MACHINE LEARNING TECHNIQUES FOR CROSS SHORE BEACH CHANGE FORECASTING

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INTRODUCTION

The ability to predict beach morphodynamic changes at short to medium timescales is crucial for sustainable coastal management in a changing climate. The use of data driven approaches such as Machine Learning (ML) techniques to predict coastal change have gained interest in recent years (Kim, 2022, Montano, 2020). These techniques are proving to be a more computationally efficient alternative to the traditional process-based models. The increasing availability of coastal data (e.g., earth observations, global and regional wave reanalysis, long term beach surveys) has served the data requirements of these data-driven techniques. However, it is indispensable to use such techniques alongside a solid understanding of their capabilities and constraints. Additionally, assessing suitable methods of arranging data layouts as input variables is critical for optimizing their performance.

In this study tests two high-performance ML algorithms to predict cross-shore beach change. A deep learning neural network, Long-Short Term Memory (LSTM) and an ensemble ML model, extreme gradient boosting (XGBoost) are explored, and performances analysed, compared and contrasted.

CASE STUDY SITES

Two beaches are selected as test sites for model application: Hasaki beach, Japan, and Narrabeen Beach, Australia. Both sites benefit from long-term cross-shore profile surveys and wave data. On the other hand they have distinctly different site characteristics.

For Hasaki beach, high-resolution weekly surveyed, cross-shore beach profile data and concurrent wave climate data are available from 1986 to 2018, which is ideal for an application of a data driven approach. Hasaki faces the Northwest Pacific Ocean, and it is characterized by a 16km long straight sandy coastline. Beach profile measurements are done at a pier, located 8km to Southeast of Kashima Port and extending approximately 400m offshore (Banno, 2014). The planform of the beach is such that changes in morphology are mainly driven by cross-shore sediment transport. The second site, Narrabeen beach, is an embayed beach governed by both cross-shore and longshore transport and hence a cyclical beach rotation. Measured monthly cross-shore profile data is available from 1979 until 2014, spanning over three decades (Turner, 2016), at eight locations along the beach. Here we will use cross-shore profiles measured at the central region of the beach where profile change is least impacted by longshore sediment transport.

METHODOLOGY

LSTM is a specific kind of gated Recurrent Neural Network (RNN) which has a memory function to store short- and long-term time, sequential patterns of data (Hochreiter, 1997). Beach change is a time sequential phenomenon, which results from the beach being subject to continuous and sequential wave forcing. Thus, LSTM has been selected as the primary deep learning technique for the study, to test its capability of using memory function in forecasting time sequential patterns. XGBoost, being categorized as an ensemble ML technique, is selected as a comparative model due to its reputation for time series forecasting (Paliari, 2021).

Beach change phenomenon is framed as a supervised learning series such that the current state of the beach depends on wave force response and morphological inheritance response by preceding beach state, in order to develop the input variable matrices demanded by the LSTM and XGBoost algorithms.

Two proxies were selected to describe and model cross-shore beach change: shoreline position measured at the still water level (measured horizontally from the vertical through beach chest) and cross shore beach profile area between the fixed beach crest and the lowest available profile depth (from the considered profile measurements). Shoreline position and cross-shore beach area were extracted from the beach profile measurements at both Hasaki and Narrabeen. The LSTM neural network and XGBoost ensemble algorithm were trained using 22 years of weekly measured shoreline and profile area data for Hasaki and 25 years of monthly data for Narrabeen. The models were validated using 10 years of weekly and monthly data for two sites. This enables the models' capabilities of forecasting up to decadal scales to be assessed. The models were fed with different combinations of wave forcing variables (wave energy flux, with and without water level) as they are some of the primary governing forces of cross-shore beach change. The future shoreline position and the beach cross-sectional area were predicted.

The performance of the models is assessed using the standard matrix containing root mean square error (RMSE), coefficient of determination (r^2 score), mean absolute percentage error (MAPE) and cross correlation. Simultaneously, the forecasting of beach proxies at different time scales.

PRELIMINARY RESULTS

Figures 1 and 2 compares weekly shoreline position predictions for the validation period, 2009-2018 for

Hasaki and 2004-2014 for Narrabeen with measured data respectively.

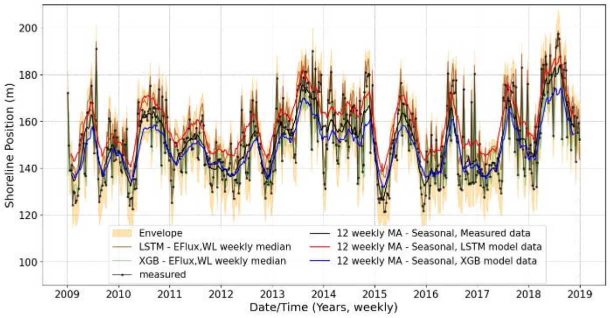

Figure 1 – Comparison of forecasting of shoreline position using LSTM and XGBoost models for Hasaki, Japan.

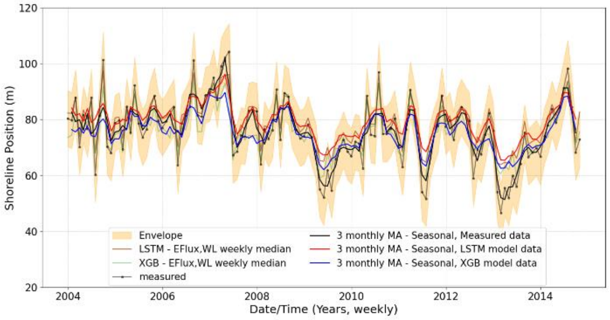

Figure 2 – Comparison of forecasting of shoreline position using LSTM and XGBoost models for Narrabeen, Australia.

The results reveal that although some differences between measured and modelled data can be found at weekly timescales, particularly at the extremes, the models predictions follow the trend of variability over a longer-term (decadal) timescale. To investigate this further, averages (12 weekly for Hasaki and 3 monthly for Narrabeen) are also generated for the predictions using two methods, which represent seasonal timescale and compared with the moving averaged measured data. An envelope of +/-10m is also considered as an acceptable buffer zone to refer whether the model predictions offset even beyond this envelope, as the standard deviations are larger, of 18m and 14m for two sites, respectively.

Both methods show encouraging performance in identifying annual to inter-annual trends of shoreline position with LSTM and XGBoost models giving an RMSE (and as a percentage of average beach width during testing periods) of 6.93m (5.2%) and 5.04m (3.38%) respectively at Hasaki and 4.73m (6.22%) and 4.75m (6.25%) at Narrabeen, respectively.

LSTM and XGBoost models predict cross-shore profile area with RMSE of 23.76m^2 and 25.40m^2 respectively at Hasaki and 24.02m^2 and 29.92m^2 respectively at Narrabeen (as a percentage of average total profile area below 0.9% for all scenarios), which indicates a good model performance with a MAPE less than 1.5% in all models. The prediction results reveal some sensitivity to the input variable combinations, demonstrating the influence, the statistical parameters of inputs have on optimum output results. Together with two proxies, beach change forecast can be facilitated comprehensively, with further optimizing of the models.

FUTURE RESEARCH WORK

The model prediction capabilities will be further assessed to address and discuss model constraints, focusing on a range of timescales from monthly to decadal beach variability. Also, model sensitivity to input data combinations and frequencies will be investigated.

Sequentially as next step forward, an ensemble of models will be forced with different combinations of wave forcing including relevant climate indices of Multivariate ENSO Index (MEI), North Pacific Index (NPI), Pacific Decadal oscillation (PDO) and regional specific, sea surface temperature (SST) based ENSO Index, in order to assess the impact of climatic variabilities on beach change, at different time scales and capabilities of models to identify them through the training process.

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