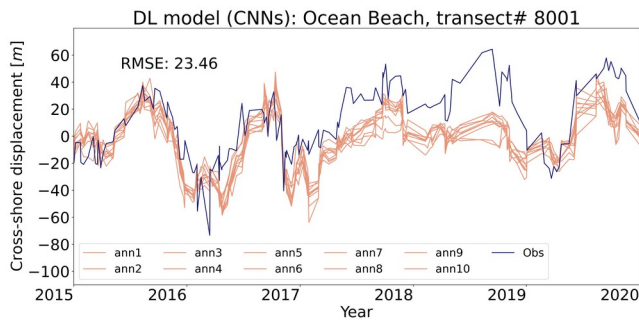


Figure 1 - CNN performance in Ocean Beach, California. Observations marked in dark blue.

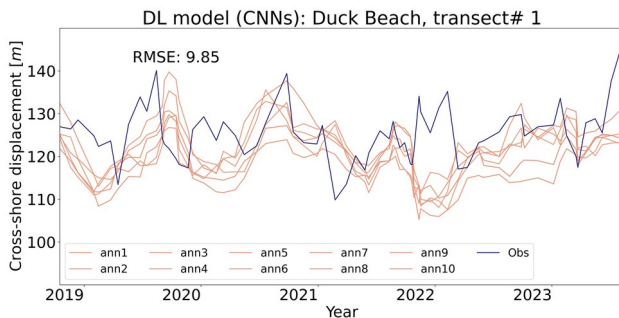


Figure 2 - CNN performance in Duck Beach, North Carolina. Observations marked in dark blue.

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