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DeepSurge: A neural network model for climate-scale storm surge risk assessment

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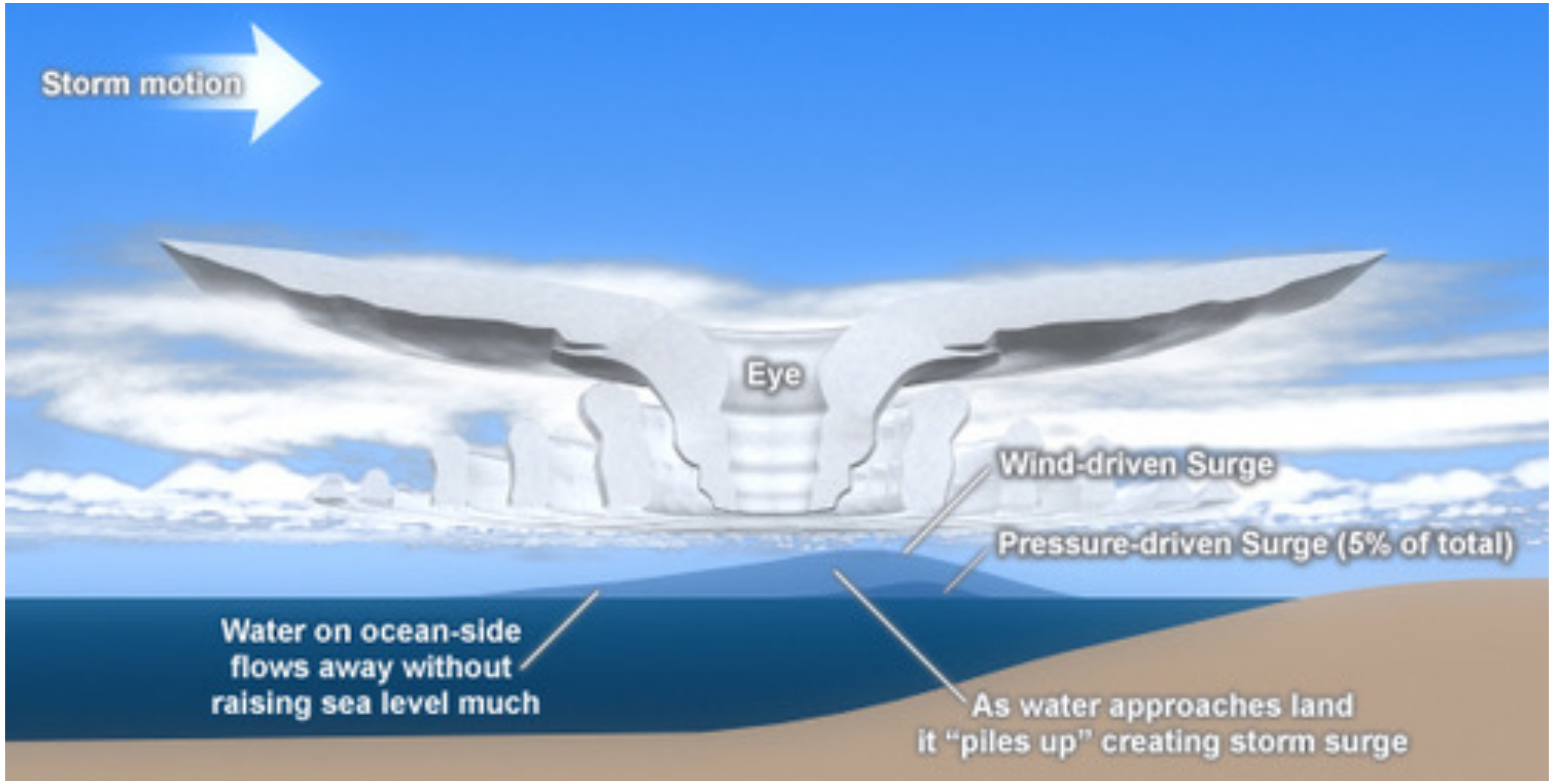
U.S. DEPARTMENT OF ENERGY BATTELLE

Outline

- Background
- Motivations
- Our approach: DeepSurge
- Training & Validation
- Evaluating Future Storm Surge Risk

Background: Storm Surge

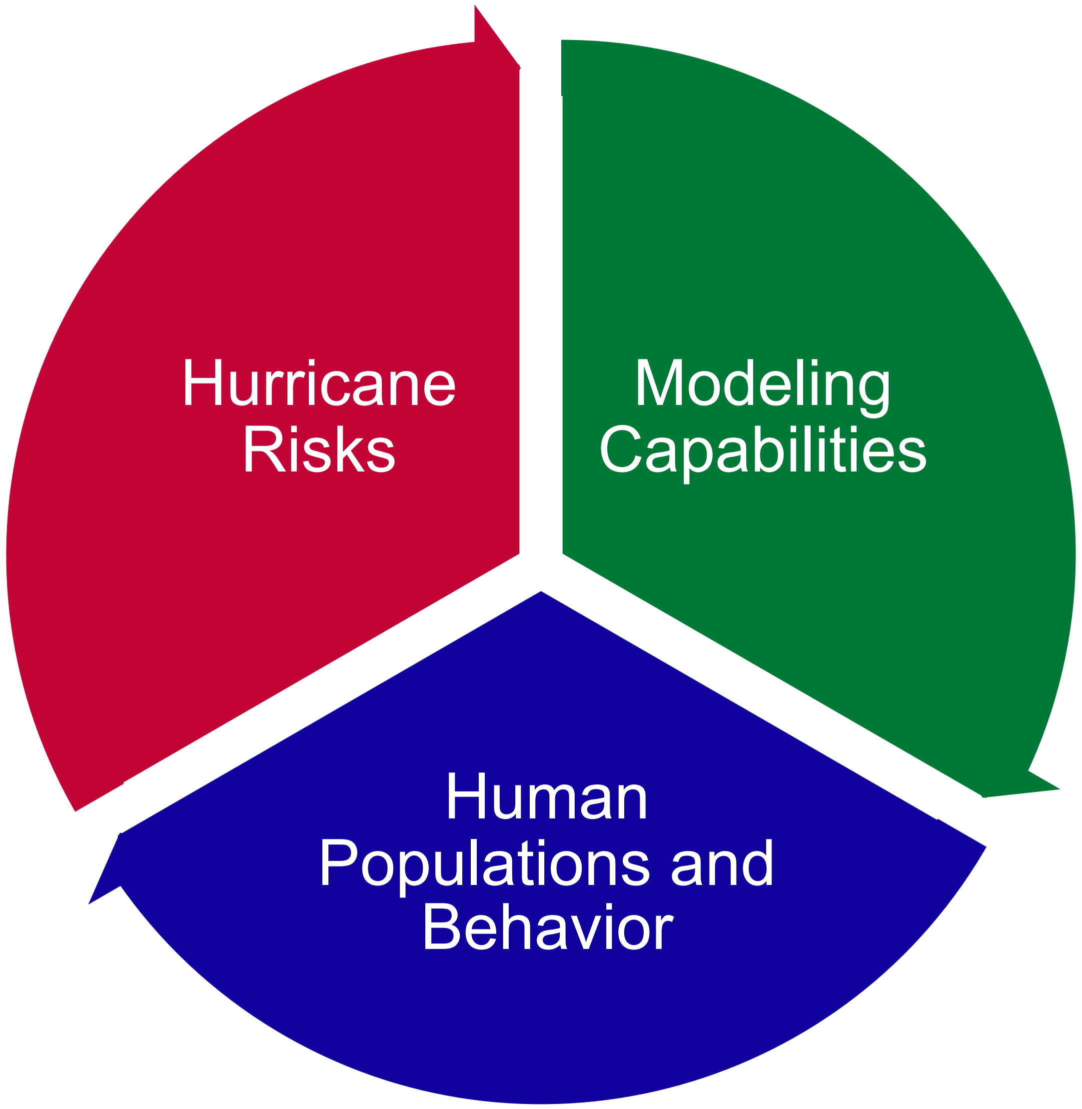


Storm surge is caused by a tropical cyclone's wind pushing water onto land (NHC, no date)

A refrigerator deposited in a tree by Hurricane Katrina's record storm surge in 2005
(Fritz et al., 2007)

Motivations

- Storm surge is historically the largest single cause of death from tropical cyclones the United State (Rappaport 2014)
- The historical record is too short to gain an accurate understanding of current risk
- Future changes in tropical cyclone climatology further complicate our understanding



- A number of statistical and dynamical models exist for modeling storm surge (ADCIRC, ROMS, SLOSH, etc.)
- These models rely on increasing spatial and temporal resolution for accuracy, at the detriment of computational efficiency
- We want to explore the feasibility of ML/AI approaches to this problem

- Coastal populations have been increasing historically, and are projected to continue increasing globally (Neumann, 2015)

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Our Approach: DeepSurge

Woodruff et al. (2013) hypothesize that storm surge height is proportional to

$$\frac{(\text{Wind Speed})^2 \cdot (\text{Wind Fetch Distance})}{\text{Ocean Depth}}$$

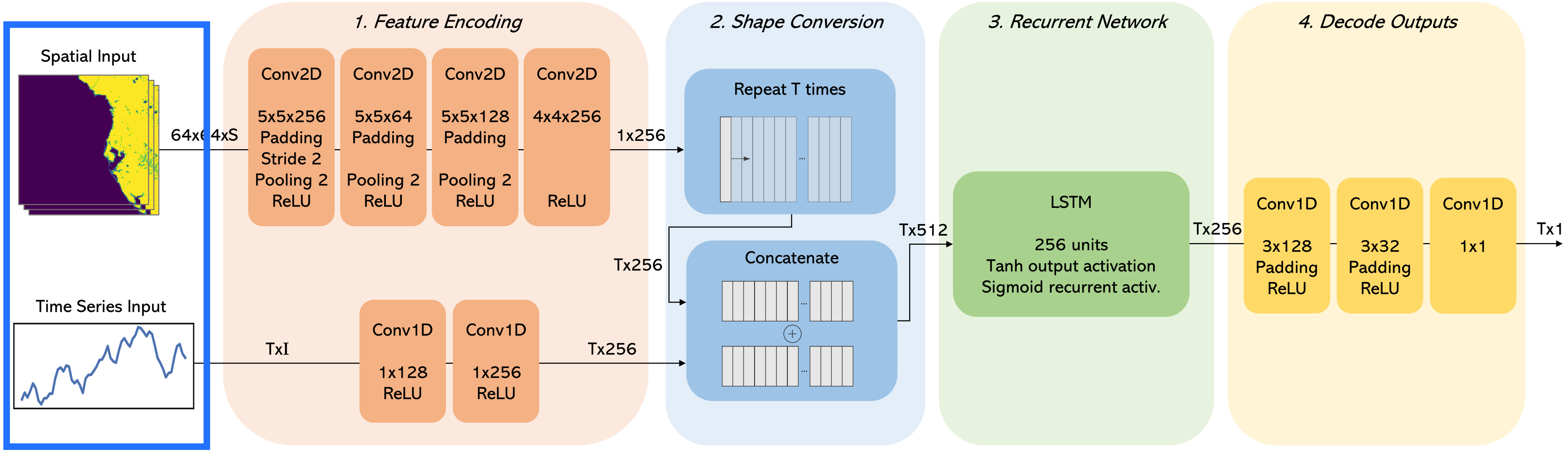
moderated by more complex interactions with coastal features such as bays, inlets, and barrier islands

Wind fields, bathymetry maps, coastal geometry, storm position and motion

Custom deep neural network

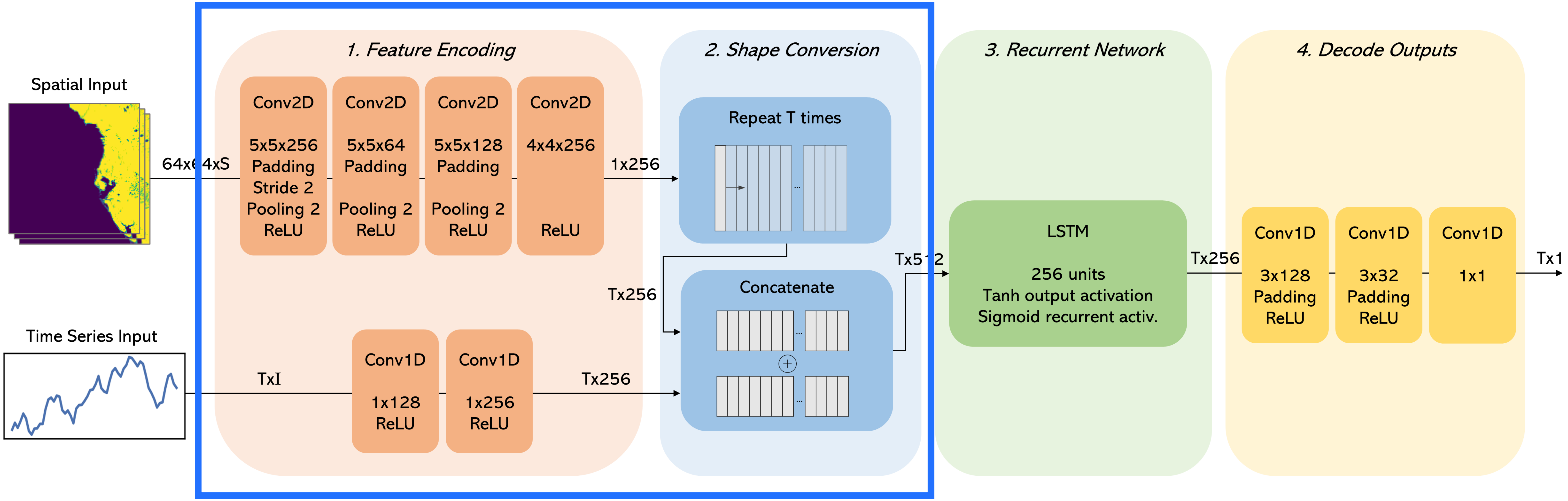
Predicted peak storm surge levels

DeepSurge: Network Architecture



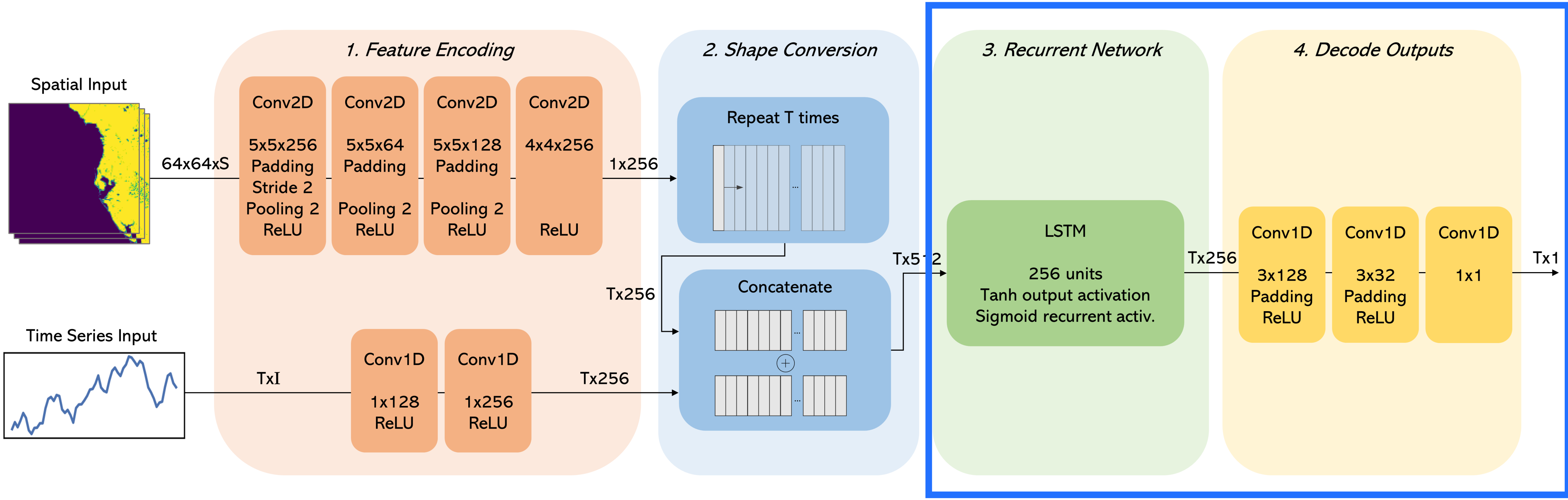
First, we gather a number of different inputs that describe the physical features which influence surge: constant spatial maps representing coastlines and bathymetry, and time-varying features such as storm location, wind speed, and direction.

DeepSurge: Network Architecture



Next, we encode these sources and combine them into one timeseries representing the storm's lifetime.

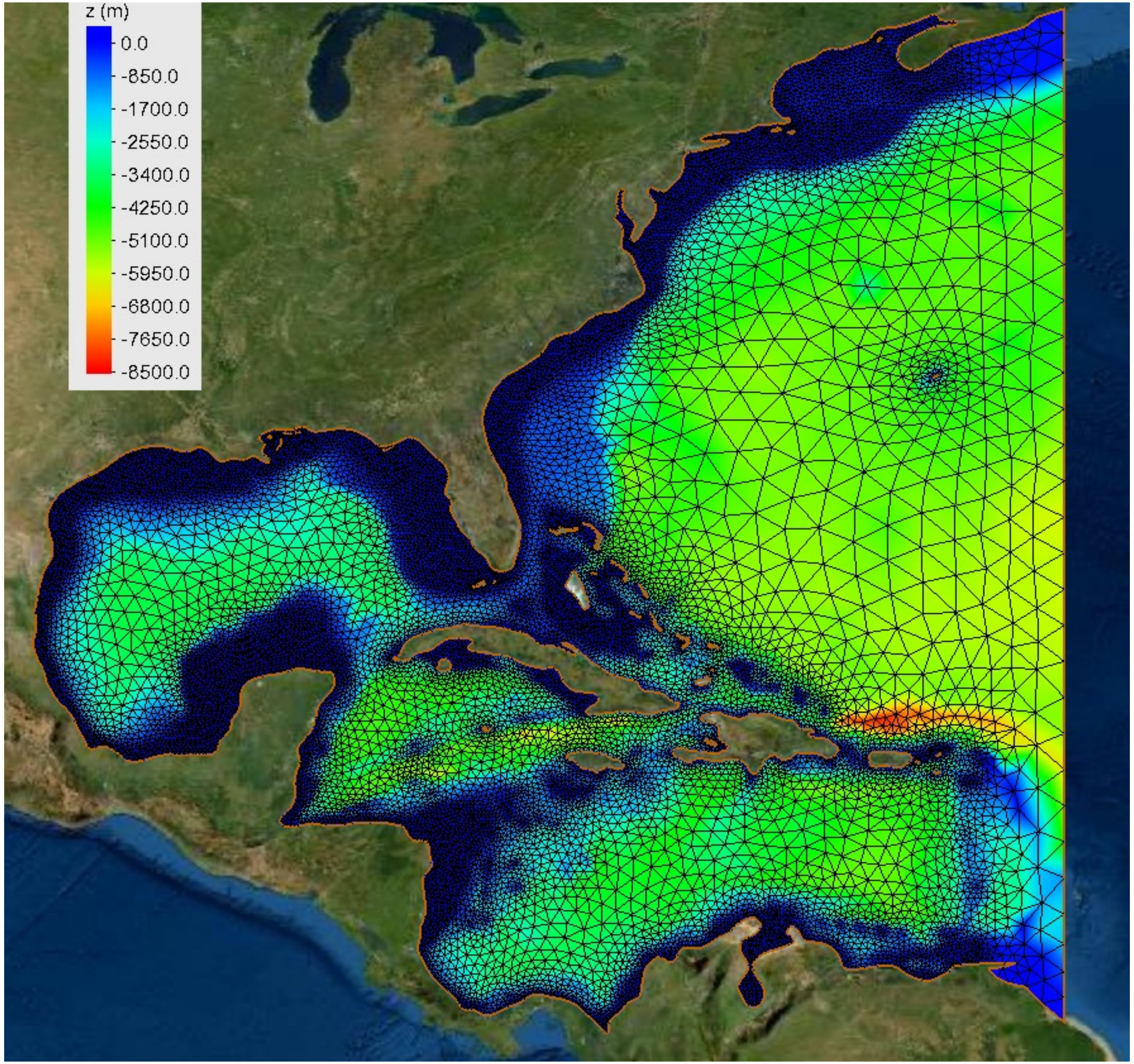
DeepSurge: Network Architecture



Lastly, we apply a Recurrent Neural Network (RNN) to process each step of the timeseries in the context of all previous steps, and then output our peak surge prediction.

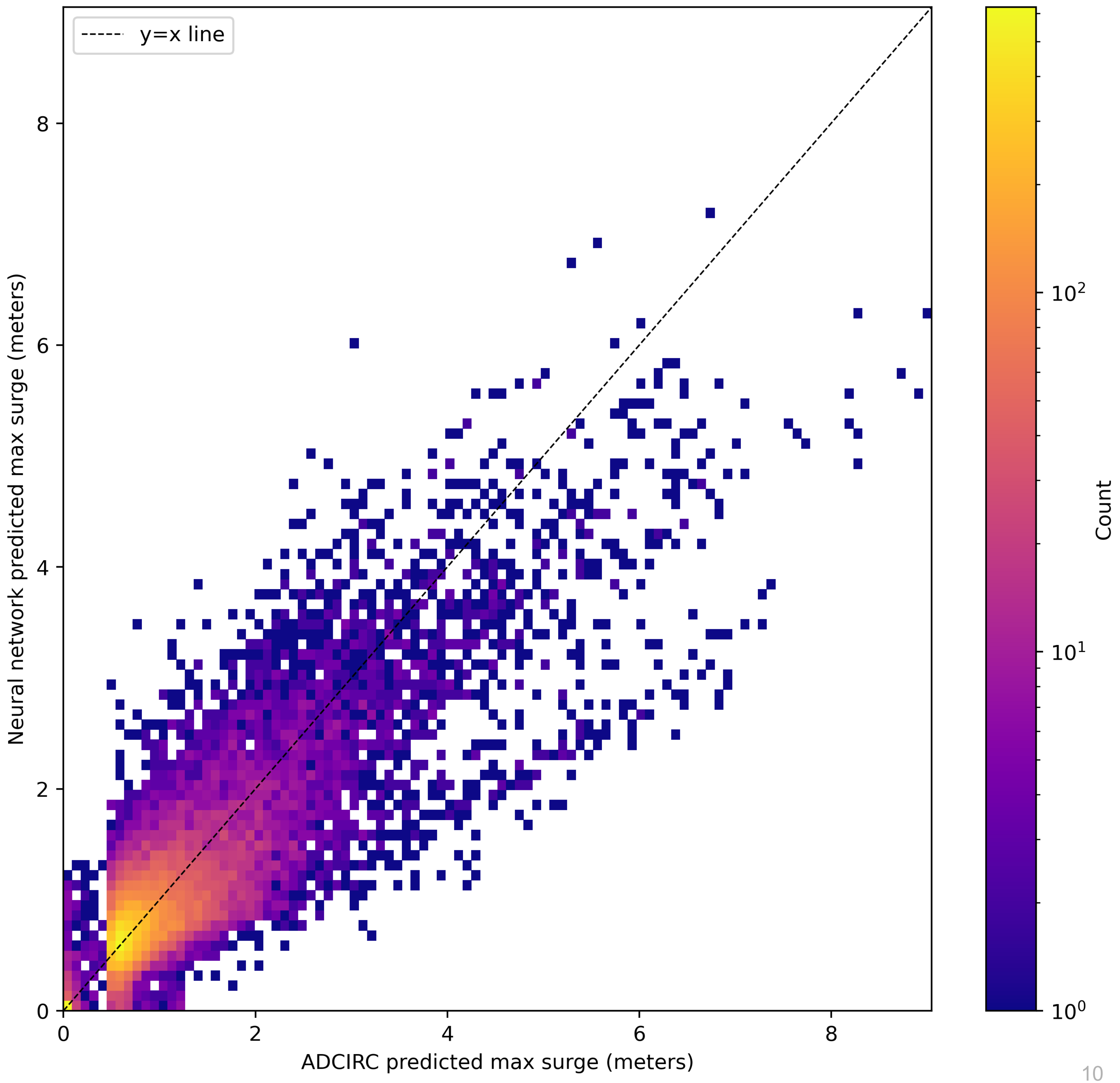
ADCIRC Training Data

- Since actual surge observations are scarce, we train on surge data generated by ADCIRC
- We only seek to model the wind-induced portion of surge, ignoring other sources of flow such as rainfall and river outflow
- ADCIRC is run on a 15,000-node mesh for 270 historical storms to generate training data



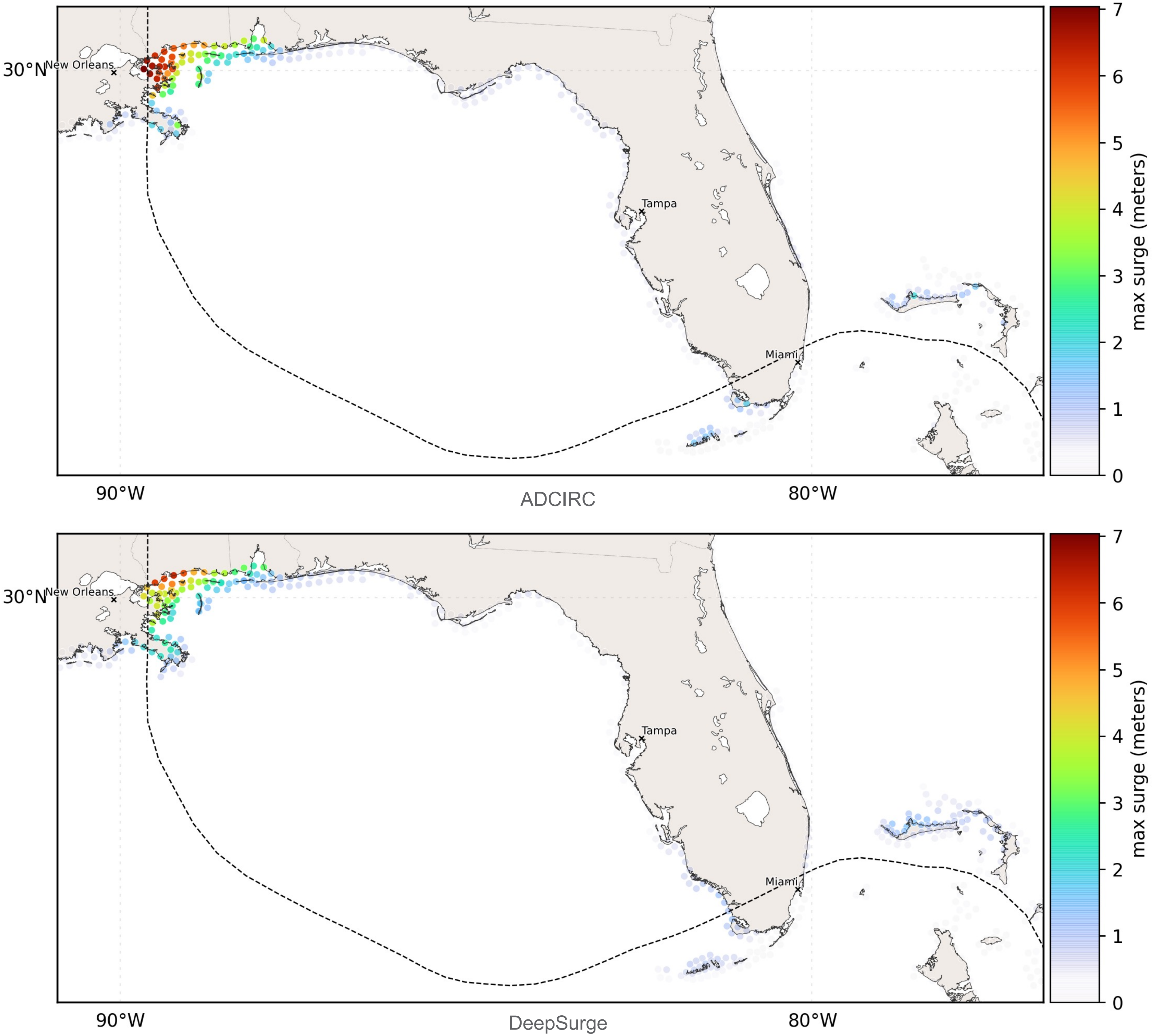
Validation

- Right: A (log-scale) density scatterplot of DeepSurge predictions (y) compared to the ADCIRC targets (x) on the held-out set
- DeepSurge matches ADCIRC predictions well on the test set (r=0.71, MSE=0.259 meters)
- There is a somewhat negative bias, especially noticeable for large surges (>4 meters)
- We find that DeepSurge and ADCIRC show similar skill when compared to a small dataset of observations from NOAA tide-gauges (not shown)



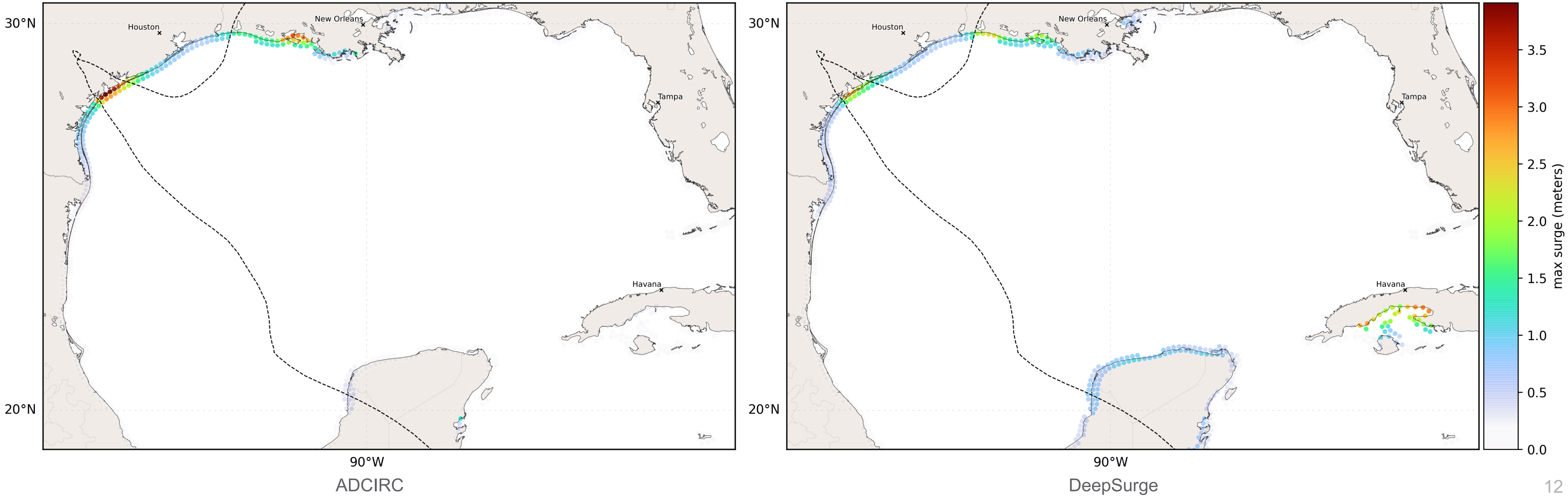
Comparison: Hurricane Katrina (2005)

DeepSurge (bottom) underestimates peak surge slightly compared to ADCIRC (top), but captures the spatial pattern of surge quite well



Comparison: Hurricane Harvey (2017)

- DeepSurge (right) again captures the spatial pattern of surge along the US Coast well
- It does have a spurious overestimation of surge in western Cuba, but otherwise does reasonably well



Computational Efficiency

Comparing ADCIRC and DeepSurge runtimes on the same computing system for Hurricane Katrina (2005), we find that DeepSurge has a 12.5x speedup.

By leveraging a shared initialization stage when predicting many storms in one run of DeepSurge, the practical speedup may be as high 96x

	Time (min:sec)	×	Nodes	×	CPUs per Node	=	CPU Hours
ADCIRC	8:00		3		24		9.60
DeepSurge	1:56		1		24		0.77
							Speedup: 12.5×

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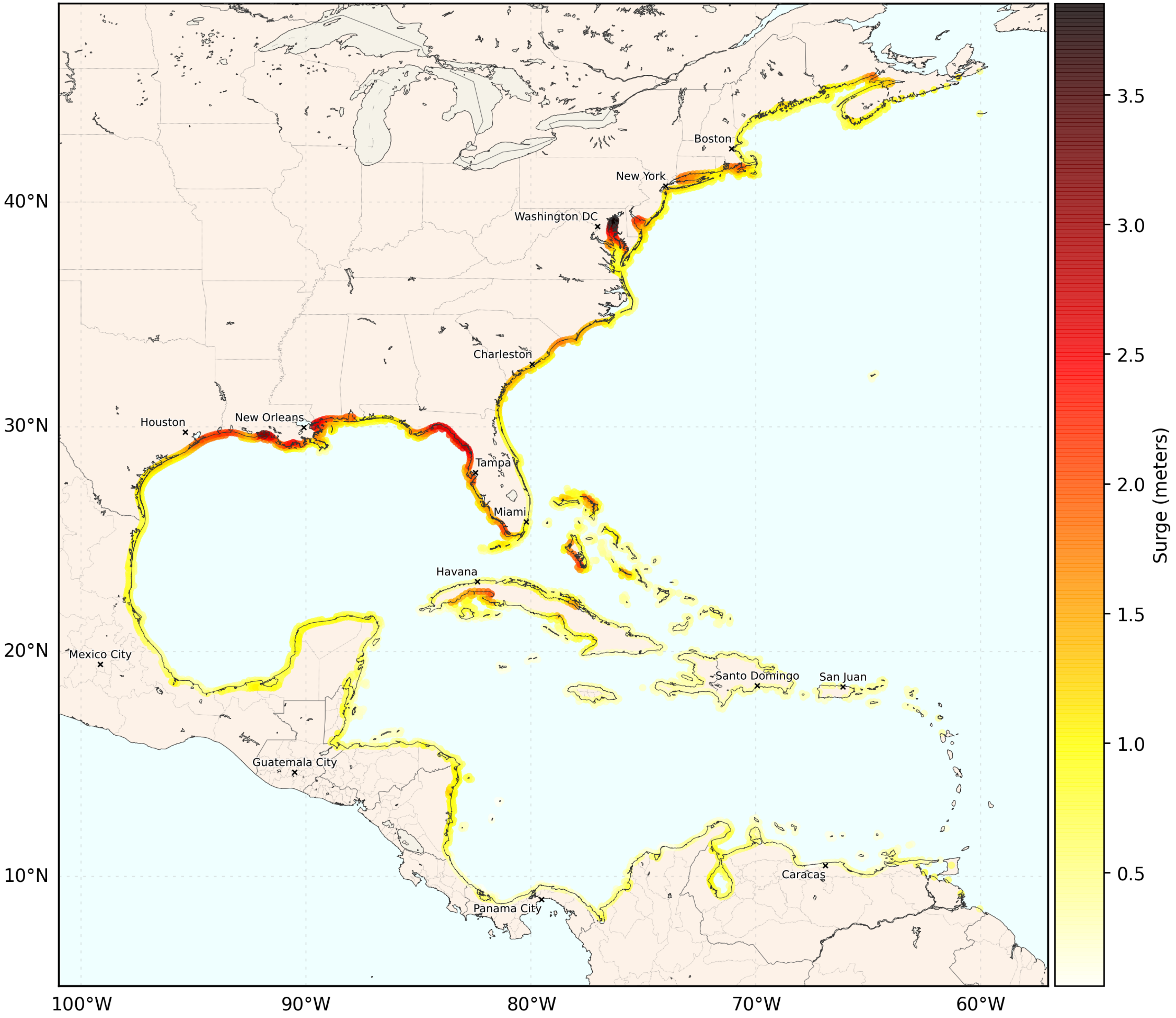
Evaluating Future Surge Risk

- Dataset: DeepSurge predictions from 10,000 synthetic storms, split between a historical (1950-2014) and future (2015-2050) period.
- Synthetic storms are extracted from eight CMIP6 HighResMIP simulations using the TempestExtremes algorithm (Roberts 2019)

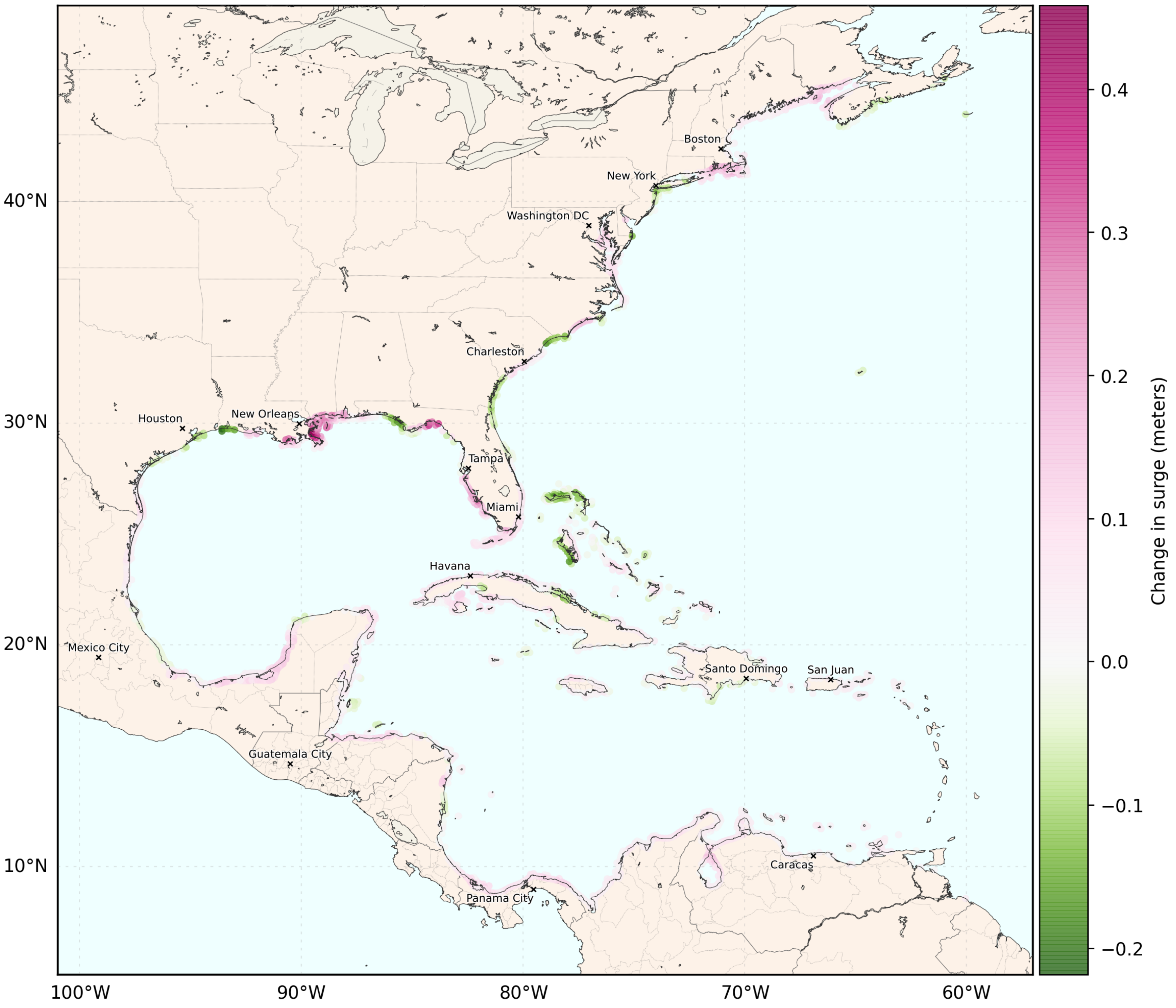
DeepSurge-modeled 15-year surge event for the historical period



Future Surge Risk: Magnitude Change

- This plot answers the question "How much stronger is the future 15-year event, compared the historical 15-year event?"
- New Orleans is highlighted as an area of risk, with the 15-year event increasing in height by ~0.45 meters on average
- Other areas with increasing risk: southern Florida, western Cuba, Chesapeake Bay, Massachusetts & Maine

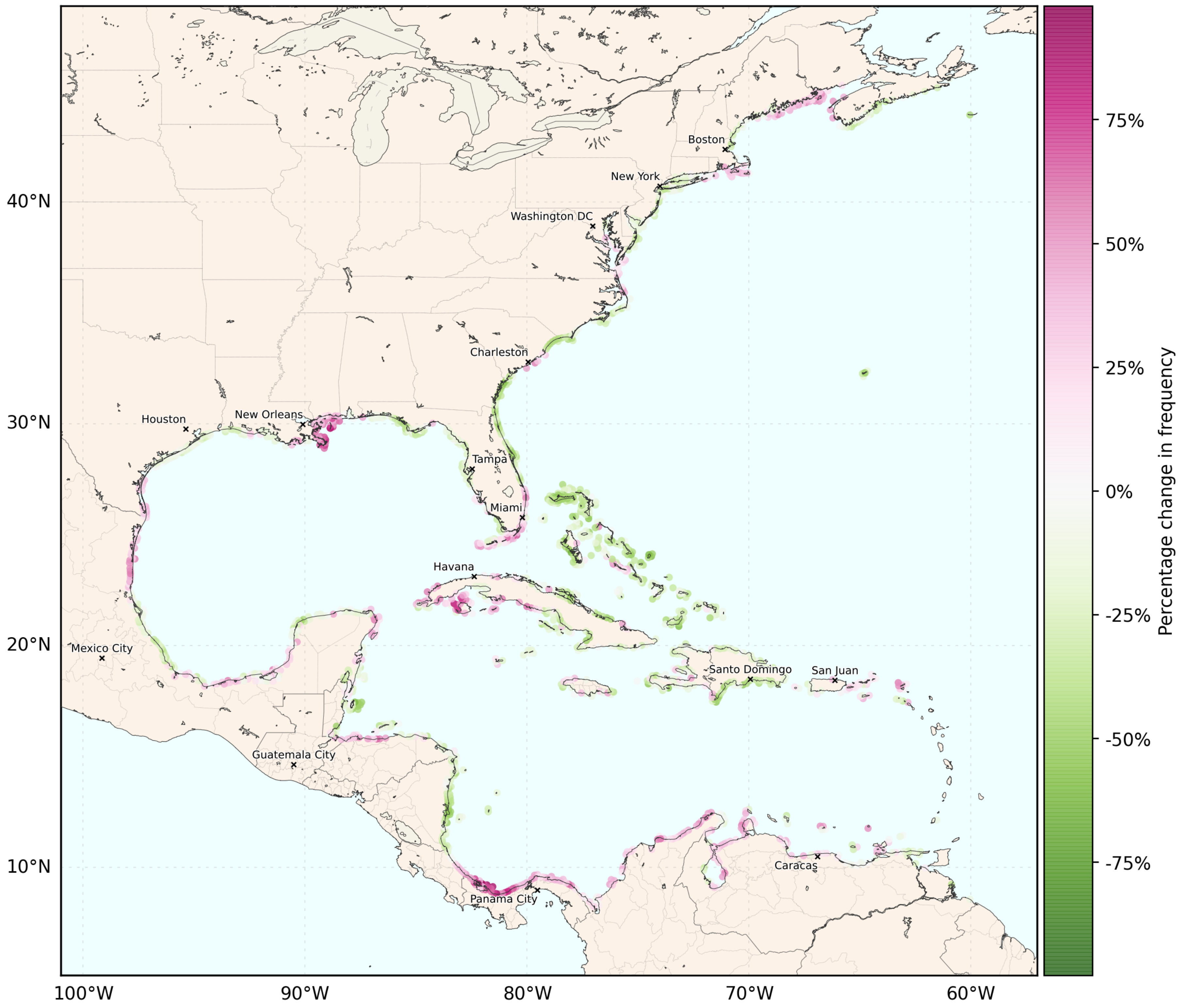
DeepSurge-modeled change in 15-year surge event for the future period



Future Surge Risk: Frequency Change

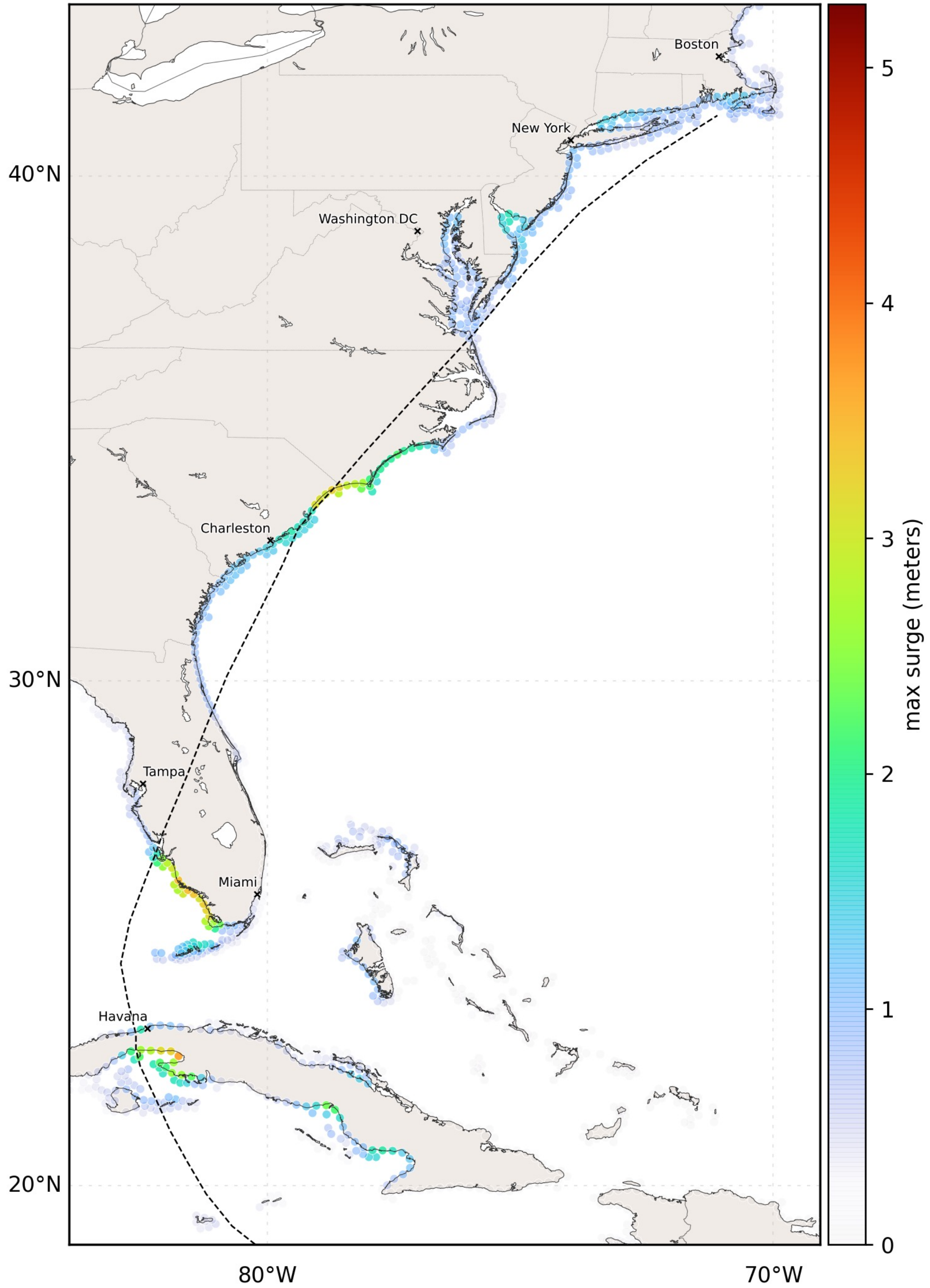
- This plot answers the question, “How much more often will the 15-year historical event occur in the future?”
- For some regions, noticeably near New Orleans, the answer is close to a 100% increase, a doubling in frequency
- Other regions, such as much of the Bahamas, show a decrease

DeepSurge-modeled change in 15-year surge event for the future period



Conclusions

- Neural networks can effectively model complex storm surge interactions on open coasts as well as bays and estuaries
- The efficient inference of neural networks uniquely enables robust analysis the tropical cyclone risk in a changing climate
- We analyze future changes in surge risk in the North Atlantic finding increasing risk in New Orleans, south Florida, and other regions



DeepSurge-modeled Hurricane Charley (2004)

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Thank you

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