MACHINE LEARNING FOR PROBABILISTIC PREDICTION OF SHORELINE CHANGE

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INTRODUCTION

The constantly changing of shorelines have long challenged the coastal engineers, geologists and oceanographers. These dynamics are driven by multiple factors, including wave height and direction. Despite the advances in numerical modeling techniques, predicting the precise position of shorelines remains uncertain. This paper investigates the uncertainty, particularly focusing on the influence of wave direction and its inherent variability. The ShorelineS numerical model by Roelvink et al. (2020) is examined as an illustrative tool, with simulations revealing the variability in shoreline positions. This exploration opens a gateway to consider alternative predictive tools, particularly machine learning (ML).

In this study, the shape of the initial shoreline is a Gaussian hump shape with 600 meters in width and 180 meters in height shown in Figure 1, and the process of its evolution under the following environmental conditions is investigated:

- Significant Wave Height = 1 m
- Wave Period = 5 seconds
- Wave direction = 45 deg
- Wave Spreading factor = 50 deg
- Sediment size $d_{50}= 2\times10^{-4}$ m $d_{90}=3\times10^{-4}$ m

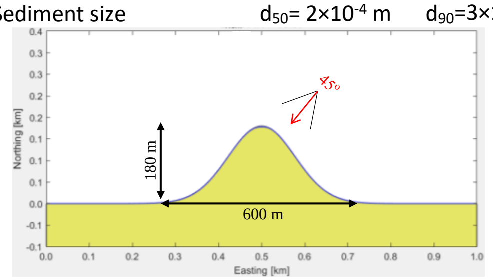

Figure 1 - Selected shoreline shape (Gaussian hump) with 600 meters width and 180 meters height.

We chose the specific wave conditions and the described Gaussian hump shape for our study to increase the likelihood of creating complex morphology such as spits, lakes, and islands in our model.

UNCERTAINTY IN SHORELINE POSITION MODELING

The development and final shorelines come with many uncertainties. One major source of this uncertainty in many process-based models, like ShorelineS, is the chronology of wave directions during the simulation. These models mainly use wave height and direction as their two primary inputs. Figure 2, shows the evolution of the initial Gaussian hump shape shoreline after one year of simulation, for two simulations with exact same input. The model internally produces different chronology of the wave directions based on mean direction and directional spreading (Figure 3) that causes the uncertainty in the results.

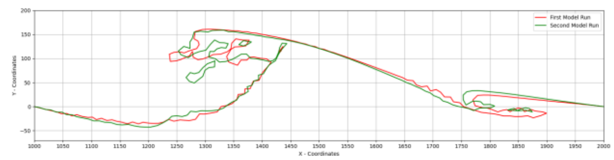

Figure 2 - Comparison of the final position of the shoreline after running the ShorelineS numerical model two times.

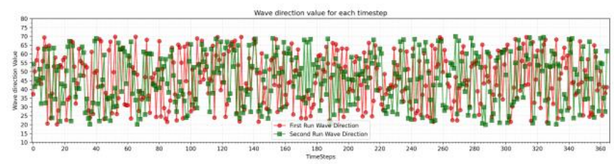

Figure 3 - Comparison of wave directions between the first and second ShorelineS model runs.

Figure 2, shows that the shoreline positions vary at the end of the simulation, due to the uncertainty driven by wave directions. For further investigation, we ran the ShorelineS numerical model 1000 times for the main scenario of this study, and the final positions of all possible shorelines are illustrated in Figure 4. From Figure 4, we can extract the probability of shoreline existence within each 2×2 meters pixel as shown in Figure 5.

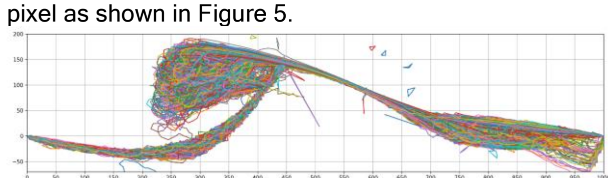

Figure 4 - All shoreline positions at final timestep for 1000 ShorelineS model runs.

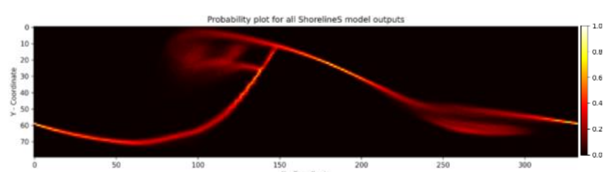

Figure 5 - Probability plot for all shoreline positions at final timestep for 1000 ShorelineS model runs.

In considering the final results of this investigation, aside from the model run times discussed in Table 1, there is a lack of continuity in the probabilistic coastline position shown in Figure 5.

METHODOLOGY

This study leverages the characteristics of machine learning (ML) models to manage the existing uncertainties in numerical modeling, as in the investigated example. To address this problem, we present a simple and straightforward method that we refer to as the “Adaptive

Model Selector", which is adapted from the "Ensemble Model" introduced by Zhou (2012).
The "Adaptive Model Selector" is not a traditional "Ensemble Model." Instead, it is built upon pre-trained models, each tailored for specific wave directions without directional spreading and with a wave height of 1.0 m. To predict shoreline positions, this method integrates the Monte Carlo simulation to select and merge predictions from these pre-trained models, depending on the incoming wave direction at each timestep. It determines which model best fits a particular wave direction.
For our study, we generated 11 sets of gridded synthetic data using the ShorelineS numerical model. These datasets represent 11 distinct scenarios where wave direction ranges from 20 to 70 degrees, increasing in 5-degree intervals, with a spreading factor of 0. We then trained a Convolutional Long Short-Term Memory (ConvLSTM) model introduced by Shi et al. (2015), for each of these datasets. These 11 models act as the sub-models in our Adaptive Model Selector, capturing changes in wave direction. By setting a spreading factor of 0 degrees for each scenario, we ensure that the ShorelineS output remains consistent, removing potential uncertainties that arise when a spreading factor is included. Our integrated approach aims to predict 1000 potential shoreline positions and determine the likelihood of shoreline presence at specific 2D grid points (2x2 meters pixel).
The whole process of using ML to predicting shoreline existence probability is summarized as follows:

A. Generate 11 dataset for 11 scenarios.
B. Train 11 ConvLSTM model for 11 scenarios.
C. Repeat the following process 1000 times:
    a. Utilize Monte Carlo simulation to generate a normally distributed random array of wave directions, ranging between 20 and 70 degrees, over 365 timesteps.
    b. Apply "Adaptive Model Selector" (following steps) for each timestep.
        1. Select two ConvLSTM models based on the wave direction for the current timestep.
        2. Predict future shoreline using two selected models and previous shoreline (resulting in two predictions).
        3. Apply a weighted average to the two predictions to obtain the most accurate result based on wave direction.
        4. Filter pixel values to achieve a clear shoreline for the current timestep.
        5. Advance to the next timestep and repeat steps "1" to "5" until the final timestep is reached.
    c. Save the shoreline position from the last timestep as the final prediction.
D. Generate the probability plot for all shoreline positions at final timestep.

The required time and final results are presented in the Table 1 and Figure 6.

Table 1 - Comparison of required time for analyzing shoreline existence probability.

Step	ShorelineS Model	ML model
1000 ShorelineS Model Runs	105 hours & 10 minutes	-
11 ShorelineS Model Runs for Sub-scenarios	-	1 hour & 9 minutes
ML training Duration	-	1 hour & 35 minutes
Probability Calculation	1.5 minutes	-
1000 Predictions & Probability Calculation	-	2 hours & 43 minutes
Total	**105 hours & 11.5 minutes**	**5 hours & 27 minutes**

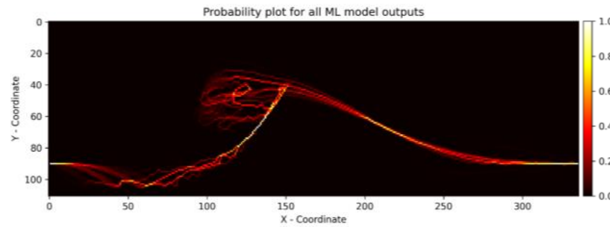

Figure 6 - Probability plot for all shoreline positions at final timestep using Adaptive Model Selector.

CONCLUSIONS

Machine learning can be used to address the uncertainty in predicting shoreline positions, by using trained ML models –such as the ConvLSTM trained on 2D gridded data– predictions can be made based on initial coastlines and changing wave directions. To effectively manage the inherent uncertainties in numerical shoreline modelling, the "Adaptive Model Selector" method was introduced.
This method selects and combines predictions from pre-trained models tailored for specific wave directions. When integrated with the Monte Carlo simulation, this approach can predict multiple possible shoreline positions.
The final results of the ShorelineS process-based numerical model do not exhibit certainty, especially regarding the head of the generated spit, even when we run the model 1000 times and combine all the results together. On the other hand, using the Adaptive Model Selector method provides us with more coherent and better-correlated results for the probability of predicting shoreline positions in future timesteps.
When comparing the time taken by the ShorelineS numerical model and the trained ML model (each run 1,000 times) to project the future shoreline position, we observe that using the introduced method considerably reduces the required runtime by 95 per cent.

REFERENCES

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