A MIXTURE OF EXPERTS APPROACH COMBINING PHYSICS INFORMED AND MACHINE LEARNING SHORELINE MODELS

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INTRODUCTION

Understanding the drivers, as well as the ability to predict sandy shoreline change, is of primary interest to coastal engineers and managers, alike. As such, significant effort has been put into a range of modelling approaches to capture both short-term and long-term shoreline dynamics (Miller & Dean, 2004; Roelvink et al., 2009). These modelling approaches also encompass a wide range of methods, from physics-based models to intricately structured multi-layered neural networks (Vitousek et al., 2017). Nonetheless, no singular technique has emerged as the superior approach, each demonstrating their own set of critical limitations. As machine learning has increasingly gained prominence in the field of environmental science, there has also been a growing emphasis on the need for models that are more interpretable. Striking the right balance between model performance and interpretability has become increasingly nuanced. After all, establishing trust in a model necessitates a degree of comprehension regarding its underlying decision-making process.

In this context, while behavioural models may oversimplify coastal processes, ML methods are prone to being overparameterized and opaque. One path forward lies in the co-evolution of both methods to arrive at a modelling approach that retains interpretability and also captures the relevant dynamics to make accurate forecasts.

In this study we develop several models combining multiple approaches designed to promote interpretability while retaining high predictive performance. Here we hypothesize that a smart mixture gate informed by prior knowledge will allow more flexibility in capturing the different modes of shoreline change which make up the overall response.

METHODOLOGY

Multi-annual shoreline datasets from five different locations (six different transects) were assembled and used to train a range of models to predict instantaneous shoreline change, *dx*. The models are forced with nearshore transformed daily average and peak significant wave height (H_s) and wave period (T_p). Some models are also given the model prediction for absolute shoreline position at the previous time step ($X_{pred\ t-1}$) as an autoregressive input.

In this work, the following candidate models were used in the mixture of experts approach: three simplified empirical shoreline models, ShoreFor (Splinter et al., 2014), Yates et al. (2009), and Harley & Turner (2009), henceforth HT09; and two neural network based approaches, an LSTM model, and a transformer based architecture (Vaswani et al., 2017). The outputs are combined using a gating function to control the relative contribution of each model at each timestep, using Bayesian inference to learn this function and represent the degree of uncertainty. Through a well-informed mixture gate, we not only seek to improve model performance but also to assess relative model strengths and shortcomings.

RESULTS

Our study unveiled significant variations in model performance across different site types, where some sites displayed strong seasonal patterns, others were predominantly influenced by storms.

Notably, we observed that the most prevalent challenge across all long-term models was accurately forecasting the timing and severity of storm events at locations like Narrabeen, which are storm-dominated. One such approach to address this issue, was on integrating an empirical storm model (HT09) with other various long-term models, including ShoreFor and an LSTM.

In Figure 1, a snapshot of our results is presented showing the development of a mixture of experts model augmenting an LSTM with HT09 (a specialized storm model). We see from the top panel, a single ShoreFor

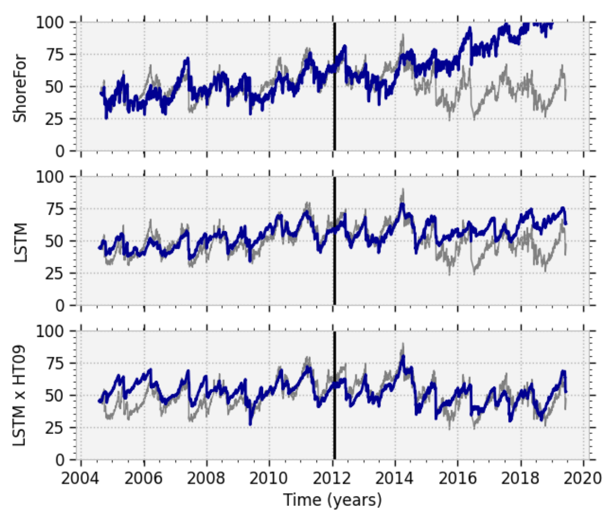

Figure 1 - Three models applied to Narrabeen, ShoreFor (top), LSTM with an autoregressive exogenous term (middle) and Physics Augmented LSTM with HT09 storm model (bottom). Black line separates training (left) and test (right) data.

model that is calibrated on the training set fails to anticipate the change in trend occurring after 2014. The presence of its strong linear term triggers such a divergence. The LSTM outperforms ShoreFor for this dataset. However, when examining the LSTM outputs at other sites, it is evident that the LSTM was most skillful at sites characterized by robust seasonal patterns. At storm-dominated systems, like Narrabeen (Figure 1) the LSTM tended to underestimate the severity of storm events and diverged from the observations in the test data. This underestimation compounded on the autocorrelative nature of shoreline movement led to a significant departure from observed values. The unpredictable nature of these storm events posed a significant challenge to any single model, made more difficult when wave conditions do not consistently produce similar effects on immediate shoreline change. The physics-augmented machine learning approach, wherein a gating function discerns when to employ the LSTM and HT09 models, holds great potential for future advancements. This approach eliminates the need for the neural network to comprehensively understand both magnitude and timing of storms. Instead a mixture of experts approach separately determines when to transition to the HT09 model, letting the LSTM operate outside of these storm periods (bottom panel, Figure 1).

DISCUSSION AND CONCLUSIONS

The ability to robustly model both short-term storm impacts, as well as longer-term multi-annual shoreline change is an ongoing challenge due to our inexact understanding of the governing physics. As such, a suite of models have been proposed that model one temporal aspect well (e.g., seasonal change), at the cost of another (e.g., accurate storm demand). Here, we explored a mixture of experts technique to develop a hybrid model that learned how to incorporate multiple model outputs. The best performing model was a combination of a simple LSTM shoreline model and the Harley and Turner (2009) storm demand model. This highlights the benefits of leveraging both highly parameterized ML methods and simplistic physics-based equilibrium models together to yield successful long-term predictions.

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