

Surrogate Models to Predict Wave Hydrodynamics on Evolving Landscapes

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Abstract

Coastal planners using probabilistic risk assessments to evaluate structural flood risk reduction projects may wish to simulate the hydrodynamics associated with large suites of tropical cyclones in large ensembles of landscapes: with and without projects' implementation; over decades of their useful lifetimes; and under multiple scenarios reflecting uncertainty about sea level rise, land subsidence, and other factors. Wave action can be a substantial contributor to flood losses and overtopping of structural features like levees and floodwalls, but numerical methods solving for wave dynamics are computationally expensive, potentially limiting budget-constrained planning efforts. In this study, we present and evaluate the performance of deep learning-based surrogate models for predicting peak significant wave heights under a variety of relevant use cases: predicting waves with or without modeled peak storm surge as a feature, predicting wave heights while simultaneously predicting peak storm surge, or using storm surge predicted by another surrogate model as an input feature. All models incorporate landscape morphological elements (e.g., elevation, roughness, canopy) and global boundary conditions (e.g., sea level) in addition to tropical cyclone characteristics as predictive features to improve accuracy as landscapes evolve over time. Using simulations from Louisiana's 2023 Coastal Master Plan as a case study, we demonstrate suitable accuracy of surrogate models for planning-level studies, with a two-sided Kolmogorov-Smirnov test indicating no significant difference between significant wave heights generated by the Simulating Waves Nearshore model and those predicted by our surrogate models in approximately 89% of grid cells and landscapes evaluated in the study, with performance varying by landscape and model. On average, the models produced a root mean squared error of 0.05-0.06 m.

Keywords

Significant wave height, Storm surge, Surrogate modeling, Flood risk, Landscape morphology, Climate change

Introduction

Storm surge, the abnormal rise of water during extreme storms above normal tides, is widely recognized as a highly hazardous event that can pose considerable risk to coastal areas and communities. Accurate prediction of storm surge, both from individual events and in a

probabilistic sense, is crucial to inform risk management decisions and emergency response. However, risk reduction projects like levees and seawalls have multi-decadal useful lifetimes, meaning that planners need to evaluate how risk will evolve over time, introducing uncertainty about climate change, land subsidence, and other relevant factors. Further, advancing surge risk estimation demands a deeper understanding of physical processes, such as tidal effects and interactions between waves and storm surges, which can significantly strengthen flooding impacts in low-lying coastal zones (Staneva et al., 2016).

The significant wave height is defined as the average height of the highest third of the waves in a given period, or largest 33% of waves. Estimates of significant wave height exceedance probabilities are commonly used to inform planning, design and maintenance of coastal and offshore structures (American Society of Civil Engineers, 2022; Berbić et al., 2017; Mahjoobi & Adeli Mosabbebi, 2009; U.S. Army Corps of Engineers, 2008). Especially during extreme events like tropical cyclones, waves can cause several hazards such as coastal flooding and erosion that can lead to human loss and significant financial damages (Moghim et al., 2023). The impact of waves on storm surges can be significant especially during an extreme event; for example, Huang et al (2010) examined a coupled surge and waves model, finding that waves can incrementally increase the risk associated with storm surges and expand the footprint of coastal inundation. Near structural risk reduction systems like levees and floodwalls, wave action can be a major contributor to overtopping volumes and produce backside scour, leading to catastrophic failures. Integrating wave predictions with tidal and storm surge estimations provides a comprehensive approach to reducing flooding risks in coastal areas. (Merrifield et al., 2021; Phillips et al., 2017; Scott et al., 2020).

Waves can cause erosion in beaches and coastal areas, negatively affecting ecosystems and infrastructure (Harley et al., 2017; Huang et al., 2010; Narayan et al., 2016). Climate change also impacts landscape characteristics, such as reduced vegetation cover, loss of elevation, and reduction in horizontal extent, reduce the landscape's ability to mitigate the storm surge and wave impacts, also increase erosion, and alter bed roughness, which can lead to increased flooding (Wamsley et al., 2009). Further, Y. Yang et al (2015) demonstrated that another factor that has significant role in waves height is vegetation cover, that has notable effects on wave attenuation mechanisms and leads to a significant decrease in wave height. Similarly, two studies showed that vegetated foreshores, mangrove forests, and seagrass beds are capable of reducing wave loads and heights. Thus, there exist feedbacks between changes to landscape morphology and surge and wave hydrodynamics; Gharehtoragh & Johnson (2024) showed that these morphological parameters can be exploited to improve the prediction of peak storm surge as landscapes evolve and sea levels rise.

In recent decades, high-fidelity numerical models (i.e., physical-based models) have been developed to model storm surge and waves generated by hurricanes and tropical cyclones (TCs). However, in terms of computational cost, these models can be expensive and require substantial computing resources (Bilskie et al., 2014). Probabilistic flood risk assessments can demand

simulation of a wide range of TC events with varying characteristics. Techniques, like the joint probability method with optimal sampling (JPM-OS), exist to reduce the number of required simulations by choosing a smaller and still representative set of TCs (Fischbach et al., 2016; Resio, 2007; Resio et al., 2009; Toro et al., 2010, 2010; K. Yang et al., 2019; J. Zhang et al., 2018). However, they still commonly prescribe running hundreds of TC events, which may be impossible for integrated planning studies considering future uncertainties.

Protection systems such as levees or flood walls, etc., need to resist extreme events over many decades, so designs should consider this uncertainty about future conditions. In the context of coastal flooding, uncertain parameters may include features of changing landscape morphology (e.g., land subsidence, land-use change, impacts of saltwater intrusion on vegetation) and boundary conditions (e.g., sea level rise). One way to address this issue is by employing scenario analysis that involves investigating future states of the world with different realizations of uncertain parameters (Kirwan et al., 2010; Sutton-Grier et al., 2018). Investigating multiple future states of the world to estimate future risk of extreme events requires a significant number of landscapes, and due to this, extensive computational resources are required, and employing more landscapes limits the number of events that can be simulated per landscape. On the other hand, using coarser resolutions in physically based models like ADCIRC (Advanced CIRCulation) or increasing mesh size could negatively affect the accuracy of the model.

One way to address this issue is by using surrogate models to predict storm surge and wave hydrodynamics (Kyprioti et al., 2021). In recent years, the utilization of surrogate models especially in water resource management field has increased (Asher et al., 2015; Razavi et al., 2012). Previous studies have used various ways to predict storm surge elevations and significant wave heights, primarily focusing on TC characteristics such as storm intensity and track parameters such as landfall location and heading, central pressure, forward velocity, radius of maximum wind speed, Holland-B parameter and/or tide level. For instance, Deo et al (2001) used an artificial neural network (ANN) to predict significant wave heights utilizing TC parameters such as wind speed and directions. Vijayan et al. (2023) employed the dynamically-coupled ADCIRC+SWAN model to predict waves, showing the relationship between sea level rise and wave heights. Similarly Londhe and Panchang (2006) utilized an ANN for one-day wave forecasting, showing that they can be useful for wave prediction but may be less accurate in predicting the magnitudes of the highest waves. Some recent studies such as Zhang et al. (2021) employed numerical long short-term memory frameworks to predict wave heights using a combination of a current wave measurement and a numerical prediction from the Simulating Waves Nearshore (SWAN) model.

In this paper, we introduce knowledge-guided surrogate models utilizing artificial neural networks (ANNs) that are able to alleviate the computational burdens of predicting peak significant wave heights. This model was trained based on synthetic tropical cyclone (TC) data produced by a coupled ADCIRC+SWAN (Simulating Waves Nearshore) model on multiple landscapes representing projected conditions in coastal Louisiana from a 2020 baseline over decadal time

slices through 2070. In addition to predicting wave heights as a function of TC parameters at landfall, we also employ morphological features (e.g., topographic/bathymetric elevations, roughness) and global boundary conditions (e.g., mean sea level), allowing us to train models on simulations from multiple landscapes simultaneously.

Moreover, we evaluate four models designed to represent different potential real-world use cases. Recent versions of ADCIRC are much faster at solving storm surge hydrodynamics, but the gains are only realized when not coupled to a wave model. Thus, a baseline model utilizing only TC landfall, landscape, and sea level data as features is compared to another model which also includes ADCIRC-simulated peak storm surge as a feature. This second model could be used in applications where ADCIRC is run in uncoupled mode but generating waves is still desirable. Of course, policy makers may still wish to run experimental designs that exceed their computational budget to support adaptive planning efforts or methods for decision making under deep uncertainty. In this case, similar surrogate models may be useful for predicting peak storm surge as well, so we evaluate a model of peak significant wave heights that includes a surrogate model-predicted peak storm surge as a feature. Finally, we compare this to a fourth model that is trained to predict peak storm surge and significant wave heights simultaneously. In addition to evaluating predictions associated with individual TCs, we statistically aggregate the predictions for TCs on each landscape to produce estimates of annual exceedance probability (AEP) distributions.

Methods

Data Description

Synthetic tropical cyclones (i.e., TCs following an idealized, regular track and patterns of intensification and decay) are used in this study, with each synthetic storm parameterized by their forward velocity, radius of maximum wind speed, central pressure, landfall coordinates, and heading. The corpus of 645 synthetic TCs used in this analysis was created using the JPM-OS methodology for flood risk assessments in Louisiana (Nadal-Caraballo et al., 2020, 2022). Table S1 provides a complete list of the landfall parameters for each synthetic storm. These parameters serve as input data for all of the predictive models.

For all 645 synthetic storms, hydrodynamic simulations were provided by a coupled ADCIRC+SWAN model from Louisiana’s 2023 Coastal Master Plan that was simulated on the plan’s “Existing Conditions” landscape (i.e., 2020) (Louisiana Coastal Protection and Restoration Authority, 2023b). Uncertainty in future conditions is represented in the plan by “Lower” and “Higher” environmental scenarios which vary in their assumptions about sea level rise, land subsidence, changes to TC intensity, and other environmental factors (Cobell & Roberts, 2021; Louisiana Coastal Protection and Restoration Authority, 2023a). A subset of 90 synthetic storms were simulated on each of ten future landscapes representing decadal snapshots of the Lower and Higher scenarios from 2030 to 2070; these 90 storms are bolded in Table S1 for reference. Peak significant wave heights were extracted from the coupled ADCIRC+SWAN outputs at 80,224

locations that comprise the Coastal Louisiana Risk Assessment (CLARA) model's grid points in Louisiana that are not located inside fully-enclosed risk reduction systems (i.e., ring levees and floodwalls). These points form a mixed-resolution mesh with a maximum 1-km spacing and higher resolution in some areas, such that every U.S. Census block contains at least one grid point (Johnson et al., 2023).

Each landscape is characterized spatially by digital elevation models (DEMs) of topography and bathymetry, and average slope of nearby cells at each location, and by GeoTIFF rasters of free surface roughness z_0 , Manning's n values (i.e., bottom roughness coefficient), and a surface canopy coefficient that captures the reduction in wind stress on water surfaces produced by local vegetation. All landscape characteristics were extracted for all 80,224 locations in the study area to be used in the developed surrogate model. All required information about the Integrated Compartment Model employed to develop the landscape representations can be found in White et al. (2019) and Reed and White (2023), and details regarding the ADCIRC+SWAN model and Louisiana mesh are found in Cobell and Roberts (2021) and Roberts and Cobell (2017).

Model Development

In this study, four different models were developed to predict peak significant wave height. All models employed the same landscape parameters, including latitudinal and longitudinal coordinates, topo/bathymetry elevation, surface canopy, Manning's n coefficient, z_0 , and average slope (estimated by calculating the average slope of the adjacent cells using DEM values). TC landfall parameters used as features included forward velocity, radius of maximum wind speed, central pressure, landfall coordinates, and heading. Finally, a global boundary condition of mean sea level in each landscape was also used as a feature.

These four models differ in their final input features and targets. The first model (Model 1), used as a baseline, predicts waves independently of surge, i.e., using only the TC landfall parameters, landscape features, and mean sea level. Model 2 includes as a feature the peak storm surge predicted by a surge surrogate model. Model 3 instead utilizes peak storm surge elevations simulated by the ADCIRC+SWAN model. Lastly, Model 4 predicts both peak storm surge elevations and significant wave heights simultaneously.

The surrogate model configuration consists of a Convolutional Neural Network (CNN) followed by multiple dense layers. The developed CNN models consisted of several convolutional layers, each one of them containing a range of 128 filters to 256 filters, followed by batch normalization layers, dropout layers, and RELU activation functions. Further, to address vanishing gradient and allow information to flow across layers and train a deeper model, three skip connections were implemented to pass the information from early layers to the last layers.

In addition, four dense layers that include a range of 128 to 256 neurons were defined. In defining the number of neurons, one should be cautious, since having too few neurons and filters could

prevent models from training correctly, and having too many of them could result in overtraining/overfitting (Albawi et al., 2017; Alemu et al., 2018). Moreover, a similar skip connection is also implemented in the dense layers too, to pass the information from the first layer directly to all next layers, with the same for subsequent layers.

Further, for all layers including convolution and dense layers, the RELU activation function was selected with the callback approach that has an adaptive learning rate starting at 0.01; if validation loss does not decrease in two time steps, it reduces learning rate by a factor of 0.75, potentially going to a minimum value of 0.00001 (Smith, 2017). In the last layer, a linear activation function was implemented to predict wave values at each location. For all models except Model 4, an output layer of 1 dimension was used. However, for Model 4 a 2-dimensional output layer was utilized to predict both peak wave and surge height simultaneously. The entire simulation was executed on GPU resources (Nvidia A100) taking less than 5 hours for training the models; inference on a new landscape takes less than 5 minutes.

To have a more realistic evaluation of model accuracy, leave-one-out cross-validation (LOOCV) was performed on the future landscapes. In other words, each time a model was trained, 1 of the 10 future landscapes ($n = 90$ storms) was dropped and used as a test set, and the rest of the 9 future landscapes along with the 2020 landscape ($n = 1455$ storms) were used as a training set. The 2020 landscape was consistently utilized in training throughout the entire process. This procedure represents a potential use case of the surrogate model as a scenario generator to produce predictions for many TCs on a novel landscape, as opposed to alternative cross-validation procedures that would drop a fraction of storms or grid points from multiple landscapes.

Lastly, planners and project designers need to know how errors in predicting peak wave height manifest as differences in the estimated annual exceedance probability (AEP) distribution for wave heights in each landscape. This study leveraged the CLARA model to calculate wave hazard curves (i.e., AEP distributions) associated with the surrogate model predictions for each synthetic TC (Johnson et al., 2013, 2023). The complete methodology of the CLARA model and further details can be found in Johnson et al. (2023). The model was used to calculate wave height exceedances at 23 different return periods, covering from 50% AEP to 0.005% AEP. Further, by utilizing the CLARA model, exceedance curves (wave heights as a function of AEP) were generated from both simulated peak significant wave height of the surrogate model through the LOOCV procedure and the simulated peak significant wave height from ADCIRC model. As a final step, the empirical distributions generated from hazard curves using ADCIRC and surrogate models were compared using a two-sided Kolmogorov–Smirnov (K-S) test. The K-S test measures the maximum absolute difference between the two empirical cumulative distributions. The null hypothesis is that the two samples are drawn from the same underlying distribution. So, the K-S test can be applied at each grid point to determine how many points reject the null hypothesis at significance level of $\alpha = 0.05$.

$$\sup_x |F_{ADCIRC}(x) - F_{ANN}(x)| > \sqrt{-\ln\left(\frac{\alpha}{2}\right) \cdot \frac{1}{23}} \quad (1)$$

In the above formula, $\sup$ is the supremum over x , $F_{ANN}(x)$ is the sample CDF associated with the surrogate model predictions, and $F_{ADCIRC}(x)$ the CDF associated with the ADCIRC simulations.

Results

As expected intuitively, the use of simulated surge elevations from ADCIRC as an additional training feature led Model 3 to generally out-perform the other models with respect to root mean squared error (RMSE) over the grid points, landscapes, and synthetic storms (Figure 1). Each point in the scatter plot indicates the RMSE of an individual grid point over all landscapes and synthetic storms for a given model (e.g., Model 3 colored in red) on the horizontal axis, with the vertical placement indicating the percentage of grid points with RMSE equal to or exceeding the given value; as an example of how this is interpreted, the figure indicates that for Model 3, only 0.1% percent of grid cells have an RMSE equal to or exceeding approximately 0.32 m. Thus, plots farther toward the top-left of the figure indicate better overall accuracy.

The performance of the baseline Model 1 and Model 4 that predicts both peak surge height and significant wave height is approximately the same across all ranges of RMSE values. This was expected since Model 1, the baseline model, was trained and focused on predicting only significant wave height. Model 4 predicts both significant wave height and peak surge elevation, benefiting from the informative relationship between these two variables. Lastly, Model 2, utilizing surge elevations predicted by a surrogate model rather than ADCIRC, shows slightly weaker performance among all models and this difference can be seen particularly for RMSE values greater than 0.2 meters. That is likely associated with compounding errors and biases from the surge surrogate model, on top of biases or noise in the underlying ADCIRC simulations.

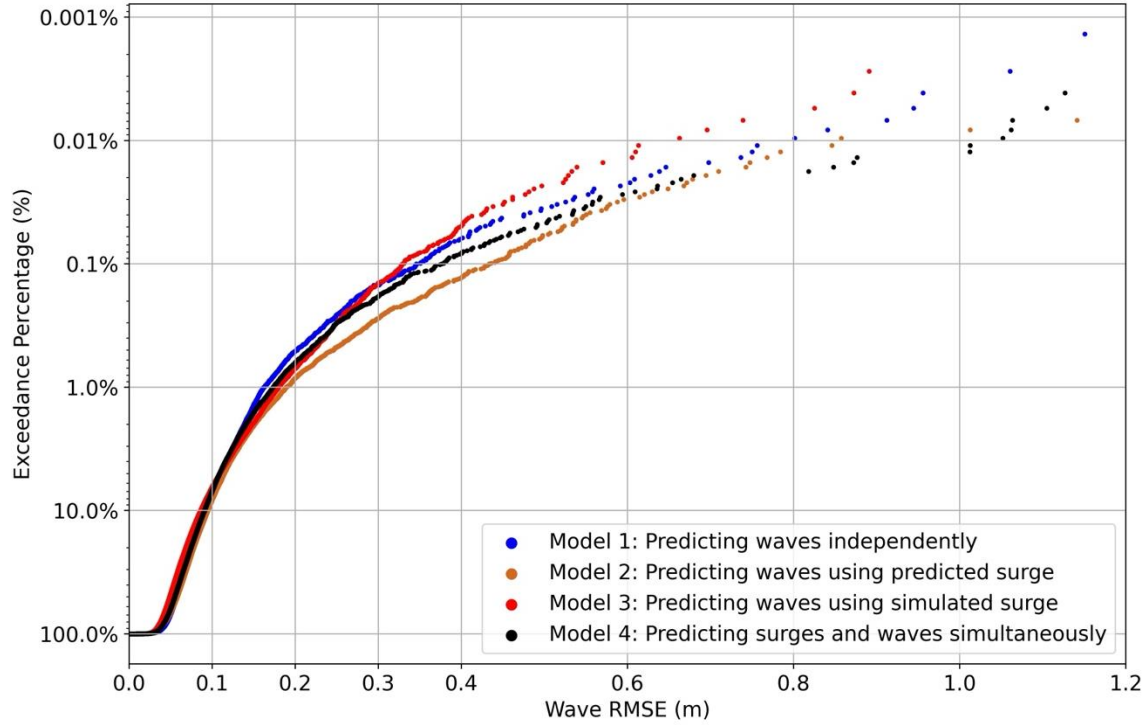


Figure 1. Exceedance percentage of RMSE values by grid point and model, with RMSE averaged across all landscapes and synthetic storms.

For the baseline Model 1, the RMSE at 90% of grid points is less than 0.09 m, at 99% of grid points less than 0.16 m, and at 99.9% of grid points less than 0.34 m (Figure 1). Including the simulated ADCIRC surge as a feature in Model 3 provides additional explanatory accuracy relative to the baseline, so due to that Model 3 showed best performance at the 99.9% of the grid points with RMSE value of less than 0.32 m, while the predicted surge used by Model 2 apparently compounds errors in the predicted wave dynamics instead of being accurate enough to yield improvements compared to Model 1. Similar to the baseline Model 1, Model 4 does not use surge data as an input, however, compared to baseline Model 1, Model 4 predicts both peak surge height and significant wave height, so as was expected, it closely mirrored the performance of Model 1 in its prediction of the wave height outcomes. By and large, besides Model 2, which uses predicted surge data and showed weaker performance than other models, the remaining models showed similar performance and were sufficiently accurate for use in planning-level studies over a large coastal domain (i.e., relatively few outliers with large RMSE compared to the RMSE of the underlying ADCIRC model).

Model 3, by using simulated surge data, was capable of performing better in comparison to other models and showed an average RMSE of around 0.04-0.05 m over all landscapes except the Higher scenario in 2070 (Table 1). Additionally, Model 4, despite predicting both surge and wave simultaneously without using surge as a feature, was able to predict surge elevations with RMSE less than 0.1 m in all landscapes but the 2070 Higher scenario. Across all four models, we see

substantially degraded accuracy in the Higher scenario’s 2070 landscape. This is a byproduct of the 2023 Coastal Master Plan’s experimental design, where sea level rise is assumed to accelerate over time, leading the 2070 Higher landscape to be the “most different” case relative to any other landscape in the training data, both with respect to the sea level boundary condition and other morphological features. Consequently, predicting hydrodynamics is a fundamentally more challenging extrapolation problem in the 2070 Higher scenario landscape than in others.

The RMSE values of the baseline Model 1, and differences in RMSE for other models compared to the baseline are shown in Figure 2 (grid cells with absolute differences less than 0.025 m not shown). Warmer yellow-to-red colors indicate a model’s improvement relative to the baseline model, while cool green-to-violet colors indicate worse accuracy at that grid point.

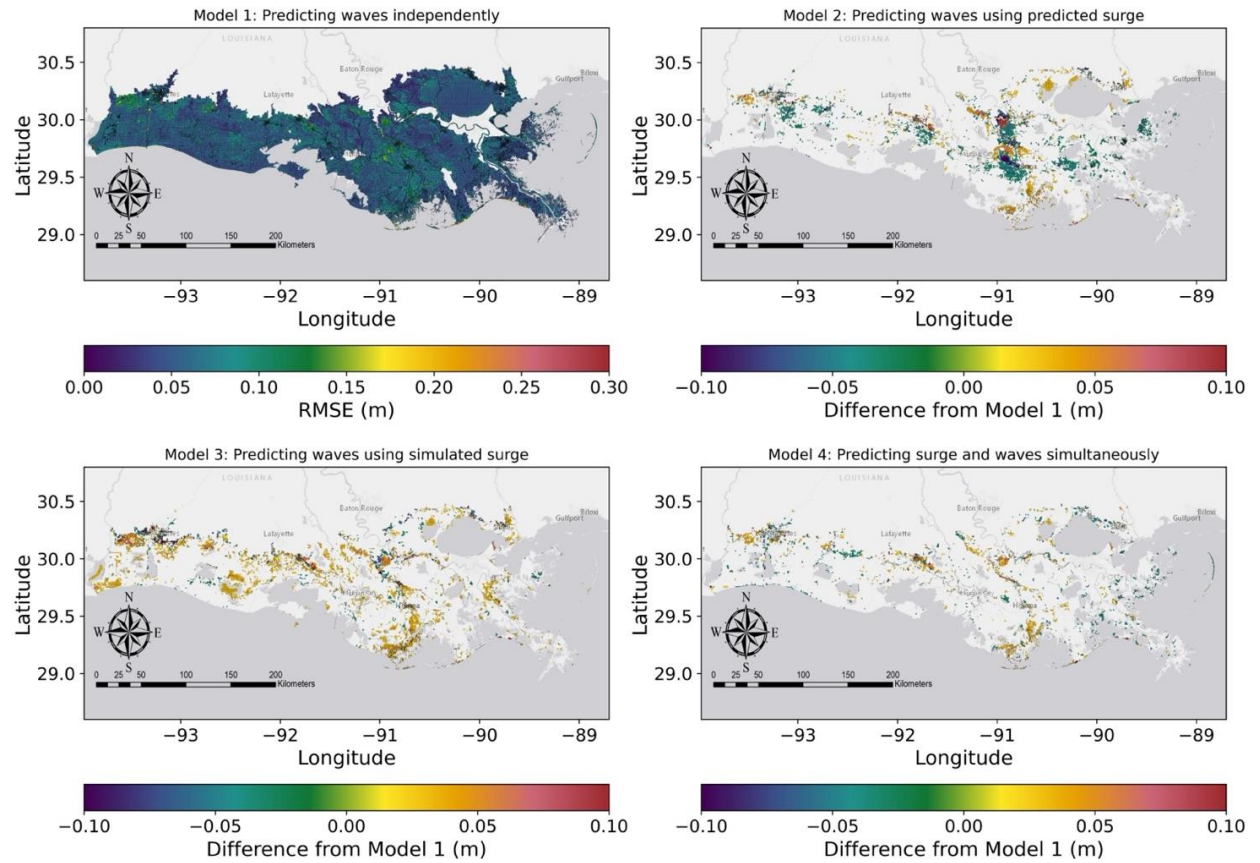


Figure 2. RMSE of Model 1 (top left pane) and difference maps for the other models relative to Model 1 (i.e., Model 1 value minus Model 2/3/4 value) across all landscapes and synthetic storms for all grid points in the study domain (differences within ± 0.025 m excluded for contrast).

Consequently, we see that the general improvements in RMSE for Model 3 are widespread across the coastal zone, with limited areas with worse accuracy near the inland extent of the model domain, such as in Lake Charles in the northwestern part of the coastal zone. Model 2 has a similar number of grid cells where differences exceed ± 0.025 m, but those differences are generally worse

performance than the baseline Model 1, especially in the wetlands of the Atchafalaya River basin. Model 4 shows the greatest similarity to the baseline, with considerably fewer grid cells exhibiting differences beyond ± 0.025 m. In Table 1, we show a summary of the statistical metrics (RMSE and Pearson correlation coefficient) used to evaluate the models.

Table 1 Summary of statistical outcomes (RMSE and correlation coefficient) for all cases evaluated.

Scenarios	Years	Model 1		Model 2		Model 3		Model 4			
		Wave		Wave		Wave		Surge		Wave	
		RMSE (m)	Corr	RMSE (m)	Corr	RMSE (m)	Corr	RMSE (m)	Corr	RMSE (m)	Corr
Lower Scenario	2030	0.048	0.995	0.048	0.995	0.042	0.996	0.063	0.998	0.055	0.993
	2040	0.047	0.995	0.050	0.995	0.043	0.996	0.093	0.996	0.054	0.994
	2050	0.049	0.995	0.053	0.994	0.044	0.996	0.084	0.997	0.054	0.994
	2060	0.050	0.995	0.054	0.994	0.046	0.996	0.072	0.998	0.057	0.993
	2070	0.064	0.993	0.066	0.992	0.054	0.995	0.088	0.996	0.064	0.992
Higher Scenario	2030	0.044	0.995	0.045	0.995	0.042	0.996	0.055	0.999	0.052	0.994
	2040	0.047	0.995	0.048	0.995	0.043	0.996	0.072	0.997	0.054	0.994
	2050	0.050	0.995	0.066	0.994	0.050	0.995	0.086	0.997	0.062	0.993
	2060	0.057	0.994	0.060	0.993	0.051	0.995	0.082	0.997	0.062	0.993
	2070	0.121	0.980	0.112	0.980	0.103	0.982	0.172	0.988	0.093	0.985

Based on the results of Table 1 and maps that reveal no troubling spatial patterns of bias, we view all four models as being accurate enough for use in planning studies. Each has a potential use case that would depend on the computational resources available for use in generating training data using more expensive models like ADCIRC+SWAN.

This conclusion is bolstered by aggregating the wave heights generated by individual synthetic TCs to estimate a hazard curve. Figure 3 shows RMSE values across all grid points, grouped by model in each column, landscape (Lower and Higher scenarios on top and bottom rows, respectively, with the year in different colors), and annual exceedance probability (AEP). The horizontal axes within each pane shows the AEP, and the vertical axis locates the RMSE values.

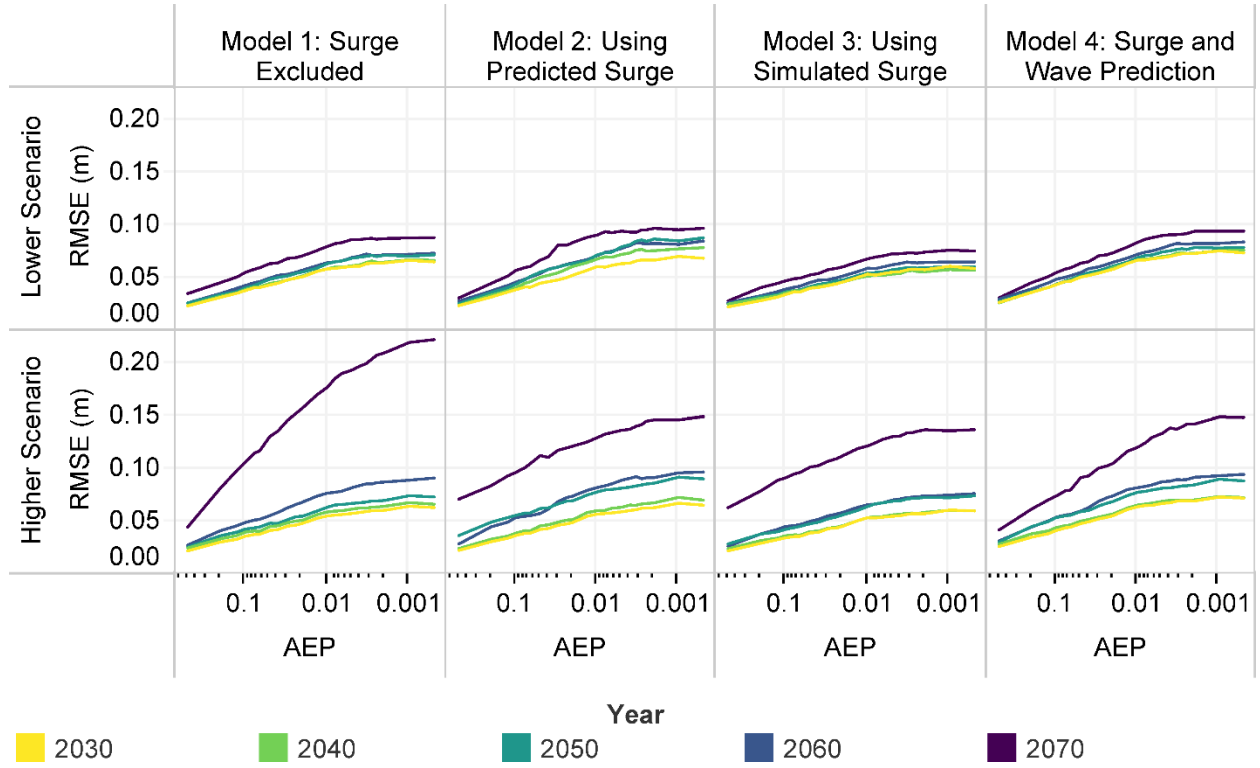


Figure 3. RMSE over all grid points, by model, annual exceedance probability, and landscape.

The results suggest that the surrogate models have broadly similar accuracy of 0.02-0.1 m across the range of synthetic storms that produce peak significant wave heights associated with a wide range of return periods, from the 0.5 AEP (i.e., 2-year) to 0.0005 AEP (i.e., 2,000-year) events. It is, however, more challenging to predict extremes, consistent with higher RMSE values farther into the tail of the distribution. To ensure this would not pose an issue for studies focused on extreme events, i.e., 100-year or 0.01% AEP and beyond, we also examine the normalized RMSE (NRMSE) in Figure 4. It shows that the average error is generally less than 2% in each of the various landscapes and across all return periods, with the exception of the 2070 Higher Scenario landscape. This landscape continued to pose a challenge to all models due to its inherent extrapolation when implementing the leave-one-landscape-out cross-validation procedure.

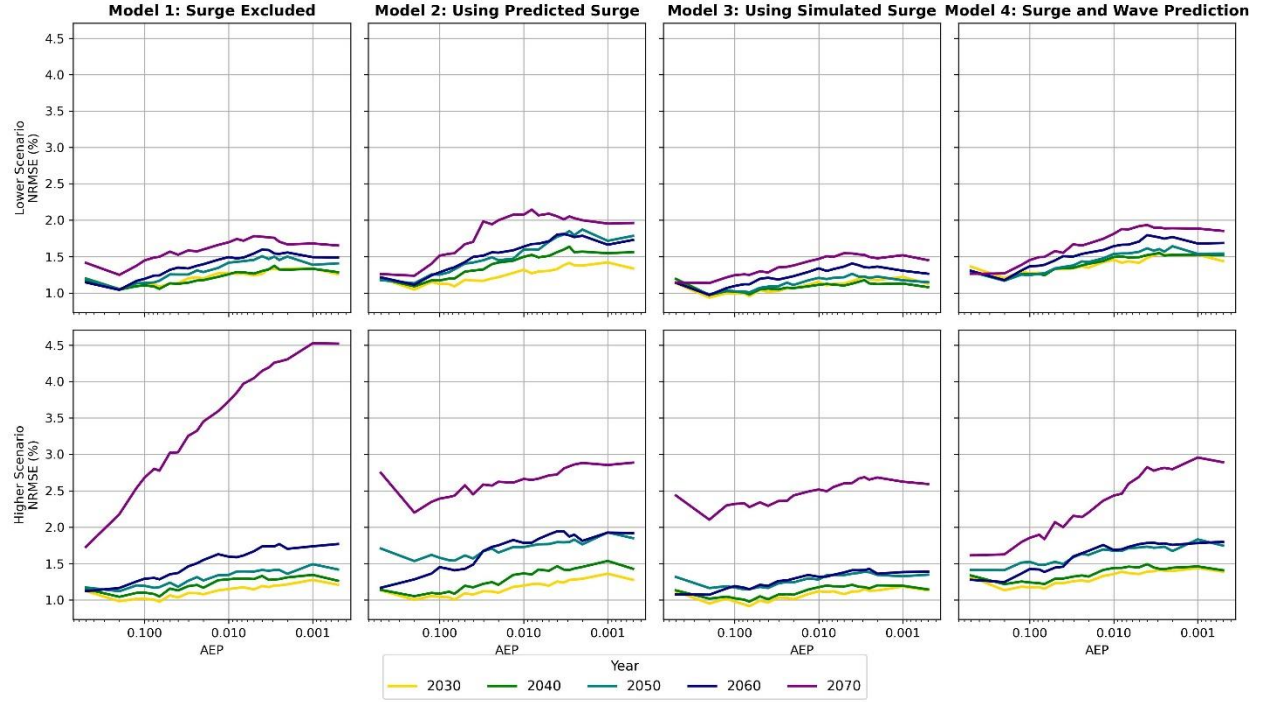


Figure 4. Normalized RMSE over all grid points, by model, annual exceedance probability, and landscape.

The small NMRSE values by return period when averaging over all grid points suggested that the surrogate models do a good job of emulating the hazard curves produced by applying the JPM-OS methodology to the original ADCIRC+SWAN simulations. Prior studies show the potential for accuracy in emulating surge hazard curves, but here we see some differences in performance across the four models producing wave height estimates. The 2070 Higher Scenario landscape again is an outlier in average performance on the NRMSE metric, but notably worse so for the baseline Model 1; Model 4, predicting surge and waves simultaneously, also performed notably better on this landscape for more frequent return periods, i.e., higher AEP exceedances. Expanding beyond the average results, Table 2 shows the comparison between the AEP distributions calculated from all four models and the AEP distributions obtained from ADCIRC predictions using the two-sample K–S test with a significance level of $\alpha = 0.05$. Values in the table indicate the percentage of grid points where the null hypothesis, that the surrogate model ADCIRC hazard curves are drawn from the same distribution over the 23 return periods estimated. Points where the null hypothesis is rejected represent outliers where the wave height predictions result in statistically significant differences in estimated hazard distributions.

Table 2 Percentage of grid points rejecting a two-sided KS test null hypothesis over each model per landscape

Scenario	Year	Model 1	Model 2	Model 3	Model 4
		Rejected %	Rejected %	Rejected %	Rejected %
Lower Scenario	2030	7%	7%	5%	8%
	2040	7%	9%	6%	9%
	2050	7%	9%	6%	9%
	2060	8%	9%	7%	10%
	2070	11%	13%	10%	13%
Higher Scenario	2030	6%	7%	6%	8%
	2040	8%	9%	6%	9%
	2050	9%	13%	8%	12%
	2060	11%	13%	8%	12%
	2070	48%	24%	22%	24%

Model 3, by using simulated surge data, achieved the smallest percentage of rejected points over all 10 future landscapes. Models 2 and 4 show similar performance with slightly higher percentages compared to Model 3. The baseline Model 1 performance in the 2070 Higher Scenario landscape is by far the worst statistical outcome, with nearly half of points failing to successfully emulate the ADCIRC hazard distribution with $\alpha = 0.05$, though all models showed their worst performance by far on this landscape.

Discussion

In this study four machine learning-based surrogate models were developed to predict peak significant wave heights. The developed models are capable of predicting either wave or surge/wave dynamics simultaneously with accuracy comparable to that of the calibration and validation accuracy of the underlying ADCIRC+SWAN model simulations.

These models demonstrated that by utilizing future landscapes with varying landscape parameters, average slope and mean sea level conditions, their accuracy could be improved relative to current models that focus on predicting hydrodynamics on static landscapes. By utilizing LOOCV in this study, one future scenario was left out each time as test data, and the models were able to predict wave heights with an approximate RMSE of 0.05–0.06 m, with Model 2 generally demonstrating slightly worse performance across the range of metrics evaluated.

Further, we utilized a two-sided K-S test on the hazard curves generated by ADCIRC+SWAN simulations and the surrogate models at each grid point to assess whether the samples were drawn from statistically different underlying distributions. The results of Table 1 and Table 2 showed that, for all cases, on average, less than 8% of grid points rejected the null hypothesis, except for

the more extreme 2070 landscape. The best performance came from Model 3, showing how the use of surge elevations are informative to making more accurate predictions under these extreme conditions. Our results did not show bias toward underestimation or overestimation.

We have mentioned several times that, by all measures, the models are less accurate in the Higher Scenario's 2070 landscape, the most extreme case with highest sea level rise. This illustrates a limitation of using training data of convenience, i.e., simulations that were already available for methods development from Louisiana's 2023 Coastal Master Plan. An important implication is that when surrogate models are being considered for deployment in a planning study, this should inform the experimental design for what should be simulated and used as training data. For example, the Coastal Master Plan uses a 50-year planning horizon, so decisions are made based in part on risk estimates in 2070; surrogate model accuracy for the Higher Scenario's 2070 landscape would likely improve if ADCIRC+SWAN simulations were available for either a 2080 landscape or a 2070 landscape under a scenario with still-higher sea level rise. As a reminder, the same 90 storms were simulated in each future landscape based on a storm selection process that considered only the baseline 2020 landscape (Fischbach et al., 2021). Future research could examine the use of adaptive sampling techniques for surrogate model training in this specific context. Instead of simulating the same 90 storms as were performed for the Coastal Master Plan, sampling different synthetic storm events for each landscape could be more effective in terms of computational efficiency.

Another key point is that surrogate models are capable of predicting both surge and wave dynamics simultaneously with sufficient accuracy. The possible logic behind this is the physical relationship between surge elevations and significant wave heights that helps the model to make more realistic predictions of both parameters. While the model architectures employed in this analysis were not physics-constrained, the models are still potentially able to learn the impact on wave heights of breaking behaviors induced by surge depth limitations or sloping topography. Model 4 achieves acceptable performance without adding a considerable amount of computational cost, making it suitable as a scenario generator for a wide range of possible futures.

The training data of this study came from the Coastal Master Plan's Future Without Action scenarios, meaning that these scenarios are limited to only slowly evolving landscapes, and no further projects—like upgrading levee systems or floodwalls—have been implemented. Although developing a machine learning framework to consider these types of linear weir features is more challenging, coastal restoration projects that affect the morphology of future landscapes can still be examined using these surrogate models. By having low computational cost, they can be used as a scenario generator, and thousands of future landscape scenarios could be evaluated, including those that reflect coastal restoration projects like marsh creation, river diversions, and barrier island replenishment. Each of the four models presented here have potential use cases for planning studies with varying computational budgets and decision frameworks, enabling the use of methods for optimization or decision-making under deep uncertainty that require a large ensemble of future states of the world, a large number of function evaluations, or both.

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References

- Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017). Understanding of a convolutional neural network. *2017 International Conference on Engineering and Technology (ICET)*, 1–6. <https://doi.org/10.1109/ICEngTechnol.2017.8308186>
- Alemu, H., Wu, W., & Zhao, J. (2018). Feedforward Neural Networks with a Hidden Layer Regularization Method. *Symmetry*, 10(10), 525. <https://doi.org/10.3390/sym10100525>
- American Society of Civil Engineers. (2022). *Minimum design loads and associated criteria for buildings and other structures*. American Society of Civil Engineers.
- Asher, M. J., Croke, B. F. W., Jakeman, A. J., & Peeters, L. J. M. (2015). A review of surrogate models and their application to groundwater modeling. *Water Resources Research*, 51(8), 5957–5973. <https://doi.org/10.1002/2015WR016967>
- Berbić, J., Ocvirk, E., Carević, D., & Lončar, G. (2017). Application of neural networks and support vector machine for significant wave height prediction. *Oceanologia*, 59(3), 331–349. <https://doi.org/10.1016/j.oceano.2017.03.007>
- Bilskie, M. V., Hagen, S. C., Medeiros, S. C., & Passeri, D. L. (2014). Dynamics of sea level rise and coastal flooding on a changing landscape. *Geophysical Research Letters*, 41(3), 927–934. <https://doi.org/10.1002/2013GL058759>
- Cobell, Z., & Roberts, H. J. (2021). *Coastal Master Plan: Attachment E1: Storm Surge and Waves Model Improvements* (p. 56). Coastal Protection and Restoration Authority. https://coastal.la.gov/wp-content/uploads/2023/05/B_ScenarioDevelopmentFutureConditions_Jan2023_v3.pdf
- Deo, M. C., Jha, A., Chaphekar, A. S., & Ravikant, K. (2001). Neural networks for wave forecasting. *Ocean Engineering*, 28(7), 889–898. [https://doi.org/10.1016/S0029-8018\(00\)00027-5](https://doi.org/10.1016/S0029-8018(00)00027-5)
- Fischbach, J. R., Johnson, D. R., & Kuhn, K. (2016). Bias and efficiency tradeoffs in the selection of storm suites used to estimate flood risk. *Journal of Marine Science and Engineering*, 4(1), 10.
- Fischbach, J. R., Johnson, D. R., Wilson, M. T., Geldner, N. B., & Stelzner, C. (2021). *2023 Coastal Master Plan: Model Improvement Report, Risk Assessment*. Louisiana Coastal Protection and Restoration Authority.

- Gharehtoragh, M. A., & Johnson, D. R. (2024). Using surrogate modeling to predict storm surge on evolving landscapes under climate change. *Npj Natural Hazards*, 1(1), 33. <https://doi.org/10.1038/s44304-024-00032-9>
- Harley, M. D., Turner, I. L., Kinsela, M. A., Middleton, J. H., Mumford, P. J., Splinter, K. D., Phillips, M. S., Simmons, J. A., Hanslow, D. J., & Short, A. D. (2017). Extreme coastal erosion enhanced by anomalous extratropical storm wave direction. *Scientific Reports*, 7(1), 6033. <https://doi.org/10.1038/s41598-017-05792-1>
- Huang, Y., Weisberg, R. H., & Zheng, L. (2010). Coupling of surge and waves for an Ivan-like hurricane impacting the Tampa Bay, Florida region. *Journal of Geophysical Research: Oceans*, 115(C12), 2009JC006090. <https://doi.org/10.1029/2009JC006090>
- Johnson, D. R., Fischbach, J. R., Geldner, N. B., Wilson, M. T., Story, C., & Wang, J. (2023). *Coastal Master Plan: Attachment C11: 2023 Risk Model* (No. Version 2; p. 33). Coastal Protection and Restoration Authority. https://coastal.la.gov/wp-content/uploads/2023/04/C11_2023RiskModel_Jan2023_v2.pdf
- Johnson, D. R., Fischbach, J. R., & Ortiz, D. S. (2013). Estimating Surge-Based Flood Risk with the Coastal Louisiana Risk Assessment Model. *Journal of Coastal Research*, 67, 109–126. https://doi.org/10.2112/SI_67_8
- Kirwan, M. L., Guntenspergen, G. R., D’Alpaos, A., Morris, J. T., Mudd, S. M., & Temmerman, S. (2010). Limits on the adaptability of coastal marshes to rising sea level. *Geophysical Research Letters*, 37(23), 2010GL045489. <https://doi.org/10.1029/2010GL045489>
- Kyprioti, A. P., Taflanidis, A. A., Nadal-Caraballo, N. C., & Campbell, M. O. (2021). Incorporation of sea level rise in storm surge surrogate modeling. *Natural Hazards*, 105(1), 531–563. <https://doi.org/10.1007/s11069-020-04322-z>
- Londhe, S. N., & Panchang, V. (2006). One-Day Wave Forecasts Based on Artificial Neural Networks. *Journal of Atmospheric and Oceanic Technology*, 23(11), 1593–1603. <https://doi.org/10.1175/JTECH1932.1>
- Louisiana Coastal Protection and Restoration Authority. (2023a). *Coastal Master Plan: Appendix B: Scenario Development and Future Conditions* (No. Version 3; p. 18). Coastal Protection and Restoration Authority. https://coastal.la.gov/wp-content/uploads/2023/01/E1_2023StormSurge_Waves_Report_Jan2021.pdf
- Louisiana Coastal Protection and Restoration Authority. (2023b). *Louisiana’s Comprehensive Master Plan for a Sustainable Coast* (No. 4th Edition). <https://coastal.la.gov/our-plan/2023-coastal-master-plan/>
- Mahjoobi, J., & Adeli Mosabbebi, E. (2009). Prediction of significant wave height using regressive support vector machines. *Ocean Engineering*, 36(5), 339–347. <https://doi.org/10.1016/j.oceaneng.2009.01.001>
- Merrifield, M. A., Johnson, M., Guza, R. T., Fiedler, J. W., Young, A. P., Henderson, C. S., Lange, A. M. Z., O’Reilly, W. C., Ludka, B. C., Okihira, M., Gallien, T., Pappas, K., Engeman, L., Behrens, J., & Terrill, E. (2021). An early warning system for wave-driven coastal flooding at Imperial Beach, CA. *Natural Hazards*, 108(3), 2591–2612. <https://doi.org/10.1007/s11069-021-04790-x>

- Moghim, S., Gharehtoragh, M. A., & Safaie, A. (2023). Performance of the flood models in different topographies. *Journal of Hydrology*, 620, 129446. <https://doi.org/10.1016/j.jhydrol.2023.129446>
- Nadal-Caraballo, N. C., Campbell, M. O., Gonzalez, V. M., Torres, M. J., Melby, J. A., & Taflanidis, A. A. (2020). Coastal hazards system: A probabilistic coastal hazard analysis framework. *Journal of Coastal Research*, 95(SI), 1211–1216.
- Nadal-Caraballo, N. C., Yawn, M. C., Aucoin, L. A., Carr, M. L., Melby, J. A., Ramos-Santiago, E., Gonzalez, V. M., Taflanidis, A. A., Kyprioti, A. A., Cobell, Z., & Cox, A. T. (2022). *Coastal Hazards System–Louisiana (CHS-LA)* [Report]. Engineer Research and Development Center (U.S.). <https://erdc-library.erd.c.dren.mil/jspui/handle/11681/45286>
- Narayan, S., Beck, M. W., Reguero, B. G., Losada, I. J., Van Wesenbeeck, B., Pontee, N., Sanchirico, J. N., Ingram, J. C., Lange, G.-M., & Burks-Copes, K. A. (2016). The Effectiveness, Costs and Coastal Protection Benefits of Natural and Nature-Based Defences. *PLOS ONE*, 11(5), e0154735. <https://doi.org/10.1371/journal.pone.0154735>
- Phillips, B., Brown, J., Bidlot, J.-R., & Plater, A. (2017). Role of Beach Morphology in Wave Overtopping Hazard Assessment. *Journal of Marine Science and Engineering*, 5(1), 1. <https://doi.org/10.3390/jmse5010001>
- Razavi, S., Tolson, B. A., & Burn, D. H. (2012). Review of surrogate modeling in water resources. *Water Resources Research*, 48(7), 2011WR011527. <https://doi.org/10.1029/2011WR011527>
- Reed, D. J., & White, E. D. (2023). *Appendix C: Use of Predictive Models in the 2023 Coastal Master Plan* (No. Version 3). Coastal Protection and Restoration Authority.
- Resio, D. T. (2007). White paper on estimating hurricane inundation probabilities. In *Performance Evaluation of the New Orleans and Southeast Louisiana Hurricane Protection System. Appendix 8: Hazard Analysis: Vol. VIII*. U.S. Army Corps of Engineers.
- Resio, D. T., Irish, J., & Cialone, M. (2009). A surge response function approach to coastal hazard assessment—part 1: Basic concepts. *Natural Hazards*, 51(1), 163–182.
- Roberts, H. J., & Cobell, Z. (2017). *Coastal Master Plan Modeling: Attachment C3-25.1 – Storm Surge* (p. 110). Coastal Protection and Restoration Authority.
- Scott, F., Antolinez, J. A. A., McCall, R., Storlazzi, C., Reniers, A., & Pearson, S. (2020). Hydro-Morphological Characterization of Coral Reefs for Wave Runup Prediction. *Frontiers in Marine Science*, 7, 361. <https://doi.org/10.3389/fmars.2020.00361>
- Smith, L. N. (2017). Cyclical Learning Rates for Training Neural Networks. *2017 IEEE Winter Conference on Applications of Computer Vision (WACV)*, 464–472. <https://doi.org/10.1109/WACV.2017.58>
- Staneva, J., Wahle, K., Koch, W., Behrens, A., Fenoglio-Marc, L., & Stanev, E. V. (2016). Coastal flooding: Impact of waves on storm surge during extremes – a case study for the German Bight. *Natural Hazards and Earth System Sciences*, 16(11), 2373–2389. <https://doi.org/10.5194/nhess-16-2373-2016>

- Sutton-Grier, A., Gittman, R., Arkema, K., Bennett, R., Benoit, J., Blitch, S., Burks-Copes, K., Colden, A., Dausman, A., DeAngelis, B., Hughes, A., Scyphers, S., & Grabowski, J. (2018). Investing in Natural and Nature-Based Infrastructure: Building Better Along Our Coasts. *Sustainability*, 10(2), 523. <https://doi.org/10.3390/su10020523>
- Toro, G. R., Resio, D. T., Divoky, D., Niedoroda, A. W., & Reed, C. (2010). Efficient joint-probability methods for hurricane surge frequency analysis. *Ocean Engineering*, 37(1), 125–134.
- U.S. Army Corps of Engineers. (2008). *Engineering and Design DESIGN OF HYDRAULIC STEEL STRUCTURES*. U.S. Army Engineer Research and Development Center.
- Vijayan, L., Huang, W., Ma, M., Ozguven, E., Ghorbanzadeh, M., Yang, J., & Yang, Z. (2023). Improving the accuracy of hurricane wave modeling in Gulf of Mexico with dynamically-coupled SWAN and ADCIRC. *Ocean Engineering*, 274, 114044. <https://doi.org/10.1016/j.oceaneng.2023.114044>
- Wamsley, T. V., Cialone, M. A., Smith, J. M., Ebersole, B. A., & Grzegorzewski, A. S. (2009). Influence of landscape restoration and degradation on storm surge and waves in southern Louisiana. *Natural Hazards*, 51(1), 207–224. <https://doi.org/10.1007/s11069-009-9378-z>
- White, E. D., Reed, D. J., & Meselhe, E. A. (2019). Modeled Sediment Availability, Deposition, and Decadal Land Change in Coastal Louisiana Marshes under Future Relative Sea Level Rise Scenarios. *Wetlands*, 39(6), 1233–1248. <https://doi.org/10.1007/s13157-019-01151-0>
- Yang, K., Paramygin, V., & Sheng, Y. P. (2019). An objective and efficient method for estimating probabilistic coastal inundation hazards. *Natural Hazards*, 99(2), 1105–1130. <https://doi.org/10.1007/s11069-019-03807-w>
- Yang, Y., Irish, J. L., & Socolofsky, S. A. (2015). Numerical investigation of wave-induced flow in mound–channel wetland systems. *Coastal Engineering*, 102, 1–12. <https://doi.org/10.1016/j.coastaleng.2015.05.002>
- Zhang, J., Taflanidis, A. A., Nadal-Caraballo, N. C., Melby, J. A., & Diop, F. (2018). Advances in surrogate modeling for storm surge prediction: Storm selection and addressing characteristics related to climate change. *Natural Hazards*, 94(3), 1225–1253.
- Zhang, X., Li, Y., Gao, S., & Ren, P. (2021). Ocean Wave Height Series Prediction with Numerical Long Short-Term Memory. *Journal of Marine Science and Engineering*, 9(5), 514. <https://doi.org/10.3390/jmse9050514>

Supplementary Information

Table S1. Distribution of synthetic storm parameters at landfall.

Storm ID	Heading	v_f (knots)	r_{max} (nm)	Landfall lon (x)	c_p (mbar)
1	35.8	9.5	10.9	-102.376	865.25
2	35.8	15.3	14.7	-102.375	885.25
3	35.8	11.8	5.9	-102.377	905.25
4	35.8	9.1	9.2	-102.377	925.25
5	35.8	16.7	15.5	-102.378	945.25
6	35.8	8.3	31.3	-102.376	965.25
7	35.8	10.2	59	-102.377	985.25
8	35.8	9.9	23.4	-102.377	1005.25
9	62.72727	20.6	9	-98.8967	865.25
10	62.72727	7.3	5.1	-98.8991	885.25
11	62.72727	8.6	27.3	-98.8964	905.25
12	62.72727	10.2	25.3	-98.8974	925.25
13	62.72727	4.8	27.5	-98.8975	945.25
14	62.72727	9.3	22.4	-98.8986	965.25
15	62.72727	9.7	11.7	-98.899	985.25
16	62.72727	10.9	44.5	-98.899	1005.25
17	69.86364	9.8	5	-95.3612	865.25
18	69.86364	14.4	11.9	-95.3631	885.25
19	69.86364	5.1	16.4	-95.36	905.25
20	69.86364	17.2	10.2	-95.359	925.25
21	69.86364	7.8	36.8	-95.3605	945.25
22	69.86364	9.8	25.1	-95.3612	965.25
23	69.86364	4.6	9	-95.3626	985.25
24	69.86364	12.3	56.6	-95.3634	1005.25
25	69.88333	10.9	6	-91.8512	865.25
26	69.88333	5.2	8	-91.85	885.25
27	69.88333	10.5	19.8	-91.85	905.25
28	69.88333	6.7	42.3	-91.8499	925.25
29	69.88333	17.5	26.5	-91.8528	945.25
30	69.88333	8.6	11.4	-91.8494	965.25
31	69.88333	11.8	51.2	-91.8525	985.25

32	69.88333	5.2	35.9	-91.8503	1005.25
33	77.34848	11.2	7.7	-88.3561	865.25
34	77.34848	18.1	15.7	-88.3545	885.25
35	77.34848	11.4	17.9	-88.3557	905.25
36	77.34848	8.5	11.8	-88.3535	925.25
37	77.34848	9.3	49.6	-88.3521	945.25
38	77.34848	5	27.1	-88.3541	965.25
39	77.34848	4.5	19	-88.3534	985.25
40	77.34848	13.2	33.4	-88.355	1005.25
41	88.96364	6.3	8.8	-85.1718	865.25
42	89.01786	11.3	6.3	-85.1751	885.25
43	88.96364	13.2	29	-85.1714	905.25
44	88.96364	8	34.8	-85.1727	925.25
45	88.96364	6.2	17.6	-85.1724	945.25
46	88.96364	17	23.3	-85.1735	965.25
47	88.96364	8.5	21.9	-85.1722	985.25
48	88.96364	7.7	62.4	-85.1726	1005.25
49	48.39024	9.6	17.7	-96.13	875.25
50	48.39024	15.9	16.4	-96.1307	895.25
51	48.39024	8.7	8.9	-96.1314	915.25
52	48.39024	9.6	9.3	-96.13	935.25
53	48.39024	16.8	13	-96.1303	955.25
54	48.39024	11.5	50.9	-96.131	975.25
55	48.39024	4.8	32.6	-96.1309	995.25
56	49.06522	21.9	13.9	-94.9388	875.25
57	49.06522	14.9	9.4	-94.9391	895.25
58	49.06522	9.3	7.6	-94.9392	915.25
59	49.06522	10.5	22.4	-94.9383	935.25
60	49.06522	5.3	16	-94.9385	955.25
61	49.06522	11.9	48.7	-94.9389	975.25
62	49.06522	12	15	-94.9388	995.25
63	51.03846	24.4	7.6	-93.7258	875.25
64	51.03846	13.2	9.7	-93.7262	895.25
65	51.03846	5.5	19.4	-93.7253	915.25
66	51.03846	8	44.4	-93.7255	935.25

67	51.03846	8.3	9.2	-93.7247	955.25
68	51.03846	12.6	35.9	-93.7253	975.25
69	51.03846	8.4	28	-93.725	995.25
70	51.05172	5.3	13.4	-92.5434	875.25
71	51.05172	17.5	11.8	-92.5442	895.25
72	51.05172	9.6	9.7	-92.5436	915.25
73	51.05172	4.9	15.4	-92.5437	935.25
74	51.05172	5.8	27	-92.5433	955.25
75	51.05172	9.8	44.8	-92.5445	975.25
76	51.05172	6	11.2	-92.5439	995.25
77	52.05085	13.6	11.2	-91.324	875.25
78	52.05085	9.2	13.2	-91.325	895.25
79	52.05085	14.5	20.7	-91.3244	915.25
80	52.05085	9.3	48	-91.3253	935.25
81	52.05085	9.6	12.2	-91.3248	955.25
82	52.05085	6.2	28.8	-91.324	975.25
83	52.05085	15	47	-91.3246	995.25
84	54.83051	6.8	13	-90.1105	875.25
85	54.83051	15.4	12.9	-90.1105	895.25
86	54.83051	12.5	14.4	-90.1102	915.25
87	54.83051	9.1	41.7	-90.11	935.25
88	54.83051	13.6	22.5	-90.1105	955.25
89	54.83051	5.6	20	-90.1113	975.25
90	54.83051	11	55.5	-90.1107	995.25
91	57.39063	8.3	7.8	-88.9005	875.25
92	57.39063	9.4	7.2	-88.9003	895.25
93	57.39063	8.2	27.6	-88.9001	915.25
94	57.39063	13.2	14.8	-88.9003	935.25
95	57.39063	9.9	51.2	-88.9006	955.25
96	58.02985	10.9	14.6	-88.9	975.25
97	58.02985	5.1	37.7	-88.8991	995.25
98	60.03077	9.9	9.6	-87.7248	875.25
99	60.03077	5.7	18.7	-87.7257	895.25
100	60.03077	6.9	13.4	-87.7242	915.25
101	60.03077	15	10.5	-87.7249	935.25

102	60.03077	12.7	59.2	-87.7245	955.25
103	60.03077	12.2	33.4	-87.7247	975.25
104	60.03077	8.9	33.8	-87.7245	995.25
105	66.86667	12.7	15	-86.4704	875.25
106	66.86667	11.4	6.6	-86.4712	895.25
107	66.86667	5.8	18.2	-86.4713	915.25
108	66.86667	14.5	11.7	-86.4705	935.25
109	66.86667	10.7	54.6	-86.4709	955.25
110	66.86667	13.4	23.7	-86.4713	975.25
111	66.86667	9.3	69.1	-86.4709	995.25
112	69.01786	8.6	6.4	-85.25	875.25
113	69.01786	10.7	20.1	-85.2502	895.25
114	69.01786	9	10.6	-85.2499	915.25
115	69.01786	16	13.6	-85.25	935.25
116	69.01786	5.6	19.1	-85.251	955.25
117	69.01786	9.2	68.6	-85.2507	975.25
118	69.01786	7.3	22.8	-85.2501	995.25
119	29.62791	7.9	9.2	-95.5716	865.25
120	29.62791	21.2	9.8	-95.5717	885.25
121	29.62791	13.7	8	-95.5719	905.25
122	29.62791	9.9	33.2	-95.5718	925.25
123	29.62791	6.9	18.4	-95.5716	945.25
124	29.62791	15.6	9	-95.5719	965.25
125	29.62791	9.2	36.3	-95.5716	985.25
126	29.62791	4.6	15.4	-95.5718	1005.25
127	29.06522	8.5	5.6	-94.7963	865.25
128	29.06522	23.7	16.8	-94.7964	885.25
129	29.06522	8.1	10.7	-94.7971	905.25
130	29.06522	11.8	6.6	-94.7967	925.25
131	29.06522	19.4	32.8	-94.7964	945.25
132	29.06522	5.5	40.4	-94.7961	965.25
133	29.06522	10.8	26	-94.7964	985.25
134	29.06522	4.3	12.6	-94.7964	1005.25
135	28.97959	16.2	6.2	-94.0161	865.25
136	28.97959	16.3	5.6	-94.016	885.25

137	28.97959	15.4	11.4	-94.0157	905.25
138	28.97959	8.3	29.2	-94.0159	925.25
139	28.97959	5.7	35.4	-94.0148	945.25
140	28.97959	4.9	13	-94.0158	965.25
141	28.97959	15.7	31.4	-94.0163	985.25
142	28.97959	9	14.5	-94.0163	1005.25
143	30.55172	23.7	4.6	-93.2425	865.25
144	30.55172	18.7	10.1	-93.2417	885.25
145	30.55172	6.7	9.9	-93.2419	905.25
146	30.55172	14.5	26.2	-93.242	925.25
147	30.55172	10.8	9.4	-93.2426	945.25
148	30.55172	6.7	47.6	-93.2425	965.25
149	30.55172	5	30.3	-93.2418	985.25
150	30.55172	9.2	20.4	-93.2424	1005.25
151	30.48276	27	12.7	-92.4729	865.25
152	30.48276	12.4	7.5	-92.4726	885.25
153	30.48276	6.2	19.2	-92.4723	905.25
154	30.48276	8.8	12.3	-92.4727	925.25
155	30.48276	18.4	8	-92.4726	945.25
156	30.48276	13.1	38.9	-92.4725	965.25
157	30.48276	11.4	21	-92.4725	985.25
158	30.48276	7.9	40	-92.4724	1005.25
159	30.15	19.8	5.9	-91.6849	865.25
160	30.15	16.8	20.2	-91.6852	885.25
161	30.15	21	9.2	-91.685	905.25
162	30.15	7.2	13.9	-91.6848	925.25
163	30.15	14.5	7.4	-91.6843	945.25
164	30.15	5.9	37.5	-91.6849	965.25
165	30.15	13.3	35	-91.6848	985.25
166	30.15	7.3	10.7	-91.6844	1005.25
167	34.58333	13.9	13.3	-90.8992	865.25
168	34.58333	9.1	5.3	-90.899	885.25
169	34.58333	5.6	14.4	-90.8989	905.25
170	34.58333	15.4	23.6	-90.8992	925.25
171	34.58333	6.4	29.5	-90.8993	945.25

172	34.58333	9.1	32.5	-90.899	965.25
173	34.58333	11.1	72.2	-90.8988	985.25
174	34.58333	8.5	16.4	-90.8984	1005.25
175	34.83051	9.2	6.8	-90.1173	865.25
176	34.83051	9.4	13.8	-90.1173	885.25
177	34.83051	14.5	14	-90.117	905.25
178	34.83051	7.7	39.1	-90.1168	925.25
179	34.83051	15	14.8	-90.1171	945.25
180	34.83051	19.3	29.2	-90.1171	965.25
181	34.83051	9.4	27	-90.1167	985.25
182	34.83051	9.7	59.3	-90.1174	1005.25
183	35.16129	11.9	9.5	-89.3274	865.25
184	35.16129	13.2	15.1	-89.3277	885.25
185	35.16129	7.5	7.7	-89.327	905.25
186	35.16129	5.9	27.1	-89.3273	925.25
187	35.16129	15.5	22.2	-89.3271	945.25
188	35.16129	10.4	64.3	-89.3273	965.25
189	35.16129	17.7	12.6	-89.3277	985.25
190	35.16129	6.4	54.2	-89.3281	1005.25
191	37.71014	12.3	11.7	-88.543	865.25
192	37.71014	7.6	17.5	-88.5434	885.25
193	37.71014	16.5	13.6	-88.5435	905.25
194	37.71014	13.2	7.7	-88.5424	925.25
195	37.71014	7.6	19.1	-88.5434	945.25
196	37.71014	8.1	59.3	-88.5433	965.25
197	37.71014	15	24.9	-88.5434	985.25
198	37.71014	11.5	48.1	-88.5431	1005.25
199	40.03077	8.2	6.6	-87.7427	865.25
200	40.03077	17.4	7.2	-87.7434	885.25
201	40.03077	12.1	16.8	-87.7433	905.25
202	40.03077	9.3	8.2	-87.7439	925.25
203	40.03077	12.1	34.1	-87.743	945.25
204	40.03077	5.2	16.3	-87.7433	965.25
205	40.03077	9.9	66.6	-87.743	985.25
206	40.03077	10.3	32.2	-87.7432	1005.25

207	43.95082	6.6	5.5	-86.9481	865.25
208	43.95082	11.7	11.6	-86.9488	885.25
209	43.95082	14	7.3	-86.9486	905.25
210	43.95082	5.7	31.7	-86.9491	925.25
211	43.95082	9.9	30.5	-86.9481	945.25
212	43.95082	11.6	36.2	-86.9482	965.25
213	43.95082	6.4	15.3	-86.9487	985.25
214	43.95082	15.2	18.4	-86.9481	1005.25
215	47.26667	13.5	8.2	-86.1468	865.25
216	47.26667	5.5	9	-86.1468	885.25
217	47.26667	10.8	7	-86.1458	905.25
218	47.26667	12.5	21.3	-86.147	925.25
219	47.26667	8	44.1	-86.1462	945.25
220	47.26667	13.5	18	-86.1468	965.25
221	47.26667	7.2	42.1	-86.1464	985.25
222	47.26667	6	13.5	-86.1458	1005.25
223	9.627907	18.6	8	-95.6178	875.25
224	9.627907	9.8	10.4	-95.6183	895.25
225	9.627907	17.1	20	-95.6178	915.25
226	9.627907	5.3	35.9	-95.6178	935.25
227	9.627907	15.5	7.8	-95.6181	955.25
228	9.627907	5.1	17.2	-95.6176	975.25
229	9.627907	10.7	58.1	-95.6175	995.25
230	9.065217	15.3	6.6	-94.9837	875.25
231	9.065217	5.2	19.3	-94.9838	895.25
232	9.065217	11.1	6.3	-94.9839	915.25
233	9.065217	20.1	9.9	-94.9838	935.25
234	9.065217	12	31.2	-94.9831	955.25
235	9.065217	7.4	27.8	-94.9835	975.25
236	9.065217	7	18.8	-94.9836	995.25
237	9.469388	15.8	15.7	-94.3494	875.25
238	9.469388	6.9	10.7	-94.349	895.25
239	9.469388	18.5	17.1	-94.3493	915.25
240	9.469388	12.9	8.2	-94.3491	935.25
241	9.469388	18.7	20.8	-94.3494	955.25

242	9.469388	6.4	56.1	-94.349	975.25
243	9.469388	6.2	26.9	-94.3489	995.25
244	11.03846	17.3	10.6	-93.7128	875.25
245	11.03846	14	5.5	-93.7131	895.25
246	11.03846	6	15.9	-93.7127	915.25
247	11.03846	18.1	12.3	-93.7127	935.25
248	11.03846	10.2	28	-93.7128	955.25
249	11.03846	8.1	18.1	-93.713	975.25
250	11.03846	7.6	50.9	-93.7131	995.25
251	11.24138	23	7	-93.0786	875.25
252	11.24138	11.8	12.1	-93.0777	895.25
253	11.24138	15	34	-93.0781	915.25
254	11.24138	6.3	7.6	-93.0782	935.25
255	11.24138	5.1	21.6	-93.0782	955.25
256	11.24138	10.6	20.9	-93.0784	975.25
257	11.24138	11.3	35.1	-93.0782	995.25
258	10.48276	7.4	8.4	-92.4393	875.25
259	10.48276	18.9	8.2	-92.4392	895.25
260	10.48276	21.5	28.9	-92.4393	915.25
261	10.48276	10.8	17.4	-92.4393	935.25
262	10.48276	4.7	18.4	-92.4391	955.25
263	10.48276	11.2	38.6	-92.4391	975.25
264	10.48276	5.3	9.3	-92.4389	995.25
265	10.10169	11	11.5	-91.7978	875.25
266	10.10169	6	7.6	-91.7972	895.25
267	10.10169	5	26.5	-91.797	915.25
268	10.10169	10.2	29.5	-91.797	935.25
269	10.10169	7.8	10	-91.7975	955.25
270	10.10169	8.5	22.8	-91.7972	975.25
271	10.10169	4.9	42	-91.7972	995.25
272	12.82759	14.8	11.8	-91.1511	875.25
273	12.82759	13.6	14.9	-91.1512	895.25
274	12.82759	7.9	14.9	-91.1508	915.25
275	12.82759	5.6	28.5	-91.151	935.25
276	12.82759	10.4	46.1	-91.151	955.25

277	12.82759	7.6	26.7	-91.1507	975.25
278	12.82759	17	31.4	-91.151	995.25
279	12.50909	10.3	4.9	-90.515	875.25
280	10.10169	8	17.4	-91.7973	895.25
281	10.10169	15.9	36.6	-91.7974	915.25
282	10.10169	6.5	21.6	-91.7977	935.25
283	10.10169	17.7	16.7	-91.7975	955.25
284	10.10169	14.4	21.8	-91.7973	975.25
285	10.10169	9.8	43.6	-91.7971	995.25
286	14.77193	16.3	7.3	-89.869	875.25
287	14.77193	8.6	8.5	-89.8692	895.25
288	14.77193	5.3	25.5	-89.8691	915.25
289	14.77193	8.8	23.9	-89.8695	935.25
290	14.77193	11.3	44	-89.869	955.25
291	14.77193	8.3	16.4	-89.8694	975.25
292	14.77193	13.2	53.1	-89.8689	995.25
293	16.70313	10.6	9.1	-89.2264	875.25
294	16.70313	12.9	7.9	-89.2268	895.25
295	16.70313	17.8	16.5	-89.2269	915.25
296	16.70313	5.8	19.4	-89.2265	935.25
297	16.70313	6.7	40.4	-89.227	955.25
298	16.70313	15	37.1	-89.2265	975.25
299	16.70313	6.8	15.9	-89.2262	995.25
300	17.71014	5.9	16.6	-88.5732	875.25
301	17.71014	16.4	12.5	-88.5734	895.25
302	17.71014	10.2	8.4	-88.5733	915.25
303	17.71014	9.9	13	-88.5729	935.25
304	17.71014	6.5	23.3	-88.573	955.25
305	17.71014	13	59.3	-88.5727	975.25
306	17.71014	10.1	17.8	-88.5729	995.25
307	20.14925	14.4	5.2	-87.9329	875.25
308	20.14925	8.3	21.9	-87.9333	895.25
309	20.14925	15.4	15.4	-87.9336	915.25
310	20.14925	19	33	-87.933	935.25
311	20.14925	7.4	10.7	-87.9331	955.25

312	20.14925	7.2	31	-87.9329	975.25
313	20.14925	15.9	24.8	-87.9332	995.25
314	23.04762	7.1	5.6	-87.2823	875.25
315	23.04762	17	15.4	-87.2825	895.25
316	23.04762	7.6	22.9	-87.2822	915.25
317	23.04762	17.3	25.6	-87.2828	935.25
318	23.04762	8.9	14.5	-87.2822	955.25
319	23.04762	10	63.3	-87.2824	975.25
320	23.04762	10.4	30.3	-87.2825	995.25
321	23.73438	13.9	8.2	-86.6288	875.25
322	23.73438	7.7	14.5	-86.6291	895.25
323	23.73438	9.9	11.6	-86.6295	915.25
324	23.73438	12.1	39.5	-86.6291	935.25
325	23.73438	7.6	29	-86.6289	955.25
326	23.73438	5.7	41.5	-86.6292	975.25
327	23.73438	12.4	14	-86.6289	995.25
328	-10.3721	5.4	7	-95.54	865.25
329	-10.3721	19.5	8.5	-95.54	885.25
330	-10.3721	9.2	6.2	-95.54	905.25
331	-10.3721	9.6	30.4	-95.54	925.25
332	-10.3721	12.8	23.1	-95.54	945.25
333	-10.3721	8.8	15.4	-95.54	965.25
334	-10.3721	7.8	37.7	-95.54	985.25
335	-10.3721	5	21.3	-95.54	1005.25
336	-10.9348	10.5	11.3	-94.93	865.25
337	-10.9348	22.3	6	-94.93	885.25
338	-10.9348	23.9	15.8	-94.93	905.25
339	-10.9348	13.7	22.1	-94.93	925.25
340	-10.9348	7.3	12.7	-94.93	945.25
341	-10.9348	5.7	43.7	-94.93	965.25
342	-10.9348	8.3	22.9	-94.93	985.25
343	-10.9348	6.2	27.6	-94.93	1005.25
344	-10.5306	15.7	7.1	-94.32	865.25
345	-10.5306	20.3	11	-94.32	885.25
346	-10.5306	19.1	8.4	-94.32	905.25

347	-10.5306	11.1	36.7	-94.32	925.25
348	-10.5306	9.1	11.4	-94.32	945.25
349	-10.5306	14.4	33.6	-94.32	965.25
350	-10.5306	4.9	32.6	-94.32	985.25
351	-10.5306	9.4	25.5	-94.32	1005.25
352	-8.96154	21.5	4.3	-93.71	865.25
353	-8.96154	6.7	10.4	-93.71	885.25
354	-8.96154	12.9	10.3	-93.71	905.25
355	-8.96154	19.7	15.6	-93.71	925.25
356	-8.96154	9.6	13.4	-93.71	945.25
357	-8.96154	7.2	52.5	-93.71	965.25
358	-8.96154	8.7	40.6	-93.71	985.25
359	-8.96154	6.6	17.4	-93.71	1005.25
360	-8.75862	19.1	9.7	-93.1	865.25
361	-8.75862	25.4	7	-93.1	885.25
362	-8.75862	20	17.4	-93.1	905.25
363	-8.75862	5.5	11.2	-93.1	925.25
364	-8.75862	8.3	40	-93.1	945.25
365	-8.75862	6.3	30.2	-93.1	965.25
366	-8.75862	6.6	9.8	-93.1	985.25
367	-8.75862	11.2	31	-93.1	1005.25
368	-9.51724	7	7.3	-92.49	865.25
369	-9.51724	14.8	6.7	-92.49	885.25
370	-9.51724	17.7	22	-92.49	905.25
371	-9.51724	20.8	14.5	-92.49	925.25
372	-9.51724	11.1	31.6	-92.49	945.25
373	-9.51724	7.6	19.7	-92.49	965.25
374	-9.51724	5.2	49.1	-92.49	985.25
375	-9.51724	5.5	9.7	-92.49	1005.25
376	-9.77966	17.8	12.1	-91.88	865.25
377	-9.77966	12.8	8.3	-91.88	885.25
378	-9.77966	5.3	22.8	-91.88	905.25
379	-9.77966	17.9	7.1	-91.88	925.25
380	-9.77966	11.4	21.4	-91.88	945.25
381	-9.77966	4.6	10.6	-91.88	965.25

382	-9.77966	5.8	43.6	-91.88	985.25
383	-9.77966	8.7	34.6	-91.88	1005.25
384	-7.50877	17.2	10.6	-91.27	865.25
385	-7.50877	8.7	13.4	-91.27	885.25
386	-7.50877	7.2	11.1	-91.27	905.25
387	-7.50877	12.9	12.9	-91.27	925.25
388	-7.50877	10.2	46.5	-91.27	945.25
389	-7.50877	13.9	26.1	-91.27	965.25
390	-7.50877	7.6	18.1	-91.27	985.25
391	-7.50877	8.1	41.5	-91.27	1005.25
392	-6.81356	8.9	4.5	-90.66	865.25
393	-6.81356	10.7	21.7	-90.66	885.25
394	-6.81356	5.9	25.9	-90.66	905.25
395	-6.81356	11.4	18.6	-90.66	925.25
396	-6.81356	5.9	24.7	-90.66	945.25
397	-6.81356	11.3	18.8	-90.66	965.25
398	-6.81356	7	10.7	-90.66	985.25
399	-6.81356	8.3	70.5	-90.66	1005.25
400	-5.22807	13.1	7.5	-90.05	865.25
401	-5.22807	14	10.7	-90.05	885.25
402	-5.22807	18.4	23.8	-90.05	905.25
403	-5.22807	10.8	10.7	-90.05	925.25
404	-5.22807	5.2	16.9	-90.05	945.25
405	-5.22807	7.4	28.1	-90.05	965.25
406	-5.22807	9	62.4	-90.05	985.25
407	-5.22807	13.7	26.5	-90.05	1005.25
408	-2.91667	12.7	4.9	-89.44	865.25
409	-2.91667	8.2	18.3	-89.44	885.25
410	-2.91667	6.4	9.5	-89.44	905.25
411	-2.91667	15	16.8	-89.44	925.25
412	-2.91667	12.4	8.7	-89.44	945.25
413	-2.91667	11.9	49.9	-89.44	965.25
414	-2.91667	13.8	17.2	-89.44	985.25
415	-2.91667	5.7	46.3	-89.44	1005.25
416	-2.02899	5.7	4.8	-88.83	865.25

417	-2.02899	10	9.6	-88.83	885.25
418	-2.02899	10.2	31.3	-88.83	905.25
419	-2.02899	14	24.4	-88.83	925.25
420	-2.02899	5.5	25.6	-88.83	945.25
421	-2.02899	7.9	9.8	-88.83	965.25
422	-2.02899	6	39.1	-88.83	985.25
423	-2.02899	12.7	49.9	-88.83	1005.25
424	-1.38235	14.7	8	-88.22	865.25
425	-1.38235	5.8	12.3	-88.22	885.25
426	-1.38235	12.5	13.1	-88.22	905.25
427	-1.38235	9.1	15.1	-88.22	925.25
428	-1.38235	10.5	16.2	-88.22	945.25
429	-1.38235	15	34.9	-88.22	965.25
430	-1.38235	8	53.5	-88.22	985.25
431	-1.38235	7	22.4	-88.22	1005.25
432	0.030769	7.6	5.7	-87.61	865.25
433	0.030769	15.8	7.7	-87.61	885.25
434	0.030769	9	20.5	-87.61	905.25
435	0.030769	16	16.2	-87.61	925.25
436	0.030769	13.2	12	-87.61	945.25
437	0.030769	16.2	55.6	-87.61	965.25
438	0.030769	10.5	28.1	-87.61	985.25
439	0.030769	6.7	38.6	-87.61	1005.25
440	3.746032	10.2	14.2	-87	865.25
441	3.746032	8.5	5.8	-87	885.25
442	3.746032	15	12.3	-87	905.25
443	3.746032	18.7	19.3	-87	925.25
444	3.746032	8.6	19.9	-87	945.25
445	3.746032	6.5	21.4	-87	965.25
446	3.746032	12.1	56	-87	985.25
447	3.746032	10.5	19.3	-87	1005.25
448	-30.3721	16.8	6.7	-95.6029	875.25
449	-30.3721	5.5	21	-95.6032	895.25
450	-30.3721	10.5	6.7	-95.6027	915.25
451	-30.3721	21.6	11.1	-95.6035	935.25

452	-30.3721	12.4	33.5	-95.603	955.25
453	-30.3721	7.8	29.9	-95.6029	975.25
454	-30.3721	7.2	19.8	-95.6029	995.25
455	-30.9348	12	5.5	-94.9587	875.25
456	-30.9348	10.4	5.8	-94.9584	895.25
457	-30.9348	11.4	23.7	-94.9587	915.25
458	-30.9348	15.5	16.1	-94.9584	935.25
459	-30.9348	8.6	24.2	-94.9584	955.25
460	-30.9348	6.7	8.6	-94.9586	975.25
461	-30.9348	4.4	21.8	-94.9581	995.25
462	-30.5306	12.4	5.8	-94.3234	875.25
463	-30.5306	12.1	6	-94.3233	895.25
464	-30.5306	11.8	24.6	-94.3235	915.25
465	-30.5306	16.6	16.7	-94.3231	935.25
466	-30.5306	9.1	26.1	-94.3232	955.25
467	-30.5306	7	9.4	-94.3238	975.25
468	-30.5306	4.6	23.8	-94.3233	995.25
469	-28.9615	8	8.9	-93.6883	875.25
470	-28.9615	20.6	8.8	-93.6879	895.25
471	-28.9615	19.3	30.3	-93.6881	915.25
472	-28.9615	11.4	18.7	-93.6883	935.25
473	-28.9615	4.9	19.9	-93.6881	955.25
474	-28.9615	9	40	-93.6876	975.25
475	-28.9615	5.5	10.3	-93.6877	995.25
476	-28.7586	6.2	9.8	-93.0572	875.25
477	-28.7586	24.7	13.7	-93.0568	895.25
478	-28.7586	13.7	7.1	-93.0573	915.25
479	-28.7586	8.5	30.6	-93.0574	935.25
480	-28.7586	13.1	15.2	-93.0567	955.25
481	-28.7586	4.5	13.7	-93.0577	975.25
482	-28.7586	8	45.2	-93.0571	995.25
483	-29.5172	9	4.7	-92.4166	875.25
484	-29.5172	7.4	26.2	-92.4166	895.25
485	-29.5172	23.1	17.6	-92.4166	915.25
486	-29.5172	7	27.5	-92.4167	935.25

487	-29.5172	6	11.4	-92.4168	955.25
488	-29.5172	15.6	12	-92.4165	975.25
489	-29.5172	8.6	74.8	-92.4166	995.25
490	-29.8983	11.7	10.1	-91.7894	875.25
491	-29.8983	19.7	11.4	-91.7894	895.25
492	-29.8983	7.1	8	-91.7895	915.25
493	-29.8983	6	18	-91.7897	935.25
494	-29.8983	11.7	36	-91.7894	955.25
495	-29.8983	16.4	12.9	-91.7894	975.25
496	-29.8983	7.8	61.1	-91.7894	995.25
497	-27.1724	6.5	12.5	-91.1497	875.25
498	-27.1724	18.2	9.1	-91.1499	895.25
499	-27.1724	20.4	31.9	-91.15	915.25
500	-27.1724	8.3	26.6	-91.1502	935.25
501	-27.1724	8.1	8.5	-91.1499	955.25
502	-27.1724	5	34.6	-91.1502	975.25
503	-27.1724	11.6	39.1	-91.1499	995.25
504	-27.4909	17.9	9.3	-90.5184	875.25
505	-27.4909	6.3	15.9	-90.5178	895.25
506	-27.4909	12.1	18.8	-90.5182	915.25
507	-27.4909	7.8	8.7	-90.5185	935.25
508	-27.4909	9.3	38.8	-90.5184	955.25
509	-27.4909	4.8	24.7	-90.5184	975.25
510	-27.4909	13.8	36.4	-90.5181	995.25
511	-25.2281	5.6	7.2	-89.8916	875.25
512	-25.2281	11.1	16.9	-89.8916	895.25
513	-25.2281	10.8	11.1	-89.8916	915.25
514	-25.2281	13.6	20.8	-89.8916	935.25
515	-25.2281	14	17.5	-89.8916	955.25
516	-25.2281	8.7	53.3	-89.8917	975.25
517	-25.2281	5.7	25.9	-89.8917	995.25
518	-23.2969	9.3	8.6	-89.26	875.25
519	-23.2969	6.6	24.4	-89.2601	895.25
520	-23.2969	6.6	12.5	-89.2601	915.25
521	-23.2969	12.5	31.7	-89.26	935.25

522	-23.2969	16.1	13.7	-89.2602	955.25
523	-23.2969	10.3	25.7	-89.2597	975.25
524	-23.2969	6.4	40.5	-89.2599	995.25
525	-22.3971	7.7	6	-88.6229	875.25
526	-22.3971	10.1	10	-88.623	895.25
527	-22.3971	8.4	22.1	-88.6226	915.25
528	-22.3971	7.3	37.5	-88.6226	935.25
529	-22.3971	15	25.1	-88.6229	955.25
530	-22.3971	9.5	11.1	-88.6229	975.25
531	-22.3971	5.8	48.9	-88.6228	995.25
532	-19.8507	11.3	10.9	-87.9992	875.25
533	-19.8507	12.5	11.1	-87.9995	895.25
534	-19.8507	14	9.3	-87.9994	915.25
535	-19.8507	6.8	34.4	-87.9992	935.25
536	-19.8507	20	30.1	-87.9993	955.25
537	-19.8507	5.3	19.1	-87.999	975.25
538	-19.8507	12.8	29.2	-87.9994	995.25
539	-17.5	19.3	10.3	-87.3666	875.25
540	-17.5	7.1	14	-87.3669	895.25
541	-17.5	13.2	12	-87.3672	915.25
542	-17.5	11.1	23.1	-87.3669	935.25
543	-17.5	7.1	32.3	-87.3669	955.25
544	-17.5	18.5	43.1	-87.3673	975.25
545	-17.5	8.2	13.1	-87.3671	995.25
546	-49.6939	22.5	5.2	-94.1419	865.25
547	-49.6939	7.9	13	-94.1421	885.25
548	-49.6939	9.8	12.7	-94.1424	905.25
549	-49.6939	22.4	20	-94.1412	925.25
550	-49.6939	8.9	53.7	-94.1425	945.25
551	-49.6939	10.1	8.2	-94.1423	965.25
552	-49.6939	5.4	16.2	-94.1432	985.25
553	-49.6939	10	37.2	-94.1426	1005.25
554	-49.4483	6	7.8	-93.3481	865.25
555	-49.4483	11	12.6	-93.3489	885.25
556	-49.4483	22.2	18.5	-93.3481	905.25

557	-49.4483	6.4	18	-93.3482	925.25
558	-49.4483	13.6	10.7	-93.348	945.25
559	-49.4483	18	12.2	-93.3483	965.25
560	-49.4483	6.8	29.2	-93.3481	985.25
561	-49.4483	7.5	76.3	-93.3485	1005.25
562	-48.9483	14.3	8.4	-92.5574	865.25
563	-48.9483	13.6	6.5	-92.5576	885.25
564	-48.9483	17	24.8	-92.5572	905.25
565	-48.9483	6.2	20.6	-92.5577	925.25
566	-48.9483	20.8	23.9	-92.5573	945.25
567	-48.9483	10.7	14.6	-92.5574	965.25
568	-48.9483	6.2	14.4	-92.5577	985.25
569	-48.9483	4.5	52	-92.5578	1005.25
570	-49.8983	25.1	10	-91.7639	865.25
571	-49.8983	9.7	11.3	-91.7647	885.25
572	-49.8983	11.1	6.6	-91.7654	905.25
573	-49.8983	5.2	28.1	-91.7642	925.25
574	-49.8983	5	14.1	-91.7649	945.25
575	-49.8983	12.7	17.1	-91.7652	965.25
576	-49.8983	14.4	45.4	-91.7643	985.25
577	-49.8983	5.9	28.7	-91.7641	1005.25
578	-45.3509	7.2	6.5	-90.9759	865.25
579	-45.3509	6.1	16.2	-90.9762	885.25
580	-45.3509	9.6	11.9	-90.9762	905.25
581	-45.3509	16.6	22.8	-90.976	925.25
582	-45.3509	11.7	10	-90.9763	945.25
583	-45.3509	9.6	45.6	-90.9762	965.25
584	-45.3509	7.4	23.9	-90.9758	985.25
585	-45.3509	11.9	24.4	-90.9763	1005.25
586	-45.1695	16.7	5.3	-90.1883	865.25
587	-45.1695	6.4	19.2	-90.188	885.25
588	-45.1695	8.4	8.8	-90.1883	905.25
589	-45.1695	10.5	17.4	-90.1882	925.25
590	-45.1695	16.1	28.5	-90.1877	945.25
591	-45.1695	7	24.2	-90.1884	965.25

592	-45.1695	16.6	47.1	-90.1883	985.25
593	-45.1695	14.4	11.6	-90.1884	1005.25
594	-42.9167	15.2	8.6	-89.4177	865.25
595	-42.9167	12	8.7	-89.4178	885.25
596	-42.9167	7	21.2	-89.4181	905.25
597	-42.9167	7	8.7	-89.4181	925.25
598	-42.9167	6.6	20.6	-89.418	945.25
599	-42.9167	11	42	-89.418	965.25
600	-42.9167	12.5	20	-89.4176	985.25
601	-42.9167	7.1	29.9	-89.4179	1005.25
602	-42.3971	18.4	10.3	-88.6134	865.25
603	-42.3971	7	9.3	-88.6128	885.25
604	-42.3971	7.8	15.3	-88.6131	905.25
605	-42.3971	7.5	13.4	-88.6129	925.25
606	-42.3971	14	41.9	-88.613	945.25
607	-42.3971	12.3	13.8	-88.6135	965.25
608	-42.3971	12.9	33.8	-88.6133	985.25
609	-42.3971	4.8	43	-88.6134	1005.25
610	-40.9375	11.6	6.4	-87.8442	865.25
611	-40.9375	10.4	14.2	-87.8443	885.25
612	-40.9375	15.9	14.9	-87.8442	905.25
613	-40.9375	12.1	9.7	-87.8445	925.25
614	-40.9375	7.1	38.3	-87.8444	945.25
615	-40.9375	6.1	20.6	-87.8444	965.25
616	-40.9375	5.6	13.4	-87.8444	985.25
617	-40.9375	16.2	66	-87.8445	1005.25
618	-69.5172	20	12.2	-92.4188	875.25
619	-69.5172	14.5	6.4	-92.419	895.25
620	-69.5172	6.3	21.4	-92.4192	915.25
621	-69.5172	11.8	20.1	-92.4196	935.25
622	-69.5172	11	48.4	-92.4191	955.25
623	-69.5172	5.9	10.3	-92.4184	975.25
624	-69.5172	14.4	20.7	-92.4193	995.25
625	-67.5088	13.1	6.2	-91.1804	875.25
626	-67.5088	21.7	18	-91.1802	895.25

627	-67.5088	16.5	10.2	-91.1806	915.25
628	-67.5088	5.1	24.8	-91.18	935.25
629	-67.5088	6.9	42.1	-91.1807	955.25
630	-67.5088	13.9	32.2	-91.1807	975.25
631	-67.5088	6.6	12.1	-91.1807	995.25
632	-65.2281	26.2	5.1	-89.9662	875.25
633	-65.2281	8.9	23.1	-89.9663	895.25
634	-65.2281	12.9	13	-89.9661	915.25
635	-65.2281	14	7	-89.9665	935.25
636	-65.2281	14.4	34.7	-89.9657	955.25
637	-65.2281	6.6	15.4	-89.9659	975.25
638	-65.2281	9.1	64.7	-89.9671	995.25
639	-62.029	20.9	14.4	-88.7649	875.25
640	-62.029	22.9	7	-88.7646	895.25
641	-62.029	7.3	13.9	-88.7656	915.25
642	-62.029	7.5	14.1	-88.766	935.25
643	-62.029	6.3	37.4	-88.765	955.25
644	-62.029	17.3	46.7	-88.7657	975.25
645	-62.029	9.6	16.8	-88.7653	995.25