Prediction of High-resolution Maps of Storm-driven Coastal Flooding Using Deep Learning

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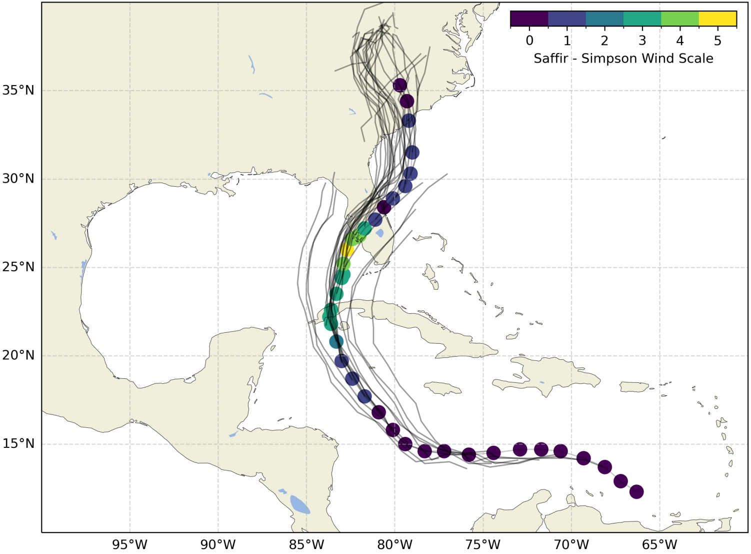
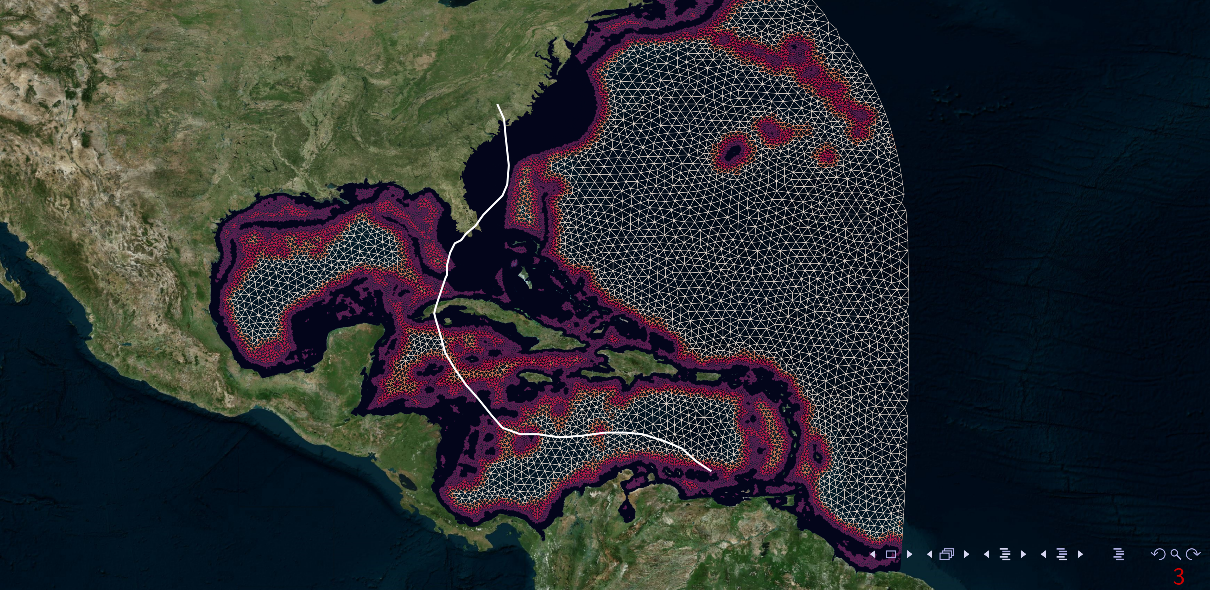
24 July 2023

Motivation: Real-time forecasting uncertainty



Motivation: Mesh resolution plays a key role

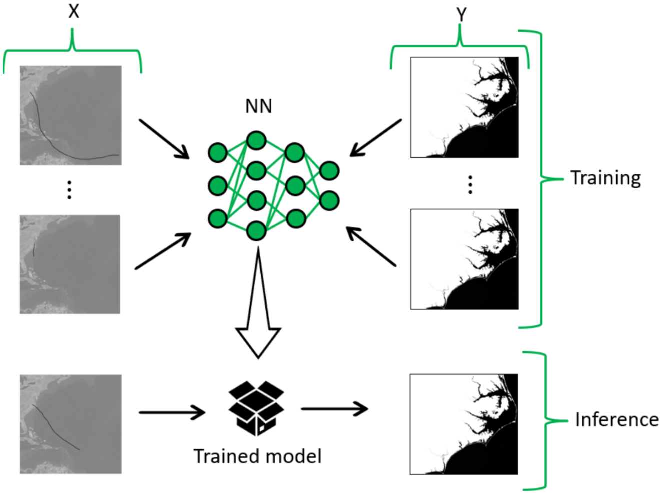
Trade-off: $\uparrow$ Resolution $\Longrightarrow$ $\uparrow$ Accuracy and $\uparrow$ Run time



Trade-off:

$\uparrow$ Resolution $\implies$ $\uparrow$ Accuracy and $\uparrow$ Run time

Motivation: Accelerate Predictions with Deep Learning



What is new?

- Astronomical tides
- Prediction of maps

Motivation: Proposed Workflow

Step 1

Data Collection

- Dataset of synthetic tropical cyclones
- MDA

Step 2

Training Library

- Hydrodynamic modeling
- Downscaling

Step 3

Deep Learning

- RNN for time
- 2D CNN for space
- Train/Test/Validate

Step 4

Final Validation

- Compare NN against hindcasts

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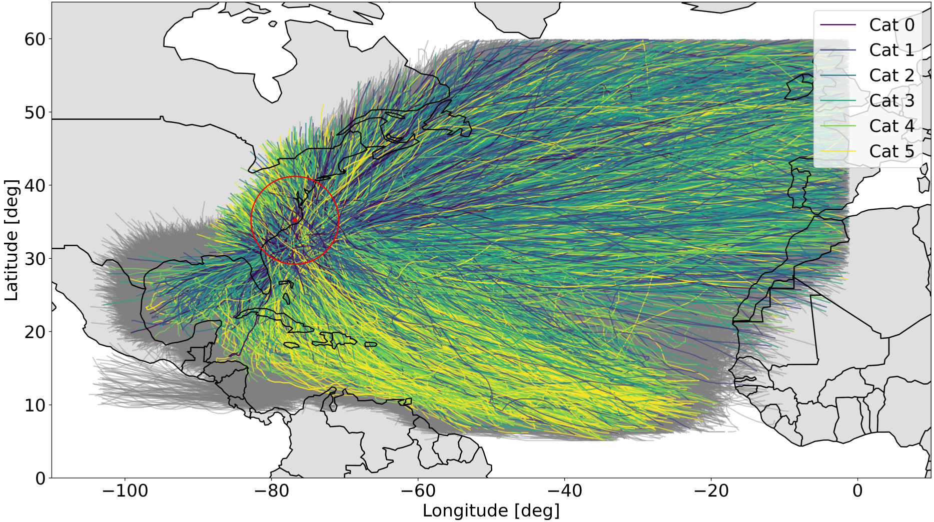
Step 1: Dataset of synthetic tropical cyclones

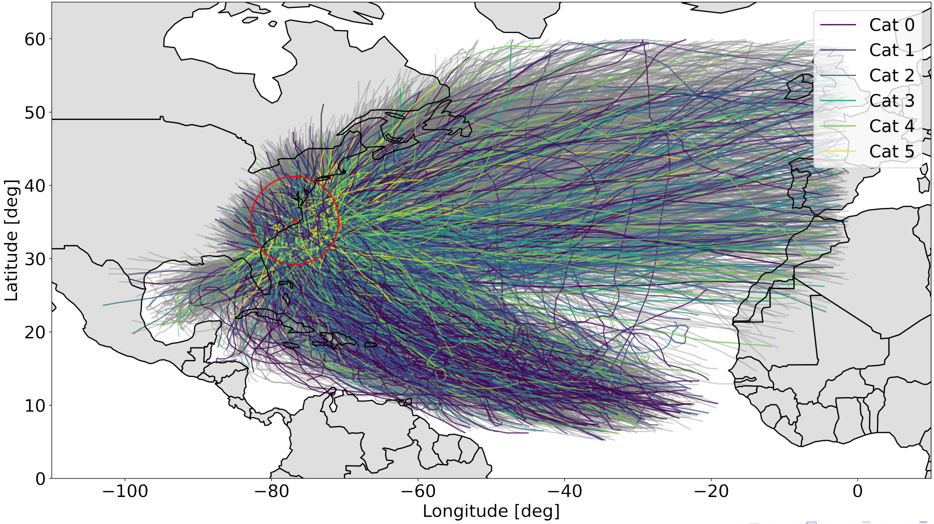
Filter storms by duration and proximity to NC



Bloemendaal et al. (2020)

Step 1: Maximum Dissimilarity Algorithm

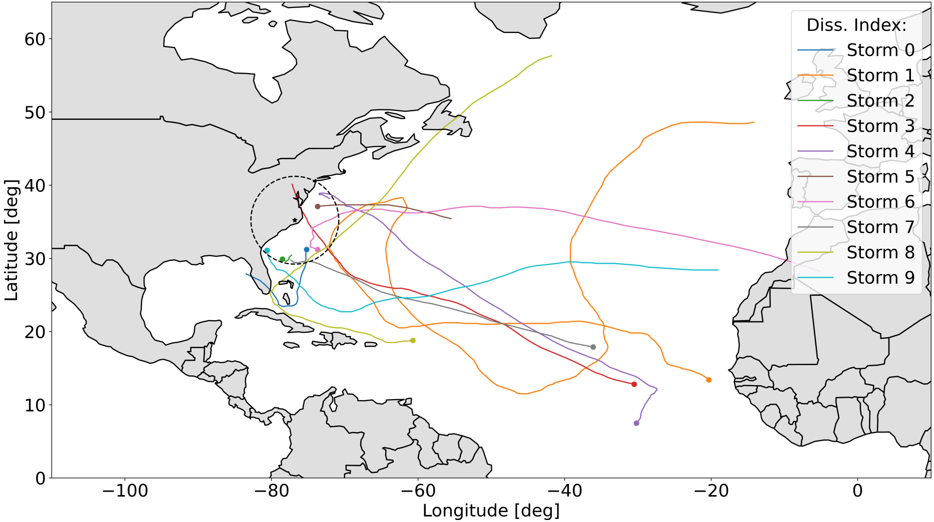
Selection of a representative set of storms – 1000 most dissimilar



Camus et al. (2011)

Step 1: Maximum Dissimilarity Algorithm

Selection of a representative set of storms – 10 most dissimilar



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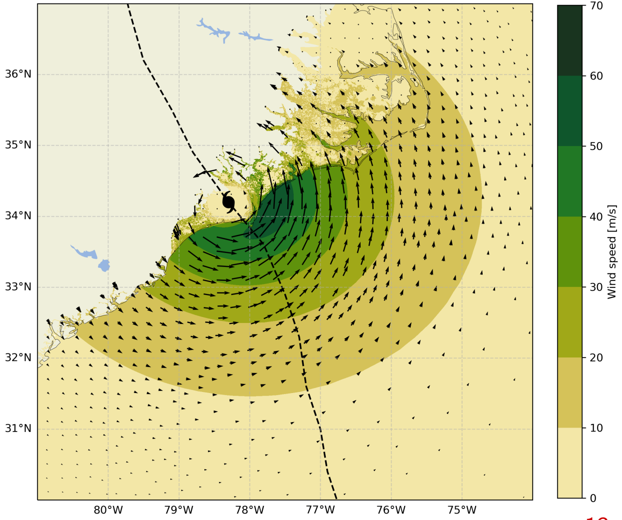
Step 2: Hydrodynamic Modeling

Setup of ADCIRC simulations

- Same mesh (NC9[a]) and nodal attributes
- Almost same configuration
  Random date $\Longrightarrow$ random tide
- Wind field: Symmetric Holland Model
  No need to compute extra parameters
  - Coords, WS, P, and RMW



[a] Blanton and Luettich (2008)

Step 2: Hydrodynamic Modeling
Postprocessing ADCIRC simulations – Log files

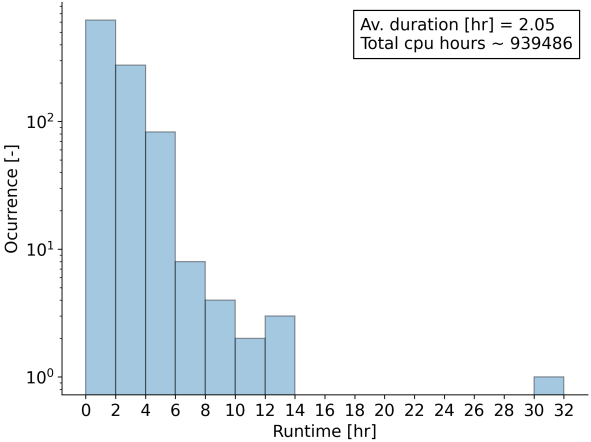
HPC systems

- NCSU Hazel
- Purdue Anvil

Automated log files reading

- Run to completion or fail
  - Type or error
- Runtime
- CPU hours

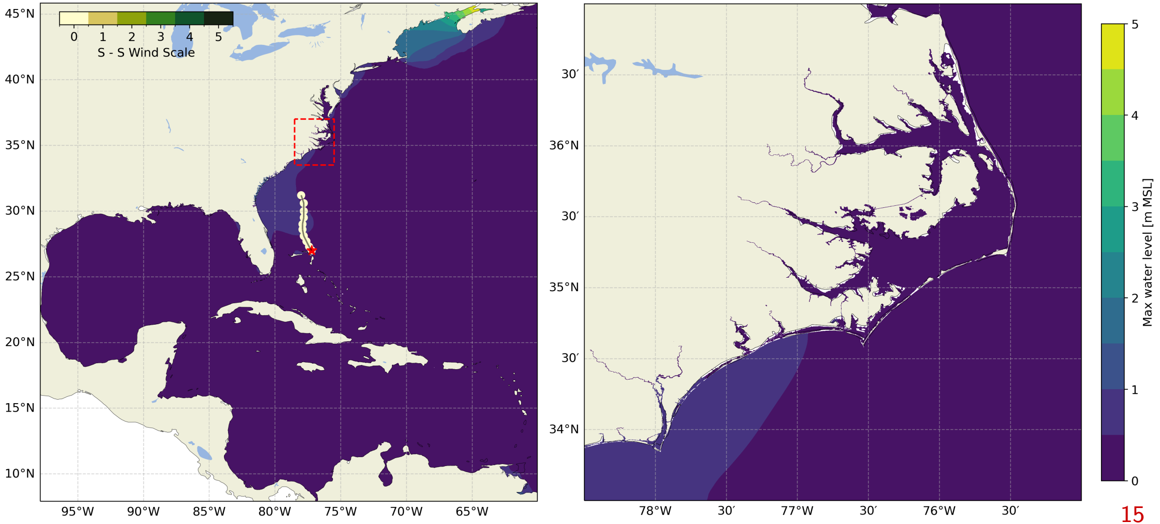
≈ 1M CPU hours and 2 months



Step 2: Hydrodynamic Modeling

Postprocessing ADCIRC simulations – 2D Maps

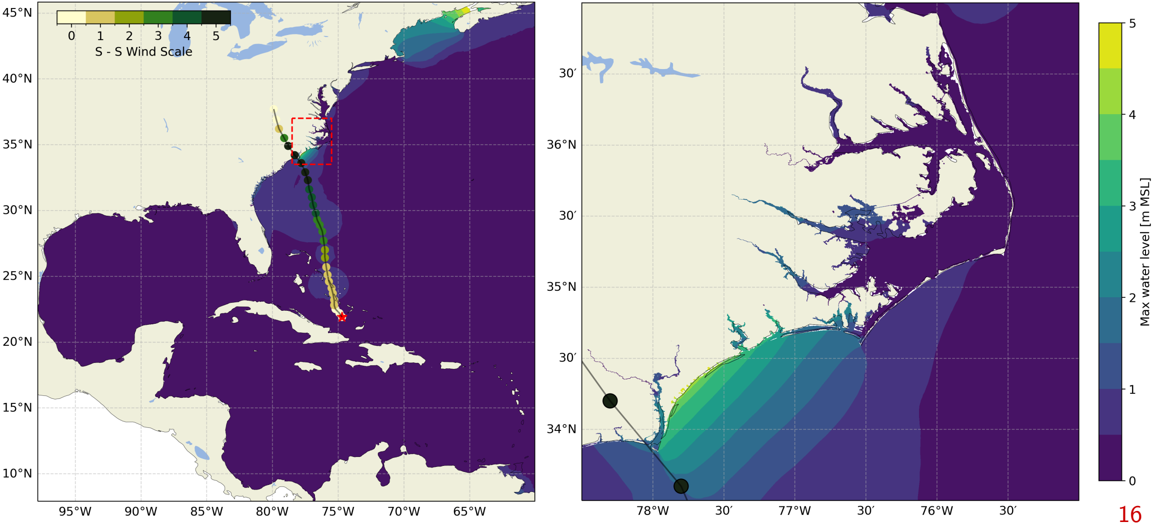
"Boring storm"



Step 2: Hydrodynamic Modeling

Postprocessing ADCIRC simulations – 2D Maps

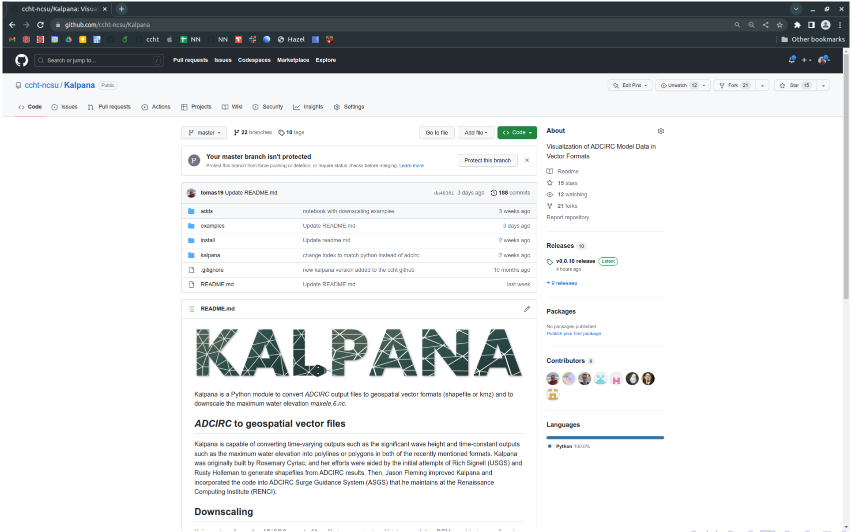
Strong storm



"An A.I.-Generated Picture Won an Art Prize. Artists Aren't Happy", The New York Times.

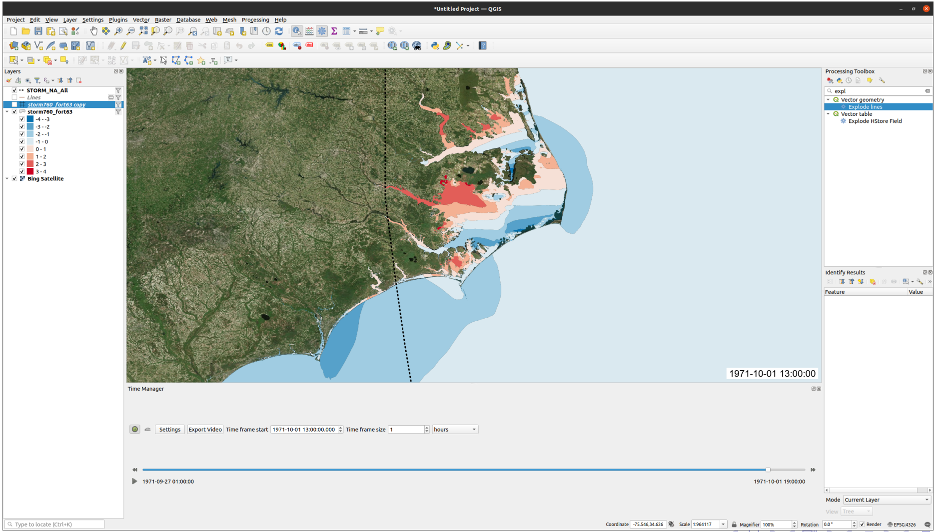
Kalpana

Software to visualize and downscale ADCIRC



Kalpana

Kalpana allows easy visualization in GIS – netCDF to shapefile

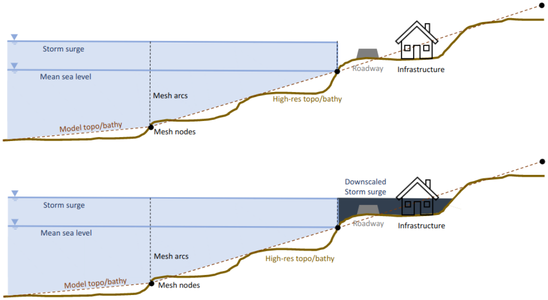


Kalpana

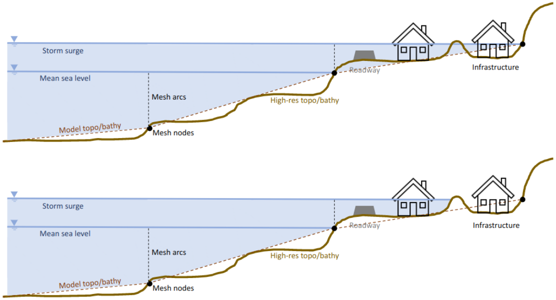
Static Downscaling Method

Use of a high-resolution topo DEM to increase ADCIRC resolution and to expand or shrink the inundation extent[1]

Expand inundation



Shrink inundation



Rucker et al. (2021)

Kalpana

Python code that calls GRASS GIS

Updated version:

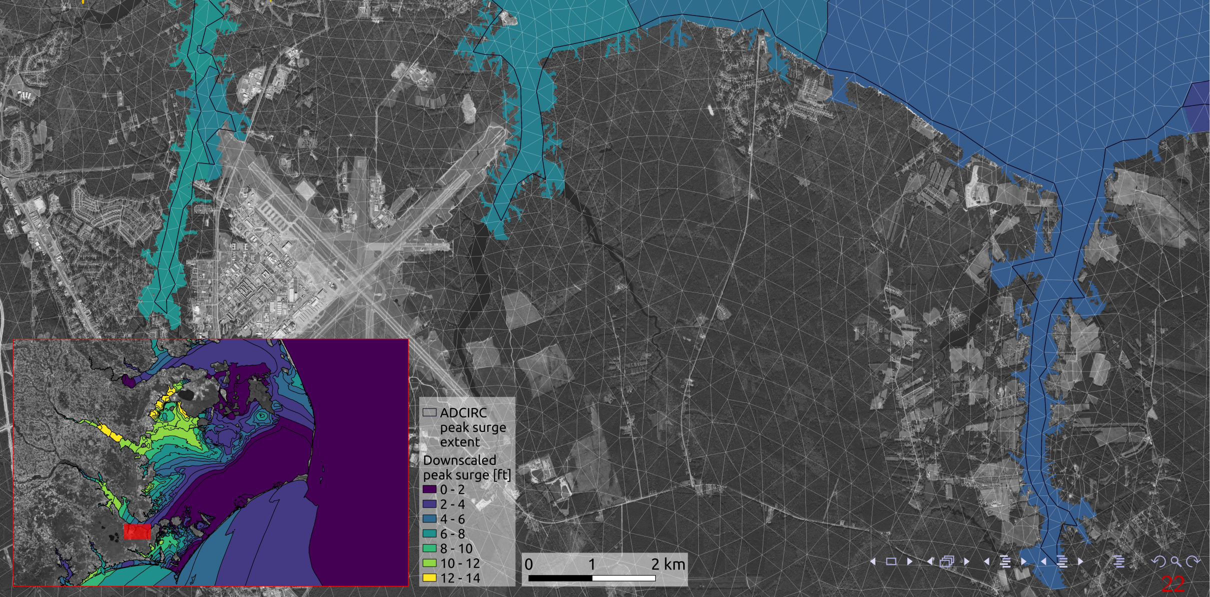
- **From Python 2.7 to 3.9 (or higher)**
- Pandas, GeoPandas, rioxarray and Dask
- Some parallelization
- From 1 single script to 2 modules
- All functions available on GitHub and documented.

Mayor improvements:

- Preprocess to accelerate the downscaling
- From 45 to 7 minutes on a 15m res DEM of NC
- **Less user-defined inputs**
- **Inputs related to mesh**

Step 2: Downscaling Max Water Elevation

Example of Neuse River, NC



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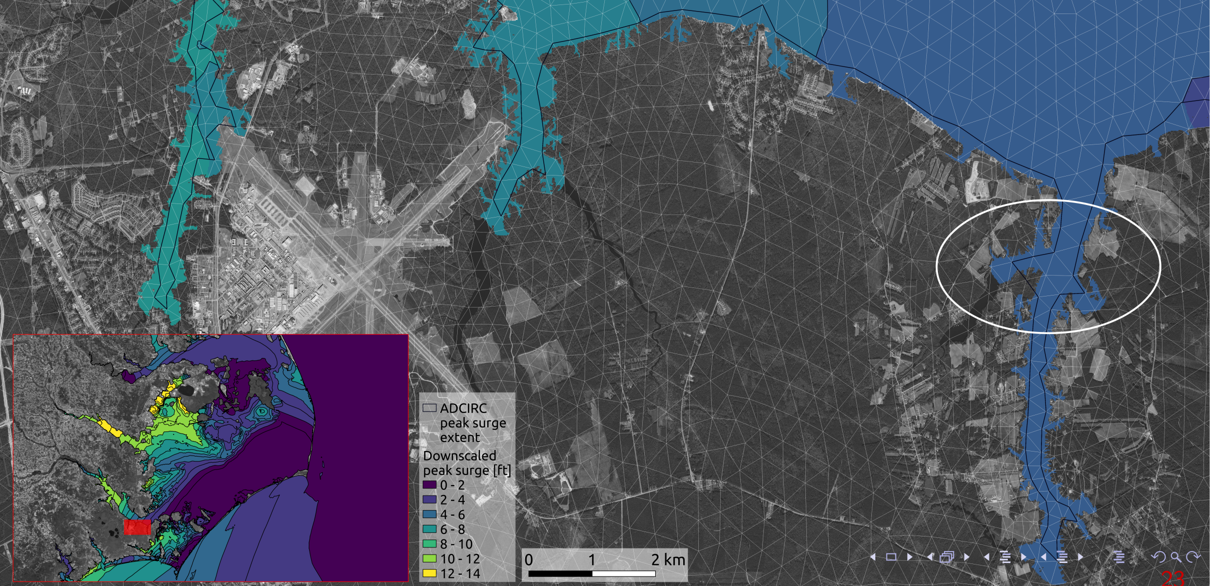

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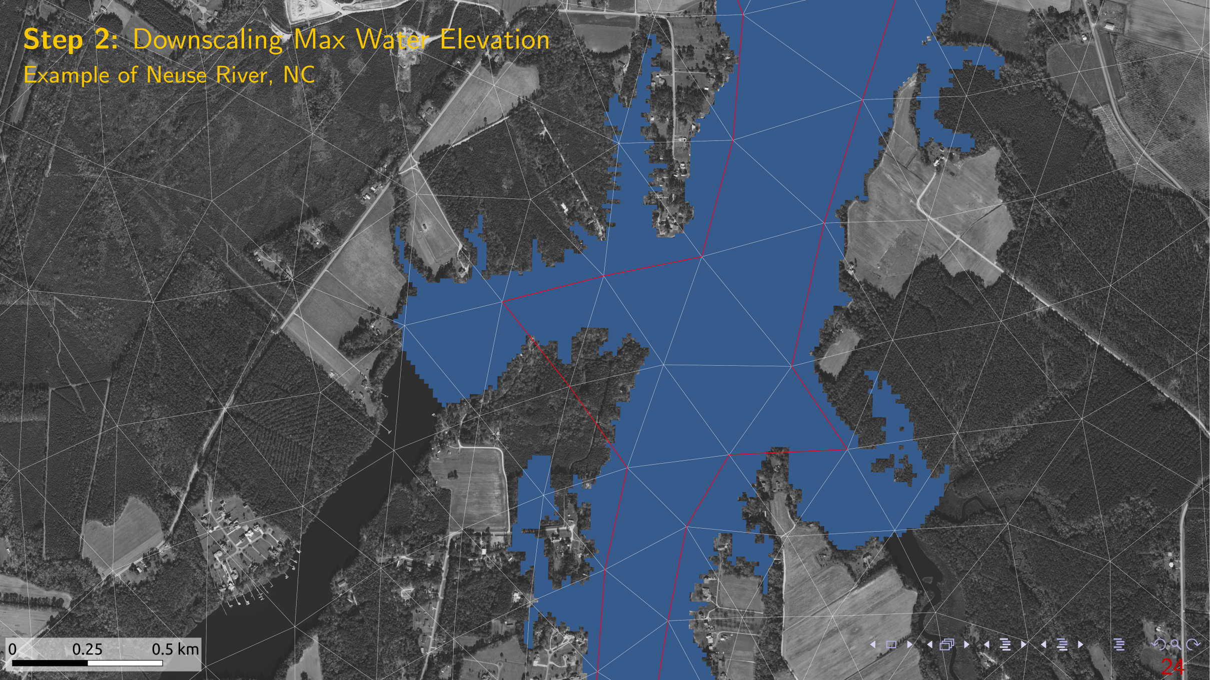

Step 2: Downscaling Max Water Elevation
Downscaled DEM to greyscale image

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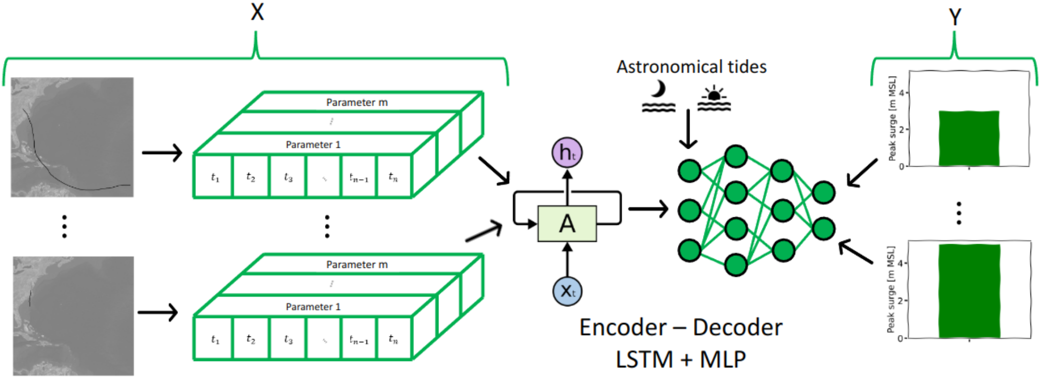
Step 3: Neural Network Development

Long-Short Term Memory (LSTM) + Multi-Layer Perceptron (MLP) to predict peak surge at a single point



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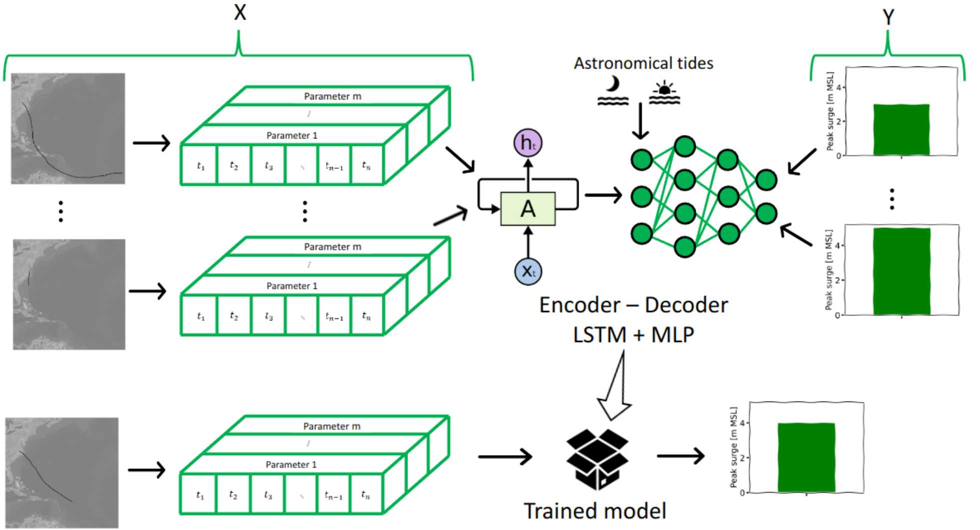


Preprocess the tracks

- 6 inputs: lon, lat, wind speed, pressure, forward speed, and rad to max winds
- Zero padding and masking

Long short-term memory units (LSTM):

- Bi-directional: from t_0 to t_n and from t_n to t_0
- 6 layers and 256 hidden units

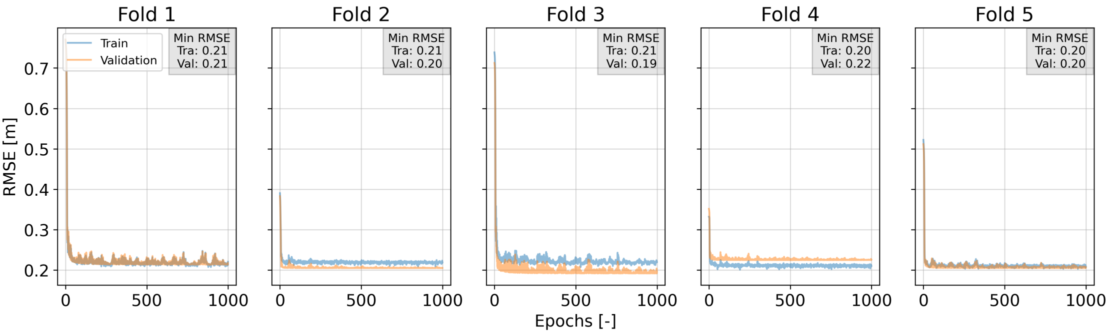
Multi-layer perceptron (MLP):

- First layer: 2 (bi-dir) $\times$ 256 (hidden units) $+$ 16 (tides) $=$ 528 neurons
- 7 dense layers: 512 to 256 to 128 to 64 to 32 to 8 to 1 neuron
- Batch normalization after each dense layer
- Dropout of 50%
- RMSE loss

Step 3: Neural Network Predictions

RMSE for training and validation is close to 20 cm

Prediction at Duck Pier (NC) tide gauge



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Summary, Current and Future Work

NN to predict high-res maps of storm-driven coastal flooding

- Selected a subset of tracks that represents the max and avg of the tropical cyclone conditions in NC
- Simulated 1000 storms with ADCIRC using $\approx$ 1M cpu hours
- Downscaled the peak surge output to produce high and constant-resolution maps
- Implemented a NN based on an LSTM and MLP layers to predict peak surge at single points

Current Work

- New set of storms to simulate already defined
- Running simulations with a 1.4M nodes mesh developed by Johnathan Woodruff

Future Work

- Neural network development
  - 2D CNN to generate maps
- Validation with real storms

Thank you!

github.com/ccht-ncsu/Kalpana