Hybrid Machine Learning Models for Storm Surge Prediction

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Abstract

Prediction of hurricane impacts is a critical aspect of being prepared for, and recovering from, local infrastructure damages or economic interruptions. Explicit computation of physical systems expressed as complex partial differential equations and the required boundary and initial conditions is usually a computationally expensive task, particularly at high spatial and temporal resolutions. Statistical and machine learning (ML) approaches can be an effective way to accelerate the prediction and forecasting process, once suitable training data is identified and the ML models constructed. In this paper, we describe the general storm surge forecasting and prediction problem and two ML approaches to predicting water levels due to hurricanes. Our work is a combination of machine learning and simulation, which uses data and scientific knowledge to create a hybrid approach.

Introduction

Storm surge caused by tropical cyclones is one of the more damaging naturally occurring phenomena along the US coastline from Cape Cod in the northeast to Gulf of Mexico, as recent events such as Hurricanes Katrina (2005), Sandy (2012), Florence (2018), Michael (2020), and Ida (2021) (among others) have demonstrated. In 2021 alone, four tropical cyclones caused in excess of $1B in damage (NOAA 2021), including substantial social and human costs associated with evacuation and displacement, property and life loss, and recovery expenditures. Forecasting of cyclones and associated impacts such as storm surge have advanced significantly in recent decades, owing to 1) better understanding of the physics governing these complex systems (Bunya et al. 2010; Thomas et al. 2019); 2) advanced numerical and computer techniques to solve the governing equations (eg, (Blanton et al. 2012)); 3) and increased awareness among the general public as to hazards and threats (Morrow and Lazo 2014; Zachry et al. 2015). However, despite these advances, it is advantageous to have faster predictions of water levels to help with decision making processes. One way to achieve more rapid prediction capabilities is to use ML approaches to time series prediction.

Machine Learning for Storm Surge Prediction

ML approaches to storm surge prediction have been pursued for the past two decades, primarily focused on time-series predictions based on observations of water level response to forcing from (e.g.) wind speeds and atmospheric pressure. Among others, Tissot, Cox, and Michaud (2002) used observations of water levels and wind velocities to build a 2-layer ANN to predict water levels in a sheltered bay on the US Texas coast, finding that short-term forecasts of 3-24 hours were a significant improvement over a linear regression model. De Oliveira et al. (2009) used an MLP approach to predict short-term variability in coastal water level anomalies (the difference between observed and purely harmonic tidal water levels) due to meteorological forcing at coastal Brazil locations. The model was designed to capture effects from cold front passages in the 3-5 day timescales and had good prediction skill out to a 24-hour forecast lead time. Londhe (2011) developed an ANN for water level predictions and applied it to three different regions, each with very different weather regimes. Anomalies in water level were reasonably predicted in the different regions, including a time period in the Gulf of Mexico during which Hurricane Ike (2008) occurred. In the latter case, the peak water levels were slightly under-predicted.

Numerical Models vs Machine Learning for Storm Surge Predictions

Explicit simulation of the governing equations is typically an expensive activity due to the need to resolve important temporal and spatial scales important to the solution. For storm surge simulations, the ADCIRC model (Luettich, Westerink, and Scheffner 1992; Westerink et al. 2008) is used for many purposes, including forecasting and prediction of water levels driven by hurricanes (Thomas et al. 2019; Dresback et al. 2013). ADCIRC solves the shallow-water equations formulated using linear triangular finite elements that allow very high spatial resolution in critical areas such as the coastal region while maintaining coarse resolution away from the region of interest. However, this flexibility results in a substantial computational resource constraint, particularly when run in a real-time, operational scenario. Typical cpu requirements for a high-resolution ADCIRC grid ranges from 500-5000 cores in order to compute forecasts in near real-time.

Statistical and ML approaches to prediction offer faster alternatives to direct/explicit numerical simulations if the ML model can be suitably trained with representative data. The ADCIRC storm surge model, as a numerical model, takes significant compute power and compute time to produce forecasts. A learned ML model can inference a forecast at a much swifter speed, yet proper training is needed to match and even improve accuracy on the numerical model. Hybrid modeling approaches are increasingly combining physical process models with the versatility of data-driven machine learning in Earth system science (Reichstein et al. 2019).

Hybrid Simulation Models

Description of Data sets

Two data sets are used for this study, both of which are generated using the ADCIRC storm surge model. The first data set is from a detailed, high-resolution storm surge simulation of Hurricane Florence (2018), which made landfall on the North Carolina coast near Wrightsville Beach, North Carolina, on 14 September, 2018. Time-series data of east-/west and north/south wind speeds, atmospheric pressure, and water level were extracted at eight locations around a central point, or node, near Wrightsville Beach, forming a 3x3 grid with 20 km spacing (Figure 1). This data that is simulated using the ADCIRC storm surge model is based on geographic locations which account for coastal geometry.

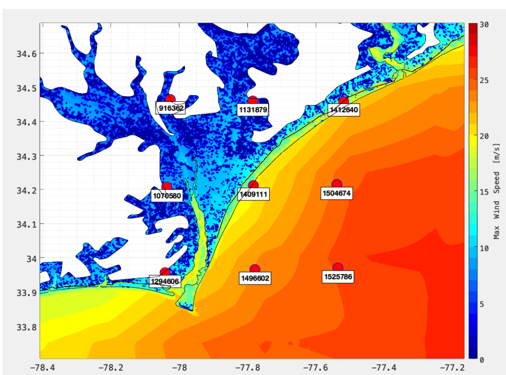

Figure 1: 3x3 grid of points where time series of variables were extracted from a large storm surge simulation for Hurricane Florence. Colors represent the maximum wind speeds (in m/s) over the simulation.

The second data set is generated using the ADCIRC storm surge model on an idealized spatial grid that represents a long channel with a relatively narrower width. This is representative of large coastal rivers such as the Cape Fear River in eastern North Carolina. An idealized hurricane track and associated parameters are used to force ADCIRC and generate a time sequence of images for wind velocity and water level responses. Since the width of the channel is much smaller than the length, the response is primarily one-dimensional in the along-channel direction. This substantially simplifies the data set and makes interpretation of the results easier. Figure 2 shows the channel grid and hurricane track used to generate the data set.

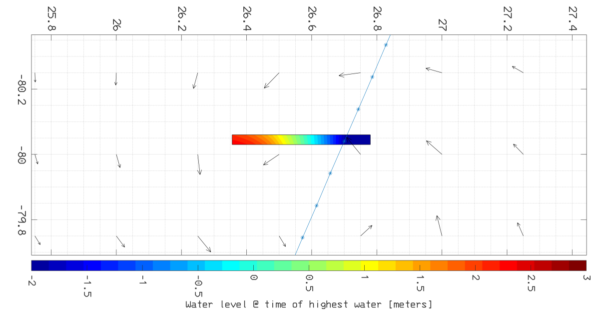

Figure 2: Idealized channel grid for storm surge prediction. The image has been rotated so that south/north is along the horizontal axis. The blue line is the hurricane track, the color surface is the water level in the channel at the time of highest water, and vectors show the hurricane wind velocity at the same time.

Geospatial Grid Based Model

A geospatial grid based dataset allows for acknowledgment of the meteorological forces at a distance from the point of interest that affect the regular tide and water conditions. A grid of spatially distant points allows for the representation of the coastal geometry to be accounted for within the data. Additionally, during cyclone events, large amounts of meteorological data are needed to better describe the complexities of these nonlinear processes (De Oliveira et al. 2009). Using time-series data inputs from a 3x3 grid (Figure 1), an Artificial Neural Network (ANN) was constructed and consists of 28 input feature time-series, corresponding to the relevant meteorological forces at each nine nodes, to predict the water level residual at the central node. To account for the amount of data needed to sufficiently describe the complexities of storm surge generation, our time-series input includes three days where the data is captured in 30 minute intervals for all nine nodes. Similar to Tissot, Cox, and Michaud (2002), we introduce a lag in the input data and the time at which the ANN predicts the water level.

Central Node Lag	**Surrounding Node Lag**	**Test Case**	$R^2 Loss$
1 hour	6 hours	All Nodes Included	0.9038
1 hour	6 hours	Overland Nodes Removed	0.9067
1 hour	6 hours	Central Node Removed	0.8994
1 hour	9 hours	All Nodes Included	0.8996
1 hour	9 hours	Overland Nodes Removed	0.9013
1 hour	9 hours	Central Node Removed	0.8951
3 hours	6 hours	All Nodes Included	0.8035
3 hours	6 hours	Overland Nodes Removed	0.7923
3 hours	6 hours	Central Node Removed	0.7749
3 hours	9 hours	All Nodes Included	0.7614
3 hours	9 hours	Overland Nodes Removed	0.7923
3 hours	9 hours	Central Node Removed	0.7850

Table 1: Table of ablation study results.

We have identified lag times that produce the best results through a series of ablation studies. These ablation studies were conducted to ensure degradation in model performance with the removal of data as well as identify which combination of nodes and lags produce the highest performance (Table 1). By changing the lag times and removing certain inputs we developed a better understanding of how these lags and inputs contributed to the predictions. When comparing performances of the different model inputs, we used the $R^2 Loss$ evaluation metric, as opposed to MAE Loss, as it shows how much variance is accounted for by the model. The results of the ablation study follow our physical knowledge of how the input forces propagate through time and space. The surrounding nodes with a lag of 6 hours improves the models predictability compared to increased lag times. Additionally, the central node, the node at which the water level will be predicted, has the best predictability at a lag of 1 hour with its own time-series data. This is due to the time it takes for wind-wave interactions to develop and propagate to the area of interest. Despite identifying the lag times for both the central node and the surrounding nodes that produce the highest performance, as well as the loss decreasing with epoch (Figure 3), the model was not able to adequately predict the storm surge due to its large area and grid points that are distant from each other.

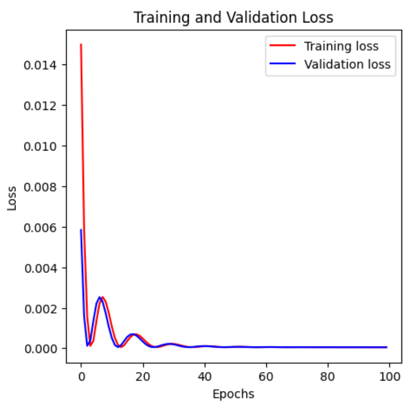

Figure 3: Training and Validation $R^2 Loss$ plot for ANN with grid based time-series data as inputs using optimal lag times determined during ablation study (Table 1).

Image and Numeric Data Regression Model

The data set made using a long narrow strip was used for the image and numeric data regression model. A combination of a multi-layer perceptron (MLP) and a convolutional neural network (CNN) was the model for this data set (Figure 4). A station's data consisted of three values, a north-south wind value (positive/negative), east-west wind value, and the water level from each of the nine stations resulted in 27 inputs for the MLP. The MLP predicts a water level for the station specified. The CNN received the water level image which consisted of a montage of four consecutive water level images directly before the predicted water level. The image is passed through a 2d-convolutional layer, a linear activation function, batch normalization, and a max pooling layer. The image is flattened and passed through two dense functions outputting a water level prediction. The model then concatenates the water level predictions of the CNN and MLP to make a final water level prediction. The model predicts the water level at one of the specified station locations ten minutes in the future.

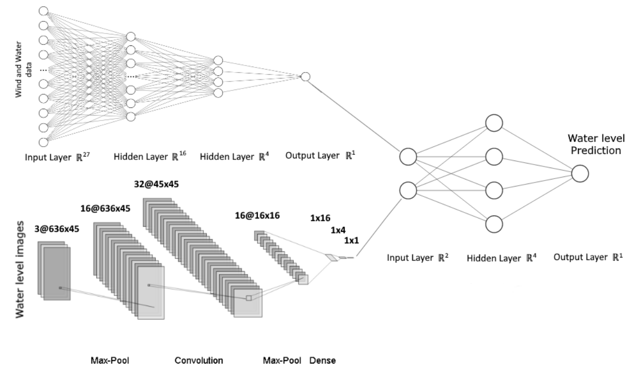

Figure 4: Architecture of the image and numerical regression model

Results

The southernmost station was used as it had the most variance in water levels. Several tests were done to determine optimal configuration for station data. Using the data from every station reduced the amount of noise in the predictions. It was discovered that a sloshing effect after the hurricane passed through the narrow channel affected the water level predictions. The sloshing effect is the water level returning to a neutral state with no strong wind influence. To determine the impact of this effect models were trained and tested using full simulation data, data during and after the hurricane, data without the sloshing effect, and data only during the hurricane (Figure 5). The models that have the sloshing effect removed result in better predictions at the hurricane's peak surge, while the models with more data perform better overall.

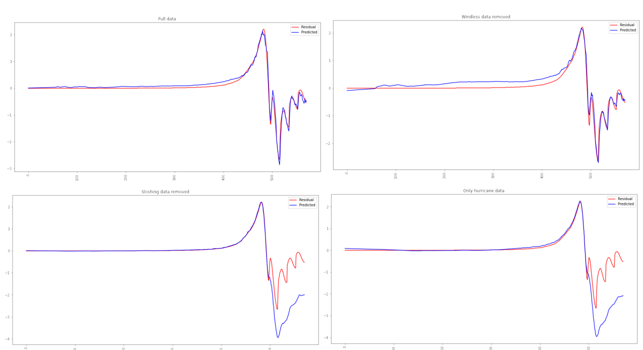

Figure 5: Surge predictions of models trained using different portions of the data. Top left: Full data of the simulation that includes the sloshing effect and the prior limited wind velocities, Top right: simulation data with just the sloshing effect (no prior limited wind velocities), Bottom left: simulation data with the prior limited wind velocities but no sloshing effect, Bottom right: simulation data using only hurricane data, omission of sloshing effect and prior limited wind velocities.

Discussion and Conclusions

With initial success in using an image based regression model, due to its spatially dense grid, we have expanded into image to image prediction. Using the same montage images of the idealized channels wind field and water level, we want to forecast water level images for the entire geospatial area rather than for a singular node. This image to image forecasting will require a CNN model architecture base to perform this task.

Additionally, data inputs thus far have been used to simplify the coastal geometry as well as more dense spatial grids. As our model becomes more refined and accurate, our inputs will be scaled to larger and more authentic geographical area in order to capture the effect of the coastal geometry on the wind-wave interactions. This expanded dataset maintains the hybrid of simulated and real data over the given geographical region. Future work will incorporate data inputs from existing National Oceanic and Atmospheric Administration (NOAA) coastline stations. The omission of these NOAA stations thus far has been done to avoid spatial and temporal gaps within the dataset due to stations or sensors being damaged or being offline. However, with the future addition of this data we will be able to assess the models ability to handle such data variability as well as the coastal geometry.

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