DATA-DRIVEN STORM SURGE MODELING FOR RESILIENCE ASSESSMENT OF ELECTRIC POWER SYSTEMS

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ABSTRACT

As the frequency and intensity of extreme weather events increases, the need for accurate modeling of their impact becomes more crucial than ever. Infrastructure losses as a result of prolonged power outages can cause severe devastation to communities. In order to make these systems more robust, grid planners must have adequate tools for modeling the impact of severe weather events. In this work, we leverage data-driven approaches to model and simulate hurricane storm surge using publicly accessible data. The data-driven models reduce the complex model dependency and facilitate computational enhancement in identifying the vulnerabilities of extreme weather events on bulk power grid assets.

BACKGROUND

Hurricanes have caused billions of dollars in damage to the electric power system [1] and is one of the largest sources of weather-related power outages [2]. Ultimately, this critical infrastructure loss translates to heavy human impact that devastates communities [3].

A storm surge from a hurricane can be caused by a multitude of factors: wind speed, pressure, geographical features of the coastline, and so forth [4]. We can model the flood output as a function of many hurricane features, This function acts as a black-box model that is represented by these inputs. Finally, this weather output is tested against a power system, as seen in figure 1.

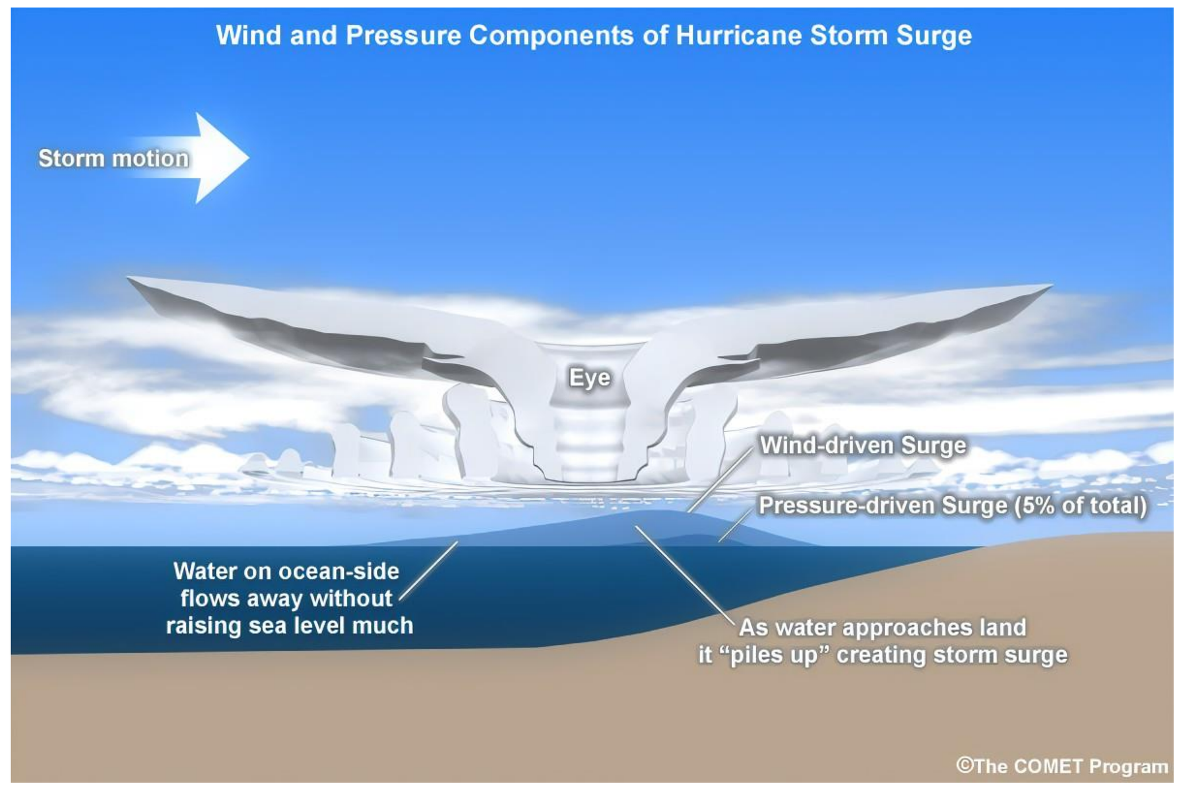

Figure 1: Wind and Pressure Components of Hurricane Storm Surge [9]

For this analysis, we use the scope of the Corpus Christi sub-basin in Texas, chosen due to its vulnerability to tropical cyclones. Ideally, this model can be replicated to other basins. We only train the model from tropical cyclones that have inundated the Texas coastline up to 20 years prior, for two reasons: recent data is more abundant, and the physics of future tropical cyclones are more likely to be determined by recent events.

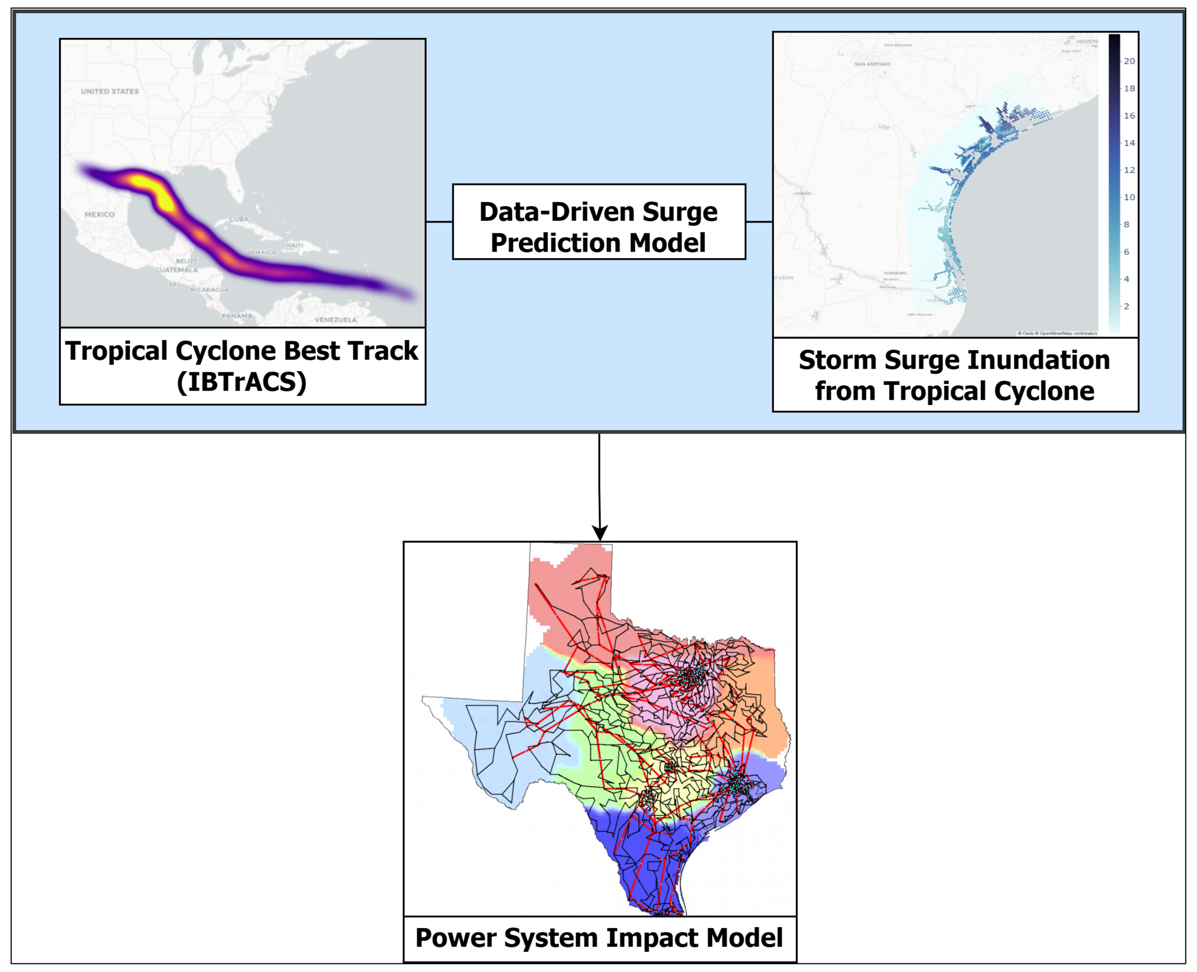

Figure 2: Coupled Wind-Surge Impact on Electric Power Systems Framework

METHODOLOGY AND USE OF DATA-DRIVEN METHODS

The most difficult part of this problem is creating the function that maps a hurricane track to a storm surge, explained earlier by its multi-variable complexity. For this reason, we exploit machine learning methods to create an efficient and accurate flood model since they have the ability to map inputs to outputs without any physics-based knowledge.

For input data, we elect the use of the National Oceanic and Atmospheric Administration's International Best Track Archive for Climate Stewardship, or IBTrACS [5]. IBTrACS is a collection of best-track historical hurricane data from multiple agencies in three-hour time intervals. This archive records many of the variables that contribute to flooding. The output data originates from the Sea, Lake, and Overland Surge from Hurricanes (SLOSH) model developed by the National Hurricane Center [6]. The SLOSH model provides the maximum predicted storm surge for each point in a basin. The two data-driven methods selected for preliminary analysis are convolutional neural networks (CNN) and the random forest regressor (RF).

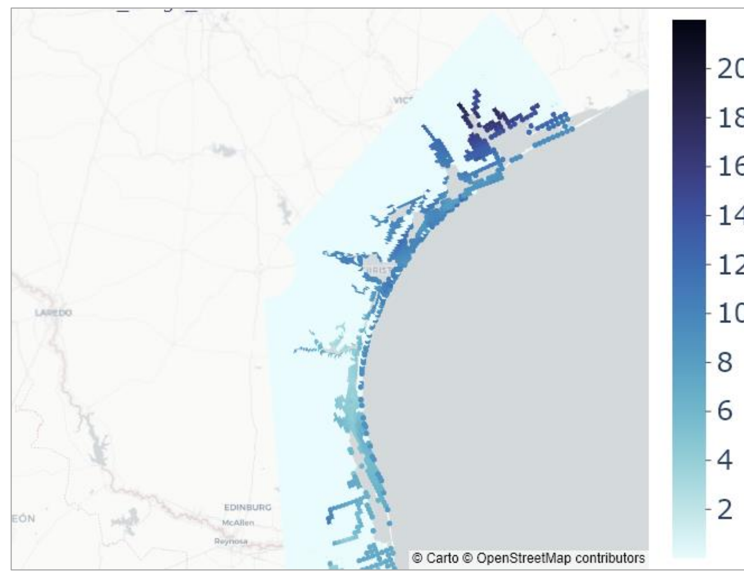

Figure 3: SLOSH Model Output for Hurricane Ivan

RESULTS AND DISCUSSION

Visual inspection is an important aspect of this problem, and thus mapping inundation levels can be compared to the SLOSH output. The coefficient of determination (R2), root- mean square error (RMSE), and the mean absolute error (MAE) are used as accuracy measurements.

Figure 4a and 4b are the outputs of RF and CNN predictions for Hurricane Ivan , respectively. Upon comparison to each other, they follow quite similar trends; however, it's notable that RF predicts higher levels of surge inundation than that of the CNN. Interestingly, CNN suffers from the sparsity of the SLOSH training data.

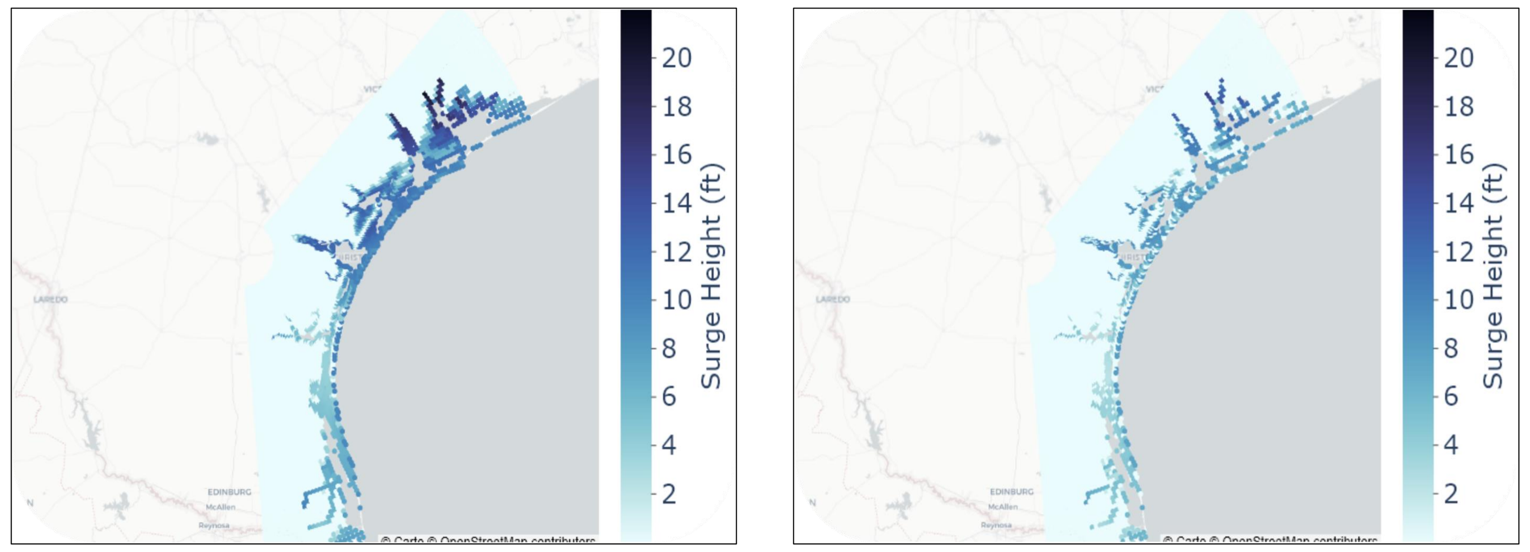

Figure 4: Output from RF (a), Output from CNN (b) for Hurricane Ivan

Finally, we evaluate quantitatively (see table 1). Interestingly, despite RF having a higher R2 value, CNN shows promise in its RMSE and MAE. This implies RF has advantage in fitting the model, but CNN has a lower probability of making large prediction errors.

Table 1: Accuracy Measurements for RF and CNN Models

Model	R^2	RMSE	MAE
Random Forest	95.28%	0.2380	0.1825
Convolutional Neural Network	90.49%	0.1757	0.1356

FUTURE WORKS

Despite the setback of limited historical data, the results of this model is promising. In future, there are several ways to improve the robustness of this prediction model, such as employing ensemble learning methods and parameter optimization. Additionally, this model still needs power system implementation. An interesting idea would be projecting this flood model based on predicted climate impacts to study how a future power grid would be affected. To conclude, data-driven modeling is essential for capturing power system impact from hurricanes.

References: [1] A. B. Smith, "2022 U.S. billion-dollar weather and climate disasters in historical context," NOAA National Centers for Environmental Information (NCEI), 2023. [Online]. Available: https://www.climate.gov/news-features/blogs/2022-us-billion-dollar-weather-and-climate-disasters-historical-context [2] N. Alemazkoor, B. Rachunok, and D. C. et al, "Hurricane-induced power outage risk under climate change is primarily driven by the uncertainty in projections of future hurricane frequency." Sci Rep, vol. 10, p. 15270, 2020. [3] V. Do, H. McBrien, N. Flores, A. Northrop, J. Schlegelmilch, M. Kiang, and J. Casey, "Spatiotemporal distribution of power outages with climate events and social vulnerability in the usa," Nature Communications, vol. 14, p. 2470, 2023. [4] "Understanding coastal flooding and storm surge," National Hurricane Center, Tech. Rep. [Online]. Available: https://www.weather.gov/mhx/UnderstandCoastalFlooding [5] K. R. Knapp, M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann, "The international best track archive for climate stewardship (IBTrACS)," Bulletin of the American Meteorological Society, vol. 91, no. 3, pp. 363–376, Mar. 2010. [6] "SLOSH display package," National Oceanic and Atmospheric Administration, Tech. Rep. [Online]. Available: https://slosh.nws.noaa.gov/sdp/