Imperial College London
Department of Earth Science and Engineering
MSc in Environmental Data Science and Machine Learning

Independent Research Project
Project Plan

Estimating landfalling hurricane wave characteristics with parametric modelling

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Abstract

Downscaling technique for nearshore wave data from offshore ocean variables is crucial in predicting tropical cyclone driven flood and in various costal engineering applications. Numerical downscaling requires huge computation and is hard to run in limited time for multiple times. In this research, several hybrid downscaling methods are compared and a new deep learning based surrogate modelling framework for downscaling is proposed. (some brief description of comparison result) The framework is demonstrated alone Florida coastline (USA), utilizing Mike21 as the dynamic simulator and (model features) as the surrogate model approach, (some model result/ improvement)

1 Introduction

1.1 Problem Description

Tropical cyclones (TCs), a significant peril to global coastal communities, pose a substantial threat to multitudes of individuals, inflicting extensive infrastructural damage amounting to billions of dollars every year. The increasing trend of coastal urbanization worldwide amplifies the detrimental impact of TCs (Volton et al., 2019). Storm surge and damaging waves are amongst the most destructive hazards caused by TCs, which significantly influence the severity of coastal flooding (Hoeke et al., 2021). Thus, prediction of nearshore wave field from TCs becomes a paramount requirement.

For nearshore wave prediction, downscaling from deep water wave field to shallow water, nearshore wave field is generally necessary. However, the current downscaling strategy with numerical models present substantial challenges. Physics-based numerical wave models, while accurate, are computationally intensive (Peach et al., 2023), making them unsuitable for real-time predictions or scenarios where large amount model simulation is required.

Apart from wave prediction, wave downscaling is also necessary in acquiring long-term historical wave data, which is essential in costal engineering and flood risk management.

Long-term historical wave data is very important. In marine structure designment and wave energy assessment, long-term database of spatial wave climate parameters is required (Camus et al., 2011). Moreover, policymakers who shoulder the responsibility of coastal defence and insurance companies who cover nearshore property consistently demand flood risk probabilistic analyses (Volten et al., 2022). These analyses generally offer design wave height for more than 100 years return periods. For example, the United Kingdom, employs 1000-year return values for coastal flood boundary conditions (Environment Agency, 2018).

However, buoy measurement does not provide enough time span and can be far from place of interest, which make it difficult to represent local wave climate (Camus et al., 2011). There is large scale, multi-years reanalysis databases, but their spatial and temporal resolution generally does not support local costal application climate. Thus, downscaling is required. Again, the downscaling leads to the use of physics-based wave model from offshore to nearshore, which is computationally intensive as prementioned.

Downscaling large-scale, deep-water wave to local nearshore wave is essential both in predicting nearshore wave field from TCs and in long-term nearshore wave data augmentation. Given the huge computational cost of traditional numerical downscaling method, there is a pressing need for new approaches that can generate high-resolution nearshore wave field at low computational cost. Such model functions as surrogate model of the traditional numerical model.

1.2 Literature Review

In the coastal engineering domain, three general approaches have been developed to downscale large-scale wave information: dynamical, statistical, and hybrid approaches. Dynamical downscaling consists of a hierarchy of numerical models capable of simulating wave transformation processes (Rusu et al., 2008), while statistical approaches make use of empirical relationships between offshore ocean variables and nearshore local variables to obtain small-scale information (Browne et al., 2007; Kalra et al., 2005). Hybrid methodologies combine the two, part of the offshore ocean scenarios is numerically downscaled first, then a statistical relationship, which is called transfer function, is built based on the scenarios numerically downscaled (Groeneweg et al., 2007; Stansby et al., 2007). Each approach has pros and cons. According to Camus et al., 2011, the dynamical downscaling is generally the most accurate, but require most computation; the statistical approach is faster but need observation data at target location to find the empirical relationship; the hybrid approach may need to dynamically downscale many offshore cases. The downscaled offshore results in hybrid method function as the local observation data in statistical method, forming training set for statistical method together with the offshore input. For this thesis, the hybrid approach is the focus. Two reasons are listed. First, the research area along the Florida coastline (USA) does not have enough observation data to build a pure statistical model. Second, as this is an external project, the company aim to build a surrogate model for their deep-water to shallow-water numerical wave model and they offered numerical model data, which can be considered as the first step in hybrid downscaling.

In hybrid downscaling, after certain number of offshore scenarios are dynamically downscaled, radial basis function (RBF) (Camus et al. 2011; Volten et al., 2022), Gaussian Process Simulator (GPE) (Pullen et al., 2018, Parker et al., 2019) and multi-layers perception (MLP) (James et al., 2018) were used to find a transfer function. More tradition method includes look-up table (LUT), which was found to need more training data to compete GPE (Malde et al., 2016). For the RBF, Volten et al. (2022) made improvement, compared with Camus et al. (2011), by compress training data using principal component analysis and significantly reduced the data dimension. For MLP, it is worth mention that though MLP is a deep learning method, the neural network in James et al., (2018) was simply a fully connected feed-forward network with 3 hidden layers, 20 nodes each layer. In Peach et al. (2023), a well-trained LUT method was compared with MLP and the MLP gave better result than LUT both in accuracy and efficiency.

Regarding sample selection technique, Maximum Dissimilarity Algorithm (MDA) is most widely used (explained in Camus et al., 2010). The MDA is a distance based recursive algorithm that chose the next point, which is most distant from the selected points and sim to select. The samples selected is supposed to represent the variability of all data.

1.3 Objectives

This research aims to build a surrogate model to numerical model that down scale offshore ocean variables to nearshore wave field, particularly, significant wave height (SWH). Depend on time and progress, the research will first try to build a model which predict SWH from offshore wave field and wind field. Then try to predict nearshore wave field directly from TCs track data, such as max wind speed, max radius. The surrogate model should be implemented with lower computational cost than numerical model such that the model can be run fast for urgent TC warning or be run for multiple times to generate long-term nearshore local wave data for costal engineering and risk management.

2 Progress to Date

The data is confidential, provided by RMS company. However, some illustration of data has been approved.

Currently, the data consists of TCs track parameters and numerical models results. The TCs tracks are simulated from another model. The tracks correspond to 189 storms (TCs). For each storm, properties including location, max wind speed, max radius, lowest pressure etc. are fed into a 2D wind field model to reconstruct a 2D wind field for the storm at each time step. The wind field, together with some other data, like bathymetry, are fed into a spectral wave model (Mike21) to run storm surge simulation. The result of Mike21 is extracted at three sets of locations which are shown in figure 1. For each point on Fig.1, there are series of wave properties, including significant wave height (SWH), peak wave period (PWP), mean wave direction (MWD) and total water depth (TWD). Also, the 2D wind field at the locations is extracted, data of which includes wind speed and wind direction.

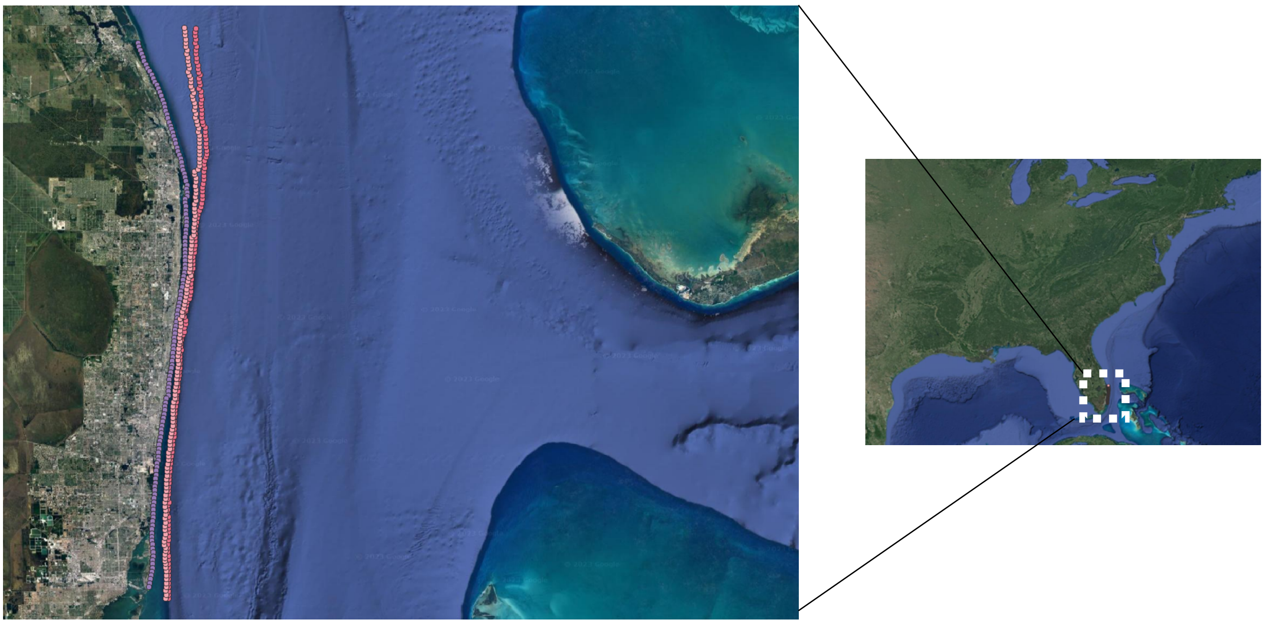

Fig 1, Research location, Florida coastline. Results of the spectral wave model (Mike21) is extracted at three sets of locations (purple, pink, red colour on the left image). The red set include 155 50m isobath points. The pink set include 155 25 isobath point. The purple set include 145 coastline points. For all the three sets, points are spaced at 0.01° (about 1km) apart.

3 Future Plan

I will first train statistical models with methods used in papers, including RBF, GPE and MLP. It is not possible to use LUT as the number of storms is limited and not enough offshore scenarios has been dynamically downscaled. The training data will first be based on offshore wind and wave variables, then be based on storm tracks. If the result is promising, I am planning to use a recurrent neural network, like LSTM, to train the model. Different methods shall be compared and hopefully the pros and cons of each method can be explained from both model structure and the data physic bases. Trade-off should be made between model accuracy and model versatility.

Word count 1447 + 1 image

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