A DEEP LEARNING MODEL TO PREDICT SHORELINE CHANGE

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INTRODUCTION

As coastal population increases, so does the risk for social and economic losses under a changing climate. To assess future changes, much progress has been made towards developing shoreline numerical models, although producing reliable shoreline change predictions remains a challenge (Montaño 2020).

Here we present a Deep Learning (DL) model to predict long-term shoreline evolution due to waves and large-scale atmospheric patterns. The model is based on two types of Artificial Neural Networks: Long-Short Term Memory (LSTM) networks and Convolutional Neural Networks (CNN). The use of LSTMs and CNNs in coastal research is at an early stage and could be beneficial to incorporate the strong autocorrelation, and memory/storage effects of shoreline evolution. To form a better view of what might aid when predicting coastal time-series with DL, we additionally explore bootstrapping for model training, while evaluating model performance with diverse error metrics. In our study we compare our results with an established semi-analytical model (Shorefor by Splinter et al. 2014) and a data-driven model (SPADS by Montaño et al. 2021).

DATA AND MODEL

The DL model is implemented for a well-monitored beach in Tairua, New Zealand, with time-series expanding for ~20 years with data every 3 hours. The model is forced with a wave hindcast (wave height, period, and frequency), and Principal Components (PCs) of atmospheric large-scale sea-level pressure (SLP) fields and gradients maps (following Montaño et al. 2021).

The model consists of two sub models: a CNN encoder to read and encode the input sequence, and an LSTM decoder that makes predictions. This Neural Network architecture is also known as an "encoder-decoder". The model architecture and the loss function used for training were chosen after an exhaustive search, with the best performance achieved using the modified Mielke's index (Duveiller et al. 2016) as the training loss function.

RESULTS AND CONCLUSIONS

Each model showed a particular strength when compared to the observations. While the smallest root mean squared error (~4m) was obtained with Shorefor (Figure 1a), the standard deviation of the observed time-series (~5m) was better reproduced with both SPADS and the DL model (Figure 1c). At peak (accretion) events the DL model showed the most similar values when compared to the observations (Figure 1b), while at erosion events SPADS model showed the most similar values (Figure 1b).

Overall, the DL model achieved similar error metrics when compared to ShoreFor (Figure 1a). These findings support the use of DL as an appropriate tool for coastal time-series prediction, particularly to better reproduce shoreline variability, although further work is needed to improve the prediction of erosion events.

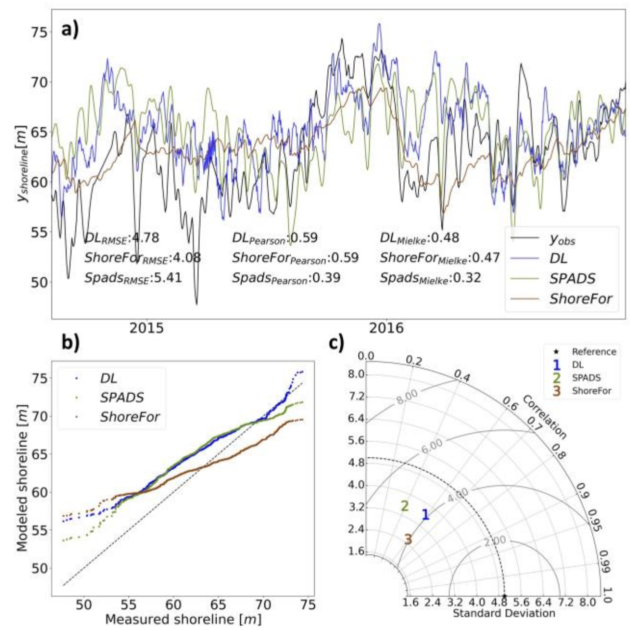

Figure 1. The developed DL shoreline model, compared with SPADS and ShoreFor. a) Time-series and error metrics b) Q-Q plot c) Taylor diagram.

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