Prediction of Peak Water Levels during Tropical Cyclones with Deep Learning

Tomás Cuevas López

MS Defense
Department of Civil, Construction, and Environmental Engineering
North Carolina State University

15 February 2024

Agencia Nacional de Investigación y Desarrollo
Ministerio de Ciencia, Tecnología, Conocimiento e Innovación
Gobierno de Chile

COASTAL RESILIENCE CENTER

About me

BS at University of Chile

Engineer at PRDW

MSc at NCSU

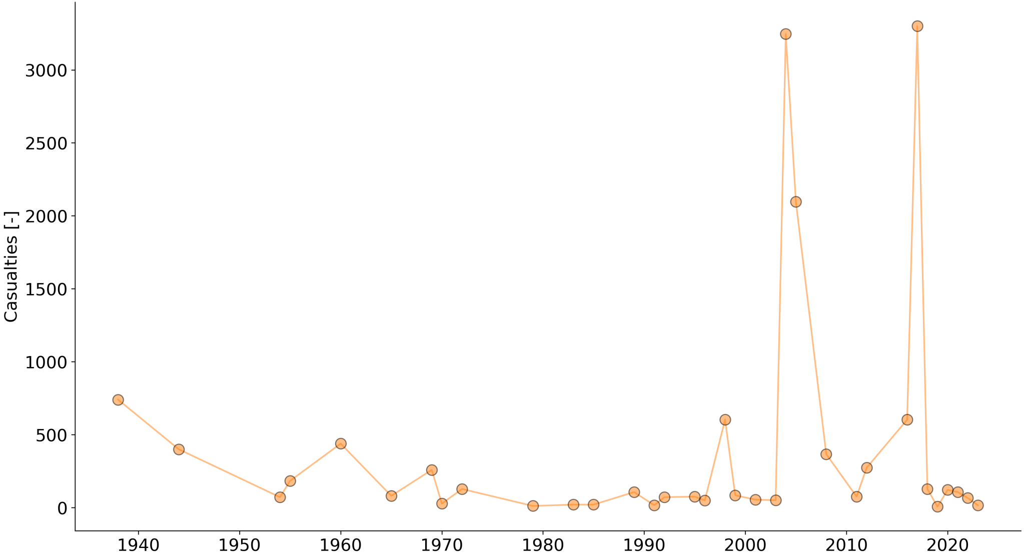
Coastal scientist at DHI


Hurricane Ian (2022)
earthobservatory.nasa.gov

Hurricane Ian (2022)

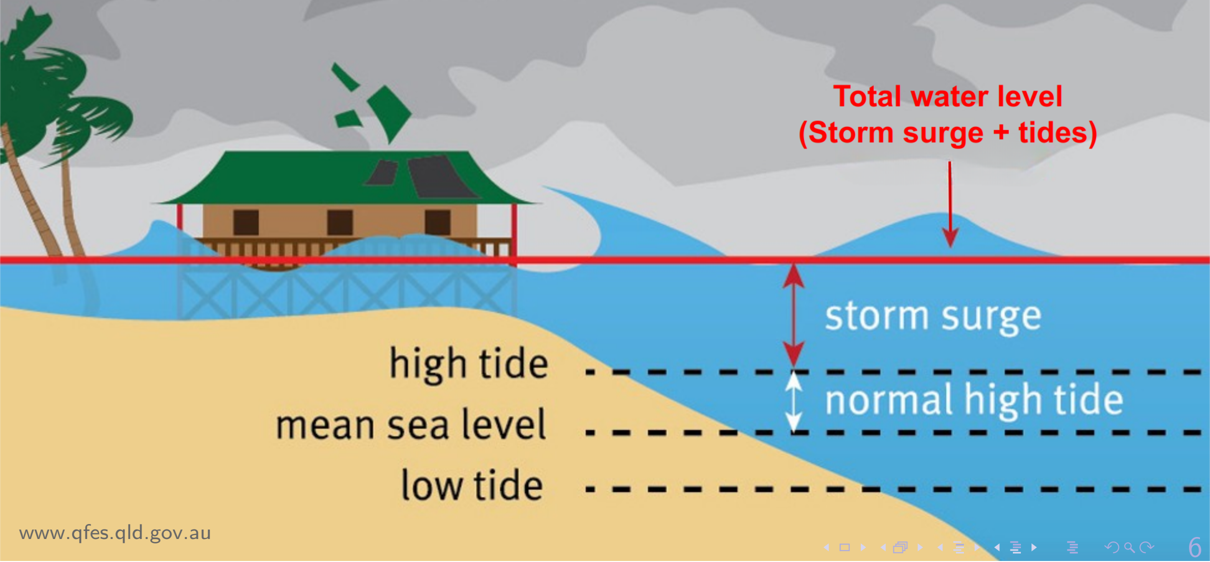
thehill.com

Casualties associated to costliest U.S. tropical cyclones



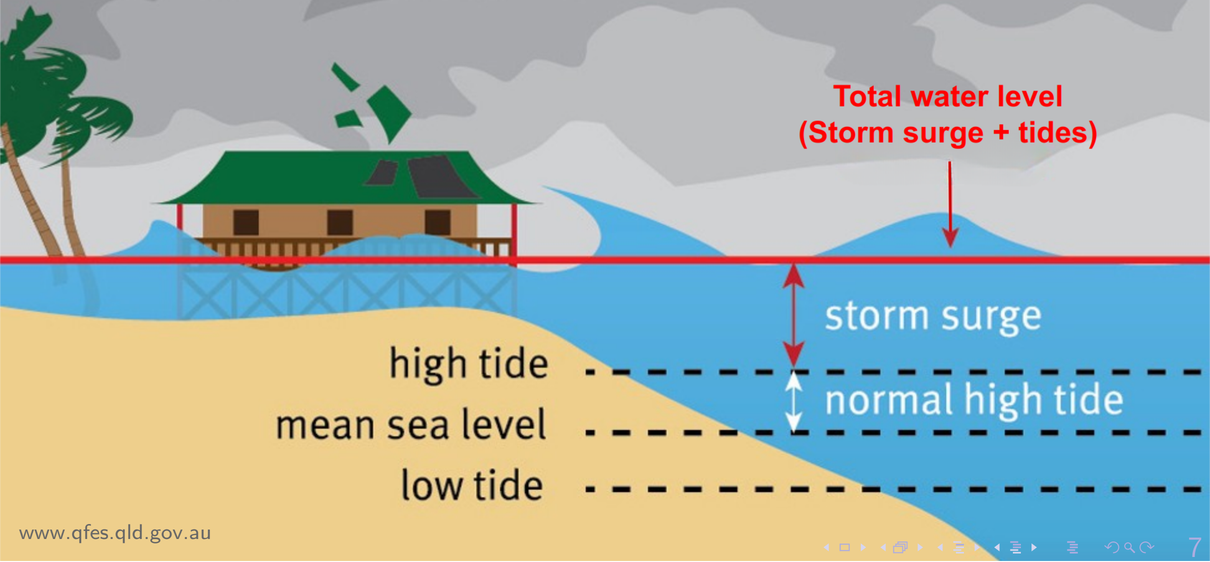
Adapted from Lau et al. (2022)

Storm surge: abnormal rise in the water due to the combined effect of wind and pressure drop



www.qfes.qld.gov.au

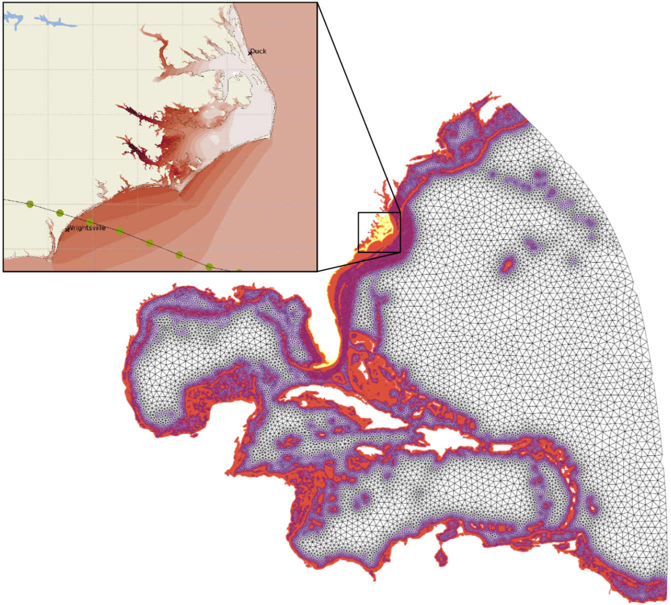
Ian's storm surge caused **66 deaths** and damages of more than **$112 billions**



www.qfes.qld.gov.au

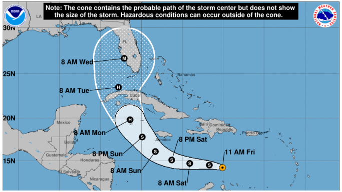
How do we predict storm surge?

- Various flavors of numerical models
- Diverse levels of physics
- Different hardware requirements
- Wind and pressure field as forcings
- Mesh for representing the coastal environment



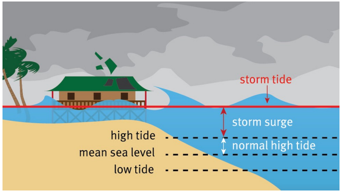
Real-time forecasting of storm surge

Workflow



NHC issues storm track and intensity every 6 hours

Storm surge is simulated for the latest advisory
1-3 hours



Predictions are delivered to emergency managers

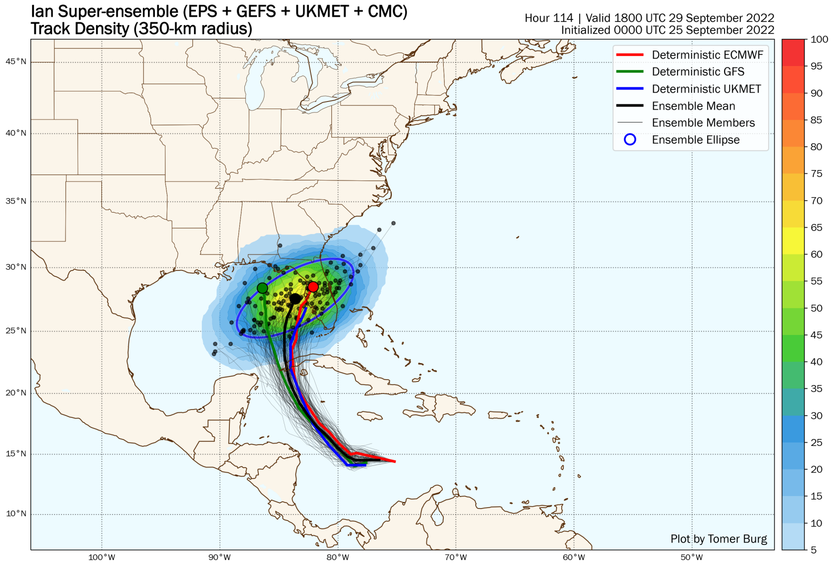
Models need to be fast!


1) Too coarse
Accuracy
Runtime


2) Too many small elements
Accuracy
Runtime


3) Good trade-off
Accuracy
Runtime

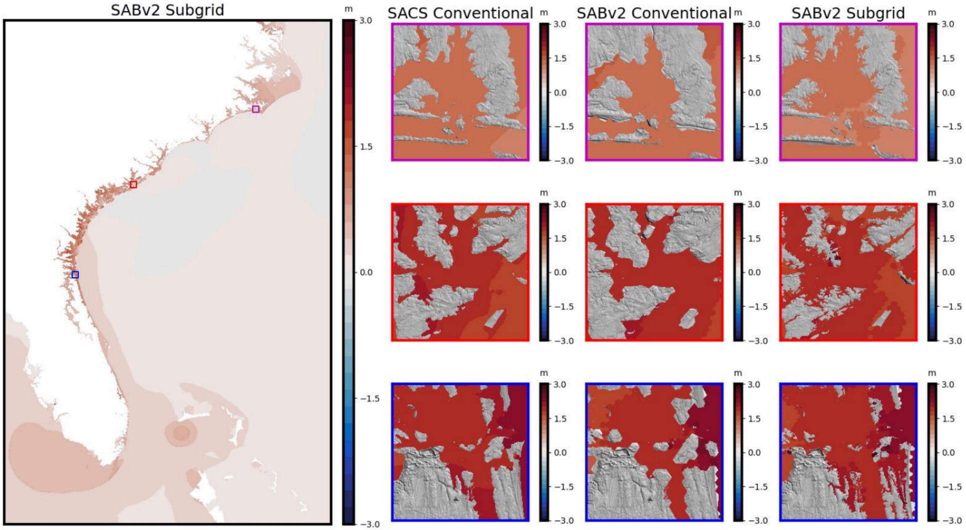
We want models fast enough to address the storm track uncertainties!



yaleclimateconnections.org

How can we speed up the models? ⇒ Subgrid corrections

13 times faster!

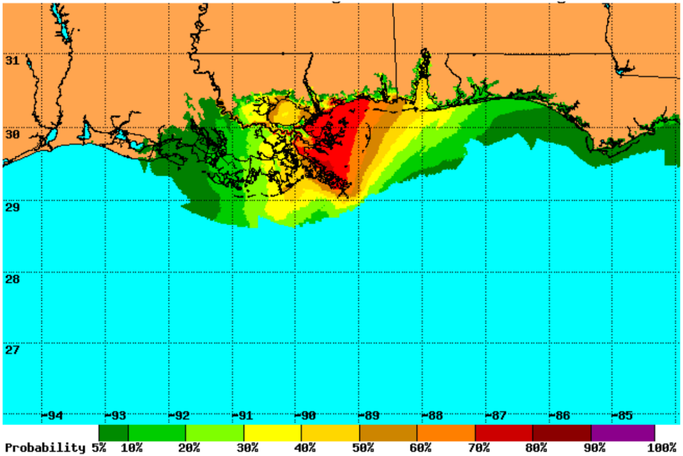


Woodruff et al. (2023)

How can we speed up the models? ⇒ Reducing the physics

P-Surge (Taylor and Glahn 2008) and SLOSH (Jelesnianski 1972):

- o Simplified physics
- o Basin-specific mesh
- o Multiple tracks
- o **Computationally cheap**



How can we speed up the models?

Surrogate Models

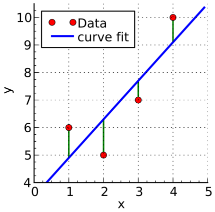
$$\begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{pmatrix} \longrightarrow \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix}$$

$$f(X) = Y$$

How can we speed up the models?

Surrogate Models

Statistical Learning

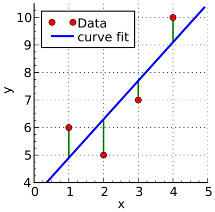


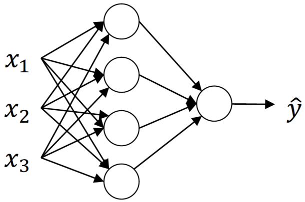
How can we speed up the models?

Surrogate Models

Statistical Learning

Deep Learning





Deep learning to predict storm surge

Applying NNs to predict storm surge is not new

- You and Seo (2009)
- De Oliveira et al. (2009)

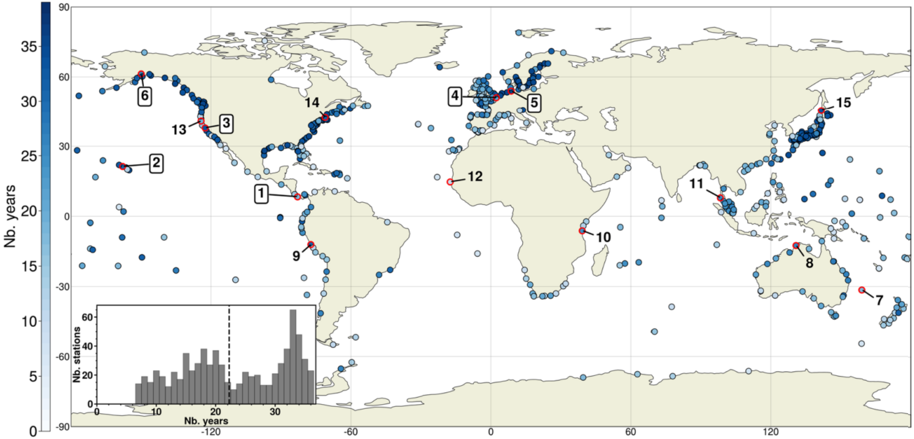
  ⋮

- Tiggeloven et al. (2021)
- Lee et al. (2021)
- Pachev et al. (2023)
- Cuevas et al. (coming soon)

Deep learning to predict storm surge

Neural networks trained using storm surge observations

Global predictions of storm surge from atmospheric reanalysis (Tiggeloven et al. 2021)



Deep learning to predict storm surge

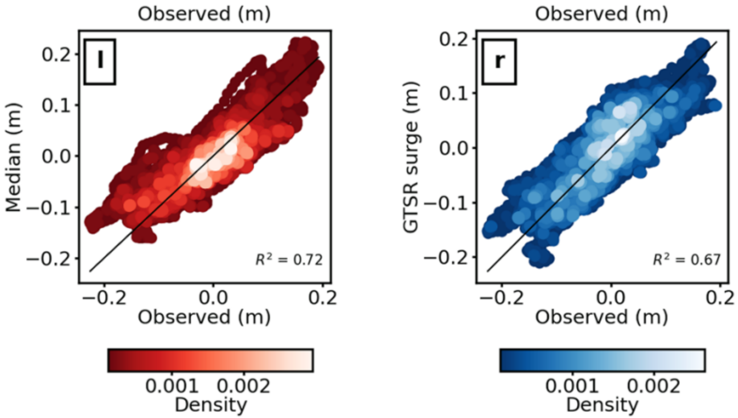
Neural networks trained using storm surge observations

Pros:

- Good results
- No need for process-based models
- Global coverage

Cons:

- Obs. are scarce
- Not full track
- Eye's dynamics is not captured
- No astronomical tide

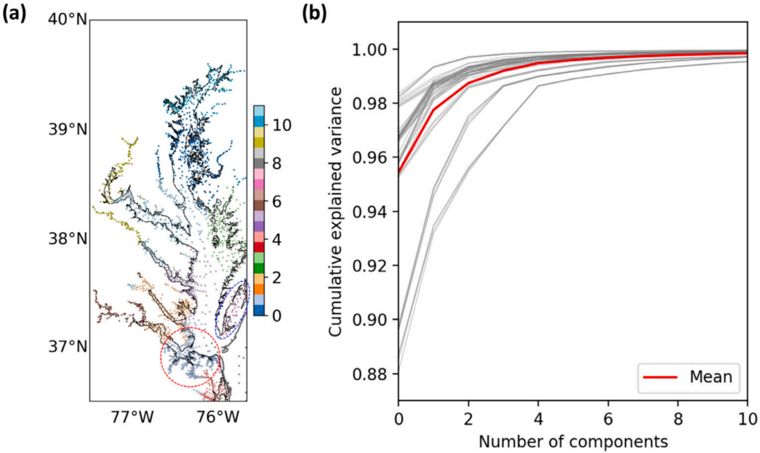


Deep learning to predict storm surge

Neural networks trained using storm surge process-based models

Storm surge predictions at Chesapeake Bay from synthetic tracks (Lee et al. 2021)

- 1,031 synthetic tracks
- K-means clustering
- Principal component analysis
- Many-to-one neural network



Deep learning to predict storm surge

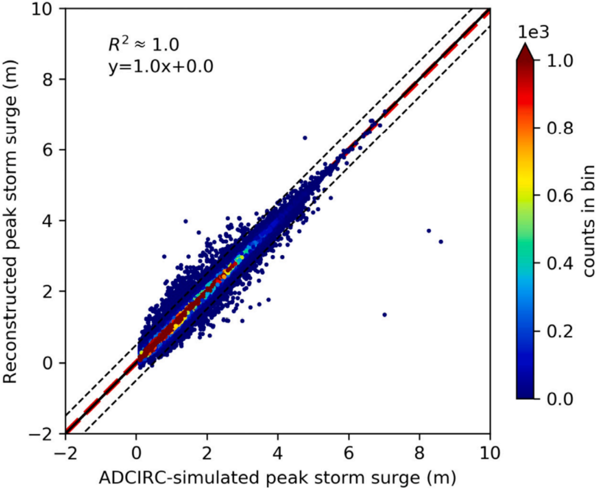
Neural networks trained using storm surge process-based models

Pros:

- Good results
- Eye's dynamics is well captured
- Predictions at many locations

Cons:

- Multiple NNs
- No astronomical tide
- Not full track
- Training data tailored to extremes



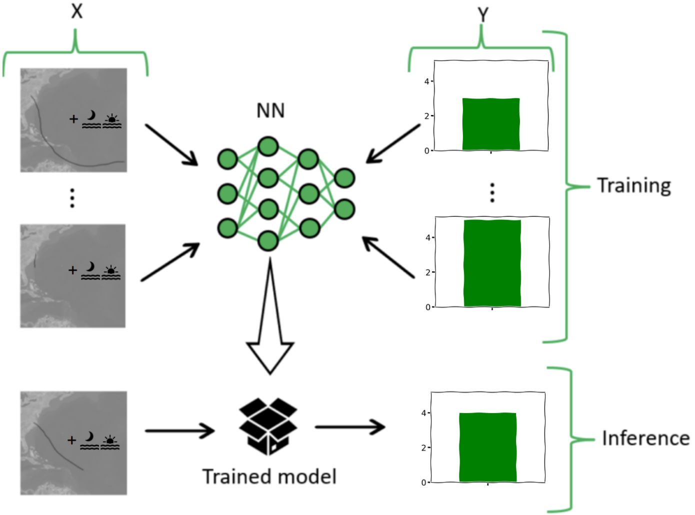
How can we take the NNs one step closer to process-based models?

Training dataset:

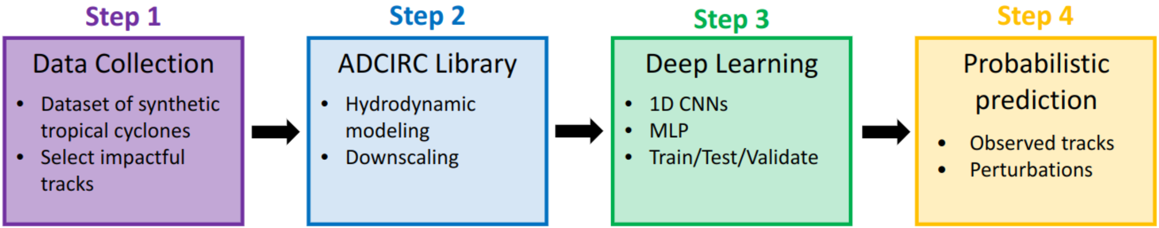
- o Tracks from a probabilistic model
- o Extreme and average conditions
- o Random astronomical tides

Neural network:

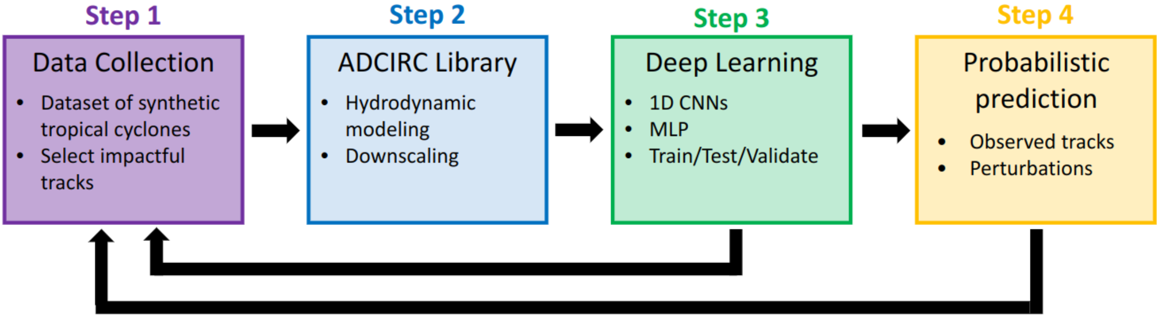
- o Tide as input
- o Tracks of any length
- o Prediction at multiple locations simultaneously



Proposed workflow



Proposed workflow



Step 1

Data Collection

- Dataset of synthetic tropical cyclones
- Select impactful tracks

→

Step 2

ADCIRC Library

- Hydrodynamic modeling
- Downscaling

→

Step 3

Deep Learning

- 1D CNNs
- MLP
- Train/Test/Validate

→

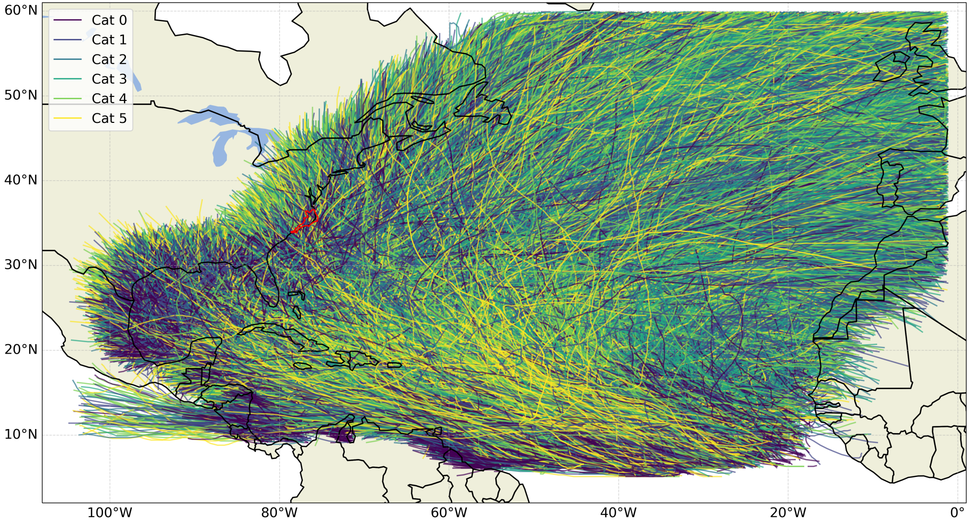
Step 4

Probabilistic prediction

- Observed tracks
- Perturbations

Step 1: Dataset of synthetic tropical cyclones

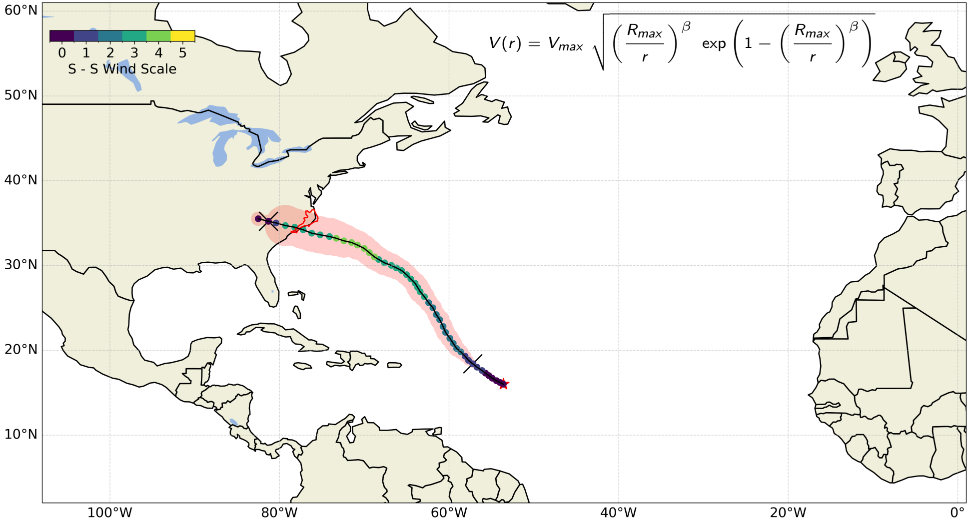
Identify a subset of impactful storms



Bloemendaal et al. (2020)

Step 1: Selection of impactful storms

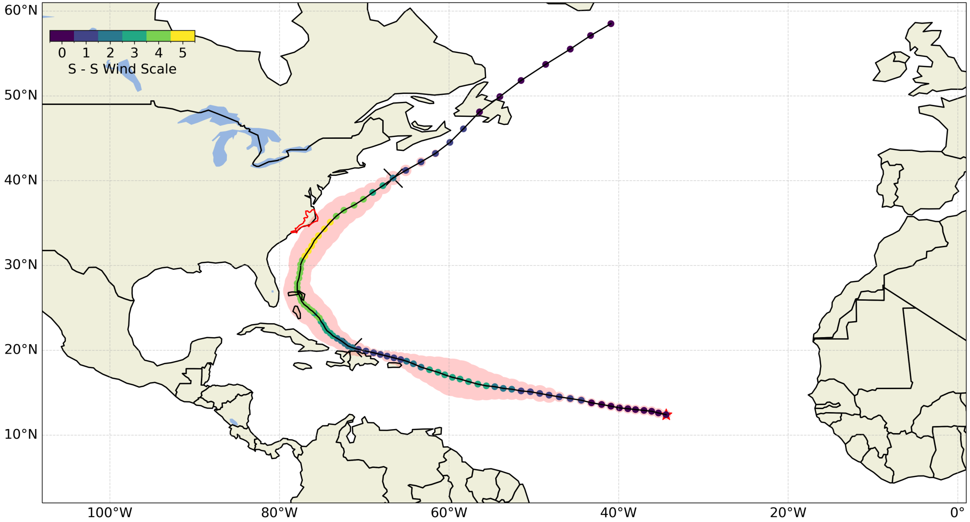
Define an area of influence



Holland (1980)

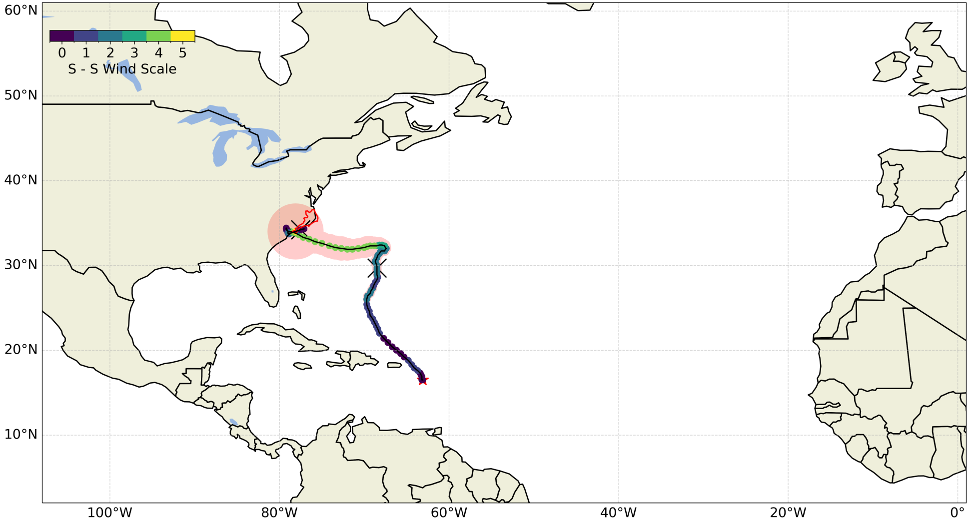
Step 1: Selection of impactful storms

Reducing track length to reduce computation – Key assumption 1



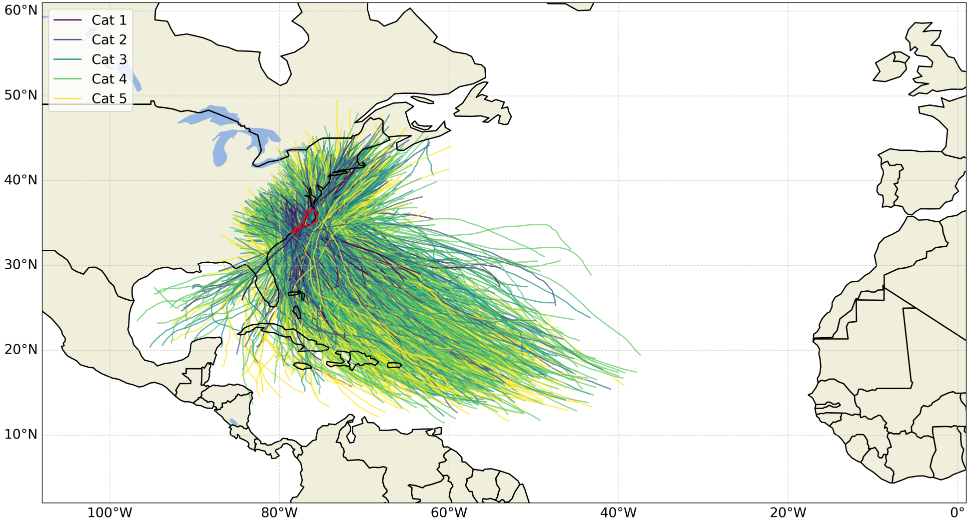
Step 1: Selection of impactful storms

High-variance dataset with some outliers



Step 1: Selection of impactful storms

Subset of 1,813 tracks that affect North Carolina



Step 1

Data Collection

- Dataset of synthetic tropical cyclones
- Select impactful tracks

→

Step 2

ADCIRC Library

- Hydrodynamic modeling
- Downscaling

→

Step 3

Deep Learning

- 1D CNNs
- MLP
- Train/Test/Validate

→

Step 4

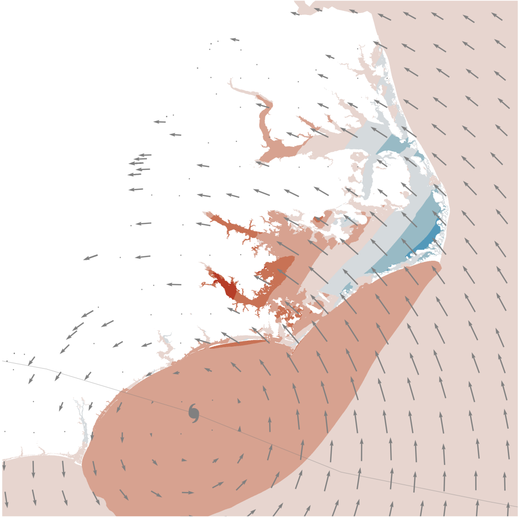
Probabilistic prediction

- Observed tracks
- Perturbations

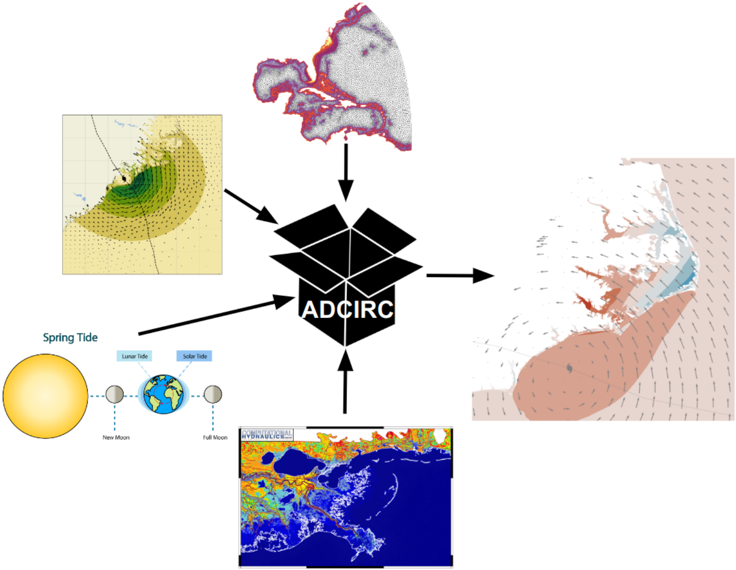
Step 2: Hydrodynamic modeling with ADCIRC

ADvanced CIRCulation (ADCIRC) model:

- Unstructured, variable resolution meshes
- Finite element in space and finite differences in time
- Solves the Generalized Wave Continuity and the momentum conservation equations
- Well validated in the U.S. Gulf and Atlantic coasts
- Very efficient in high-performance computing systems

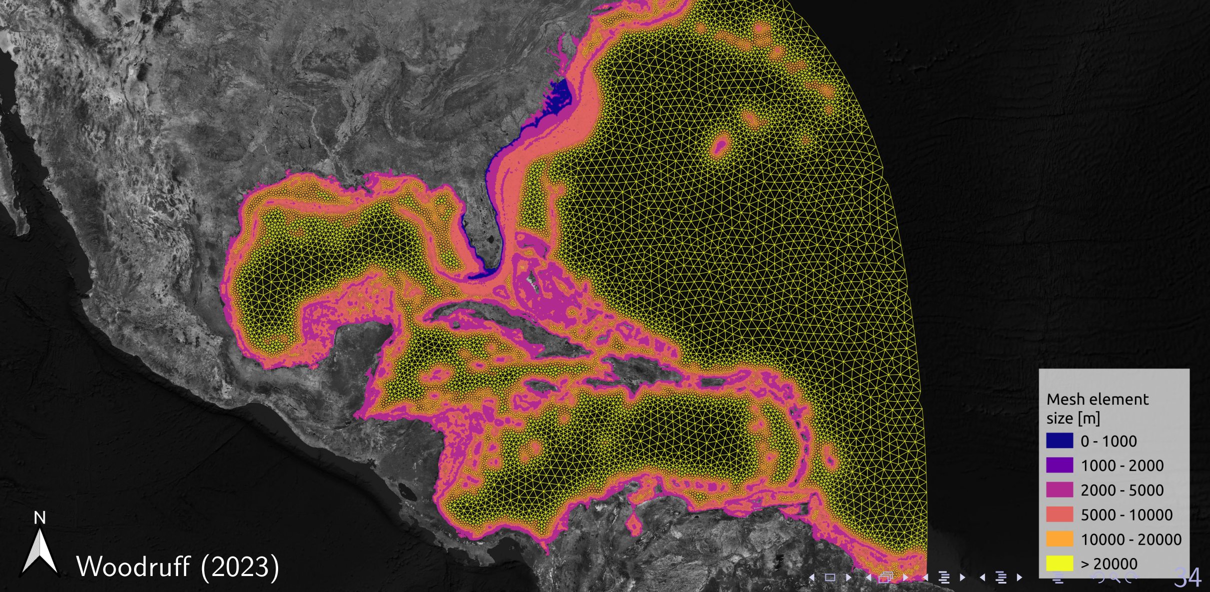


Step 2: Hydrodynamic modeling with ADCIRC



Step 2: Hydrodynamic modeling with ADCIRC

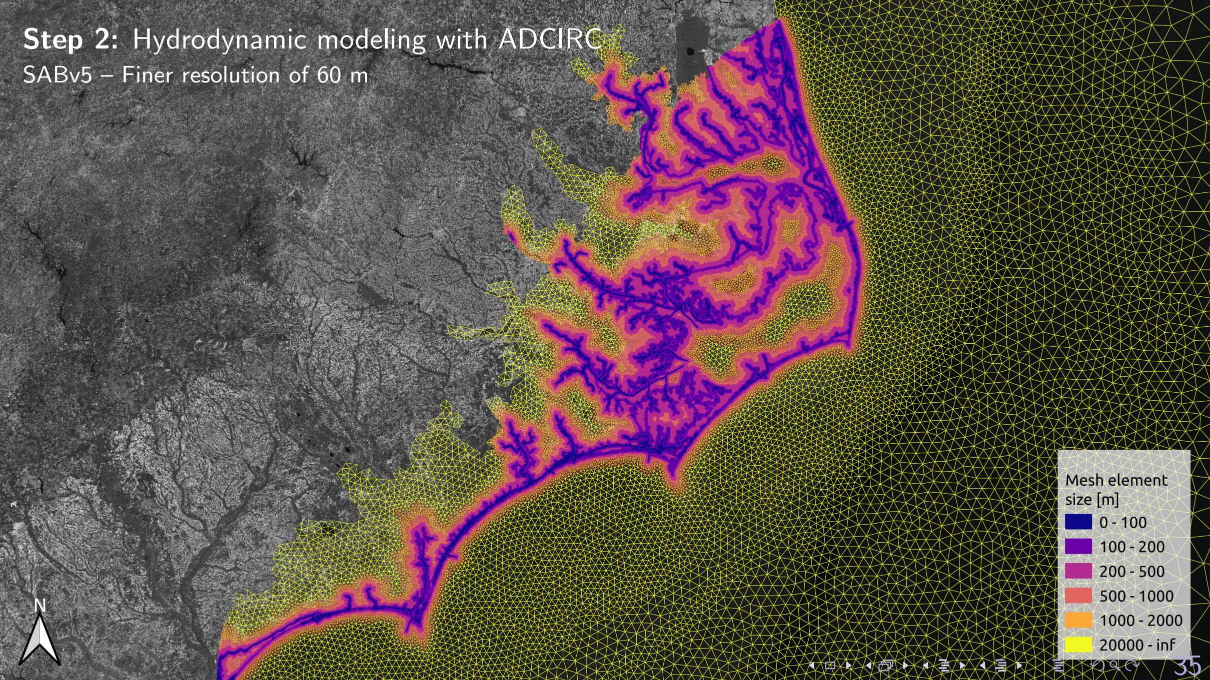
SABv5 – floodplains only in NC



Woodruff (2023)

Step 2: Hydrodynamic modeling with ADCIRC

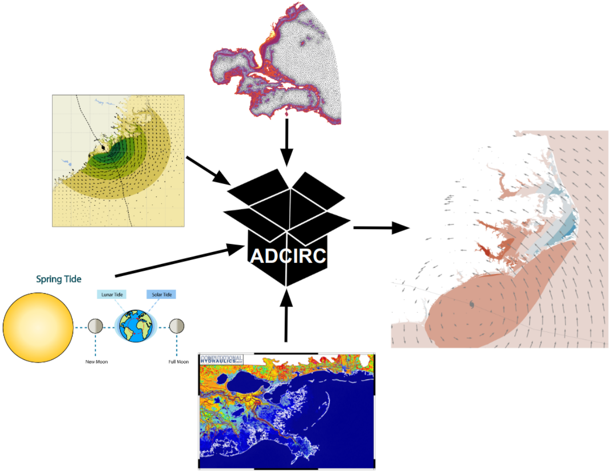
SABv5 – Finer resolution of 60 m



Step 2: Hydrodynamic modeling with ADCIRC

Simulations setup

- Same mesh and nodal attributes
- Almost the same configuration
  - o 2-month representative period (Key assumption 2)
  - o Random date $\implies$ random tide
- Wind field: Holland symmetric model
  - o No need to compute extra info.
  - o Coords, WS, P, and RMW
- 2-months tide-only simulation
- HPC systems
  - o NCSU Hazel
  - o Purdue Anvil
  - o TACC Stampede2 (RIP)

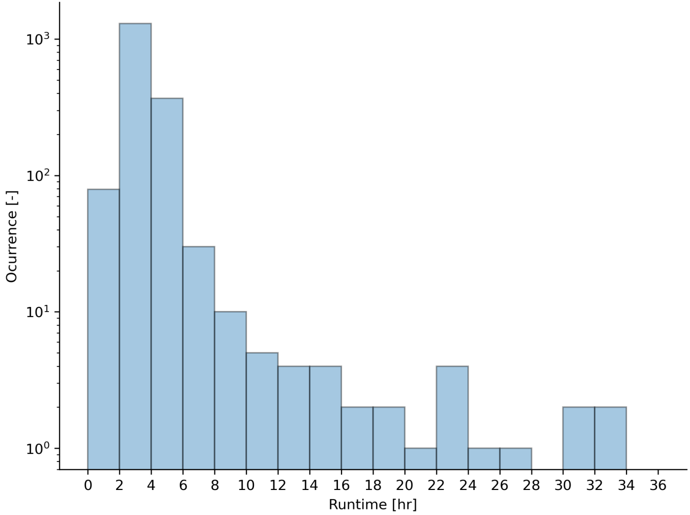


Step 2: Hydrodynamic modeling with ADCIRC

Postprocessing simulations

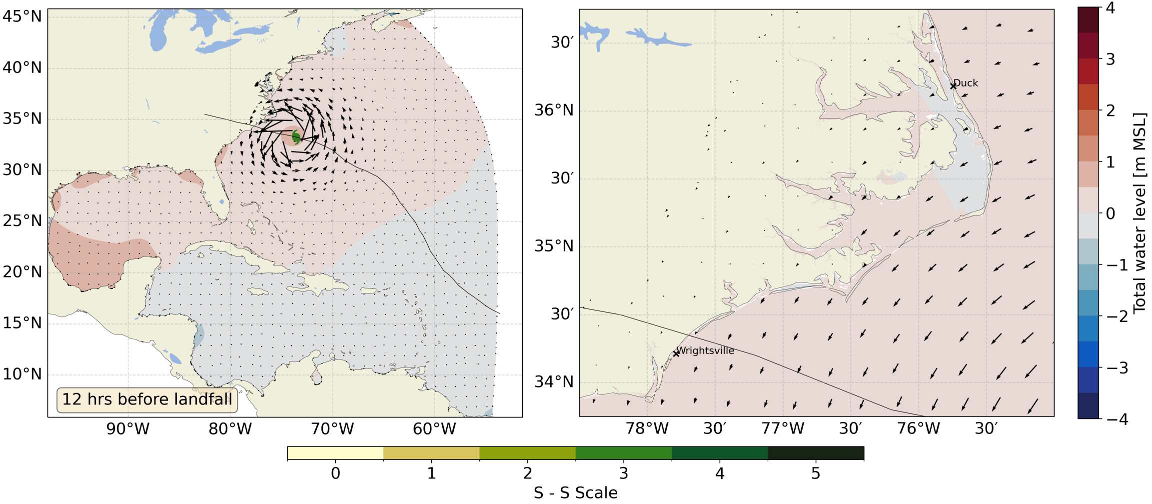
Simulation stats

- **1.3M** cpu hours
- Wall clock time ranged from 1.2 to 33 hours
- Mean wall clock time of 3.7 hours
- **17T** of data



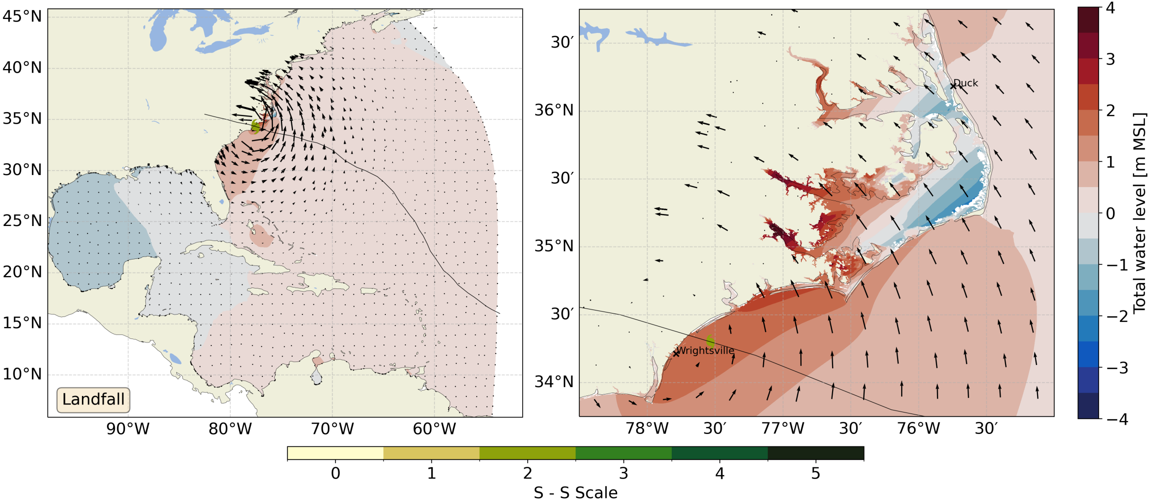
Step 2: Hydrodynamic modeling with ADCIRC

Storm 0 – 12 hrs before landfall



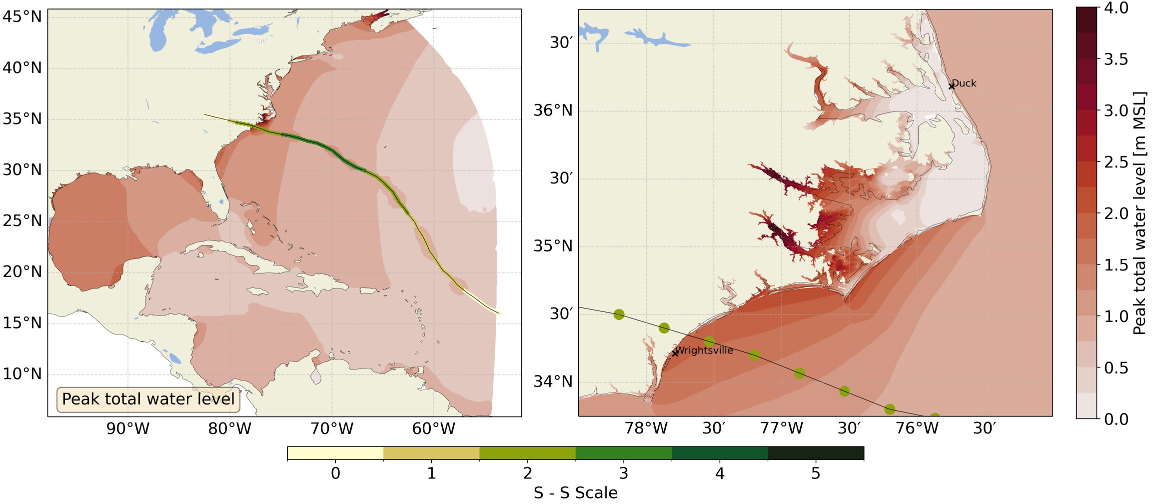
Step 2: Hydrodynamic modeling with ADCIRC

Storm 0 – at landfall



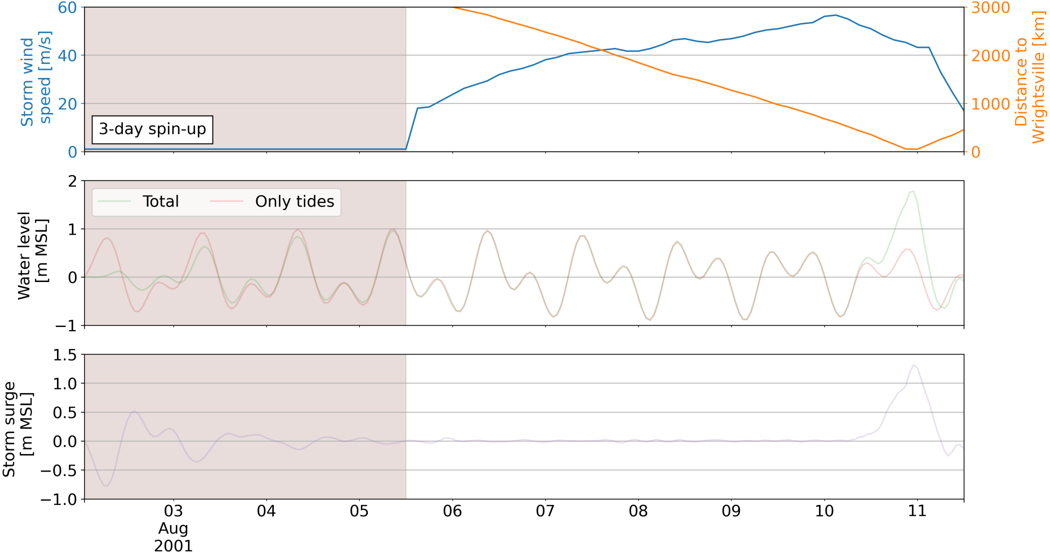
Step 2: Hydrodynamic modeling with ADCIRC

Storm 0 – max. water level



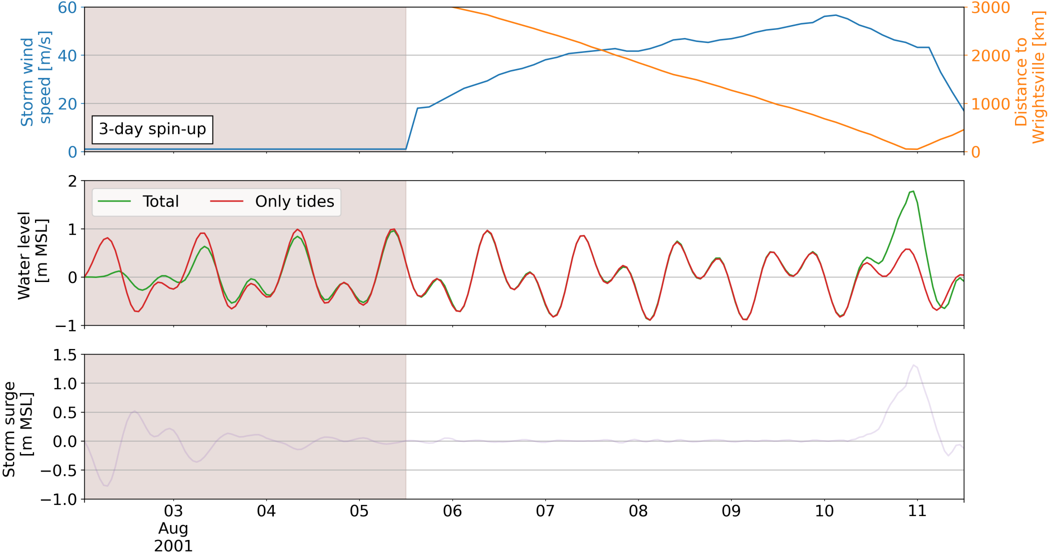
Step 2: Hydrodynamic modeling with ADCIRC

Storm 0 – Time series at Wrightsville NOAA tide gauge



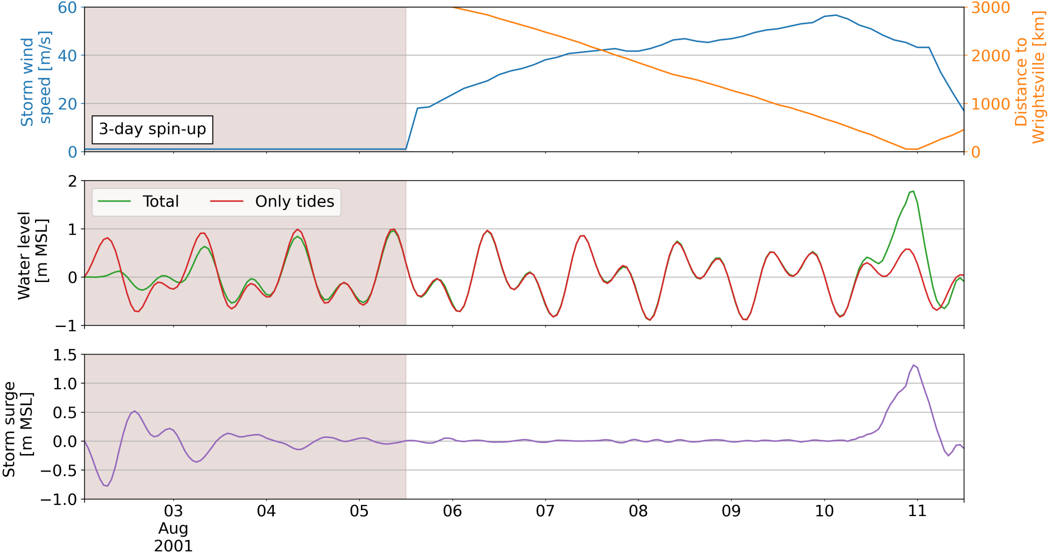
Step 2: Hydrodynamic modeling with ADCIRC

Storm 0 – Time series at Wrightsville NOAA tide gauge



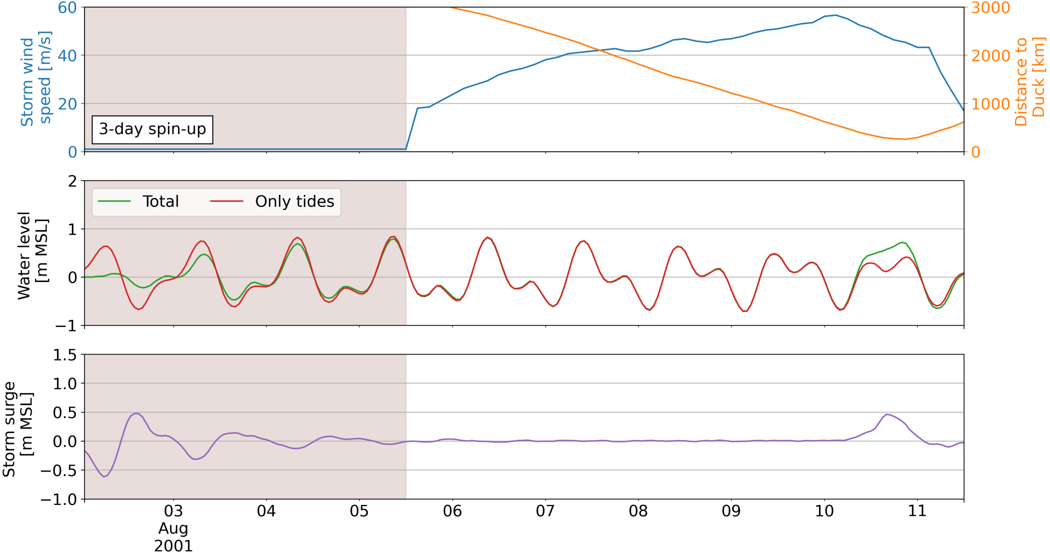
Step 2: Hydrodynamic modeling with ADCIRC

Storm 0 – Time series at Wrightsville NOAA tide gauge



Step 2: Hydrodynamic modeling with ADCIRC

Storm 0 – Time series at Duck NOAA tide gauge

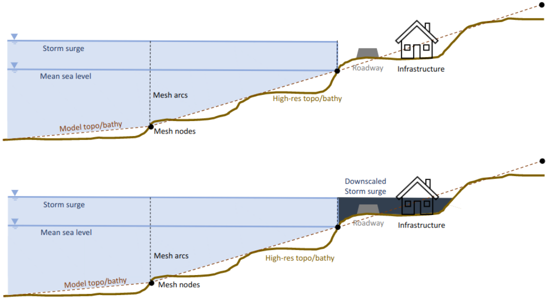


Step 2: Downscaling with Kalpana

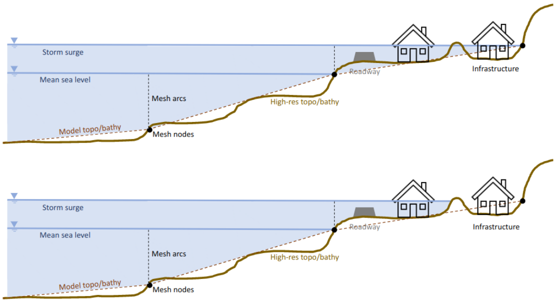
Kalpana's Static Downscaling method: peak total water level output to high-res raster

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

Expand inundation



Shrink inundation

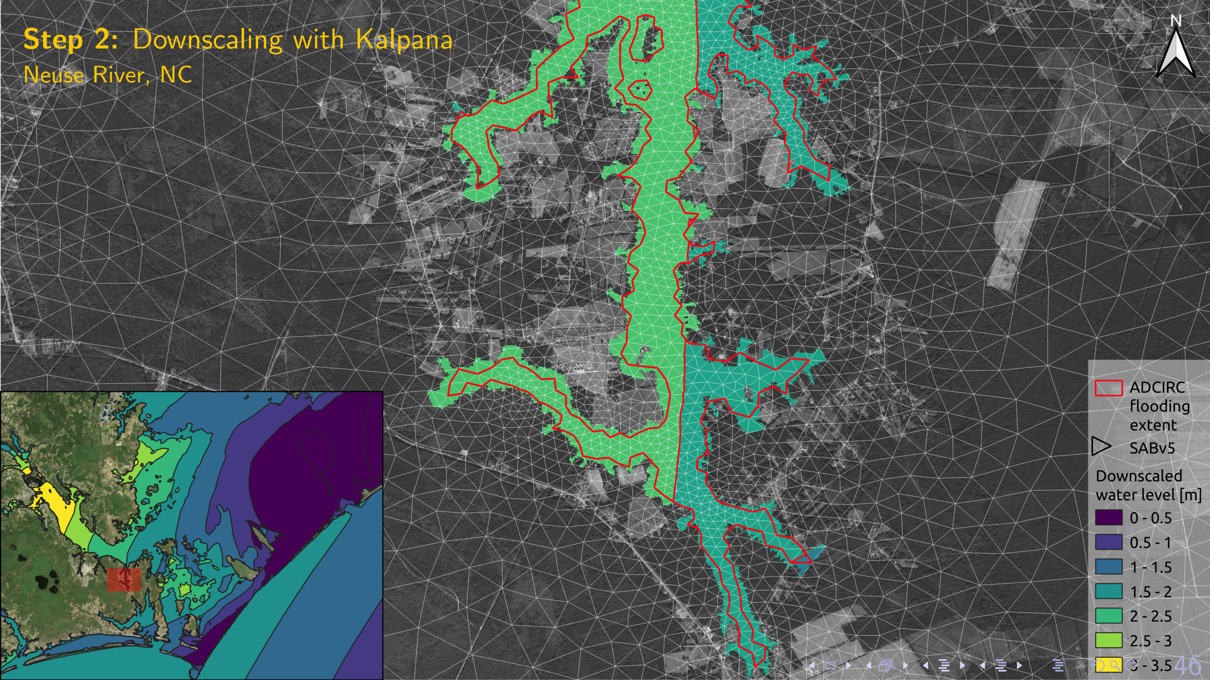


github.com/ccht-ncsu/Kalpana

Rucker et al. (2021)

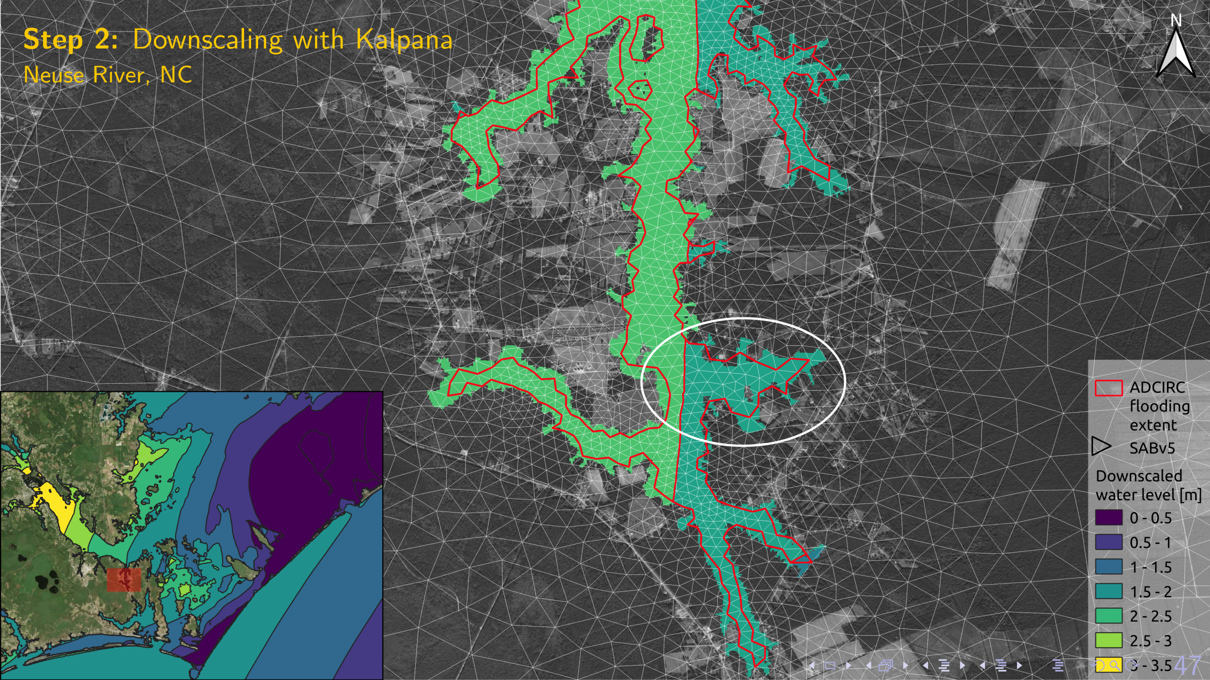
Step 2: Downscaling with Kalpana

Neuse River, NC



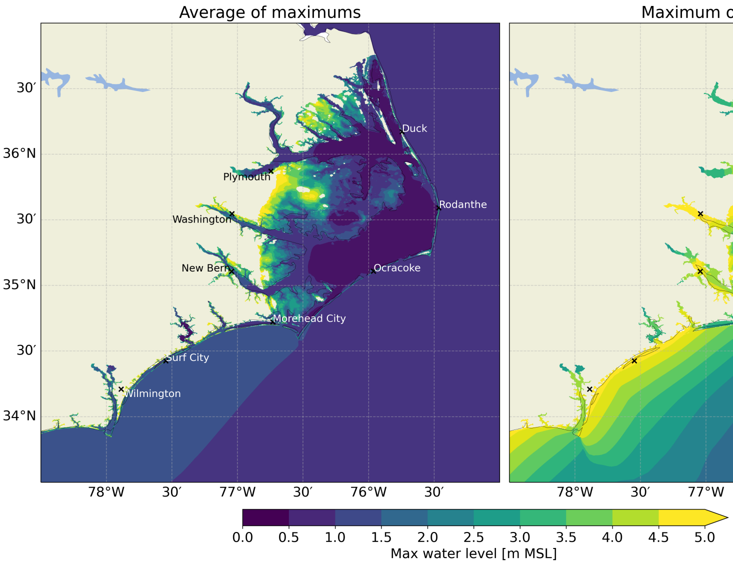
Step 2: Downscaling with Kalpana

Neuse River, NC



Step 2: Downscaling with Kalpana

Aggregated downscaled peak total water level stats – Where not to buy a house in NC?



Step 1

Data Collection

- Dataset of synthetic tropical cyclones
- Select impactful tracks

Step 2

ADCIRC Library

- Hydrodynamic modeling
- Downscaling

Step 3

Deep Learning

- 1D CNNs
- MLP
- Train/Test/Validate

Step 4

Probabilistic prediction

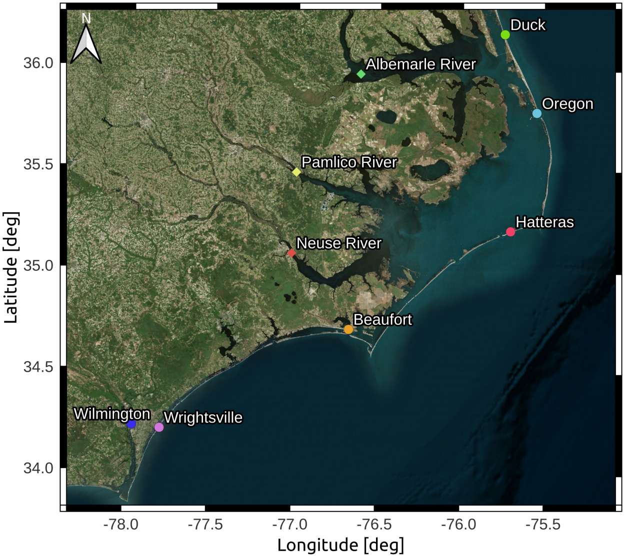
- Observed tracks
- Perturbations

Step 3: Deep learning

Data preprocessing – Extract peak total water level from downscaled maps

Stations to predict

- NOAA tide gauges:
  - o Duck
  - o Oregon inlet
  - o Cape Hatteras
  - o Beaufort
  - o Wilmington
  - o Wrightsville
- NC rivers:
  - o Albemarle
  - o Pamlico
  - o Neuse

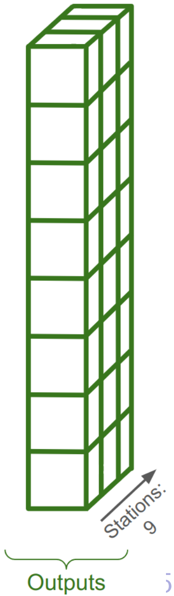


Step 3: Deep learning

Data preprocessing – Zero padding & masking

Outputs:

- Peak total water level at 9 stations



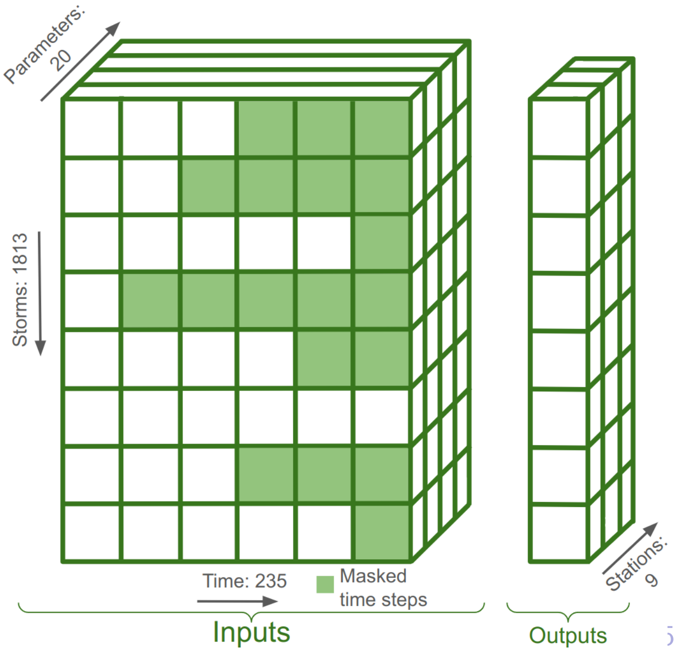
Step 3: Deep learning

Data preprocessing – Zero padding & masking

Outputs:

- o Peak total water level at 9 stations

Inputs:



Step 3: Deep learning

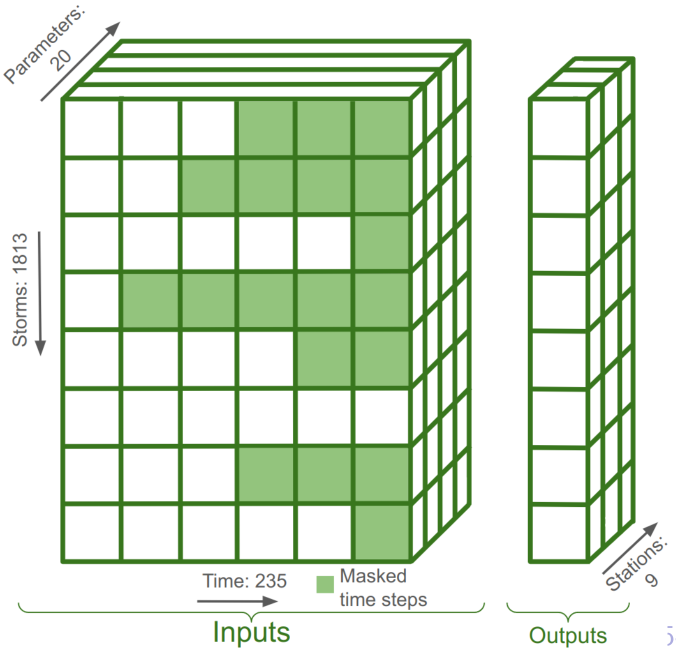
Data preprocessing – Zero padding & masking

Outputs:

- Peak total water level at 9 stations

Inputs:

- Max. wind speed
- Min. pressure
- Rad. to max. wind speed
- *u* and *v* vectors of forward speed
- FFT of 5 inputs above
- Distance from eye to the 9 stations
- Offshore tide



Step 3: Deep learning

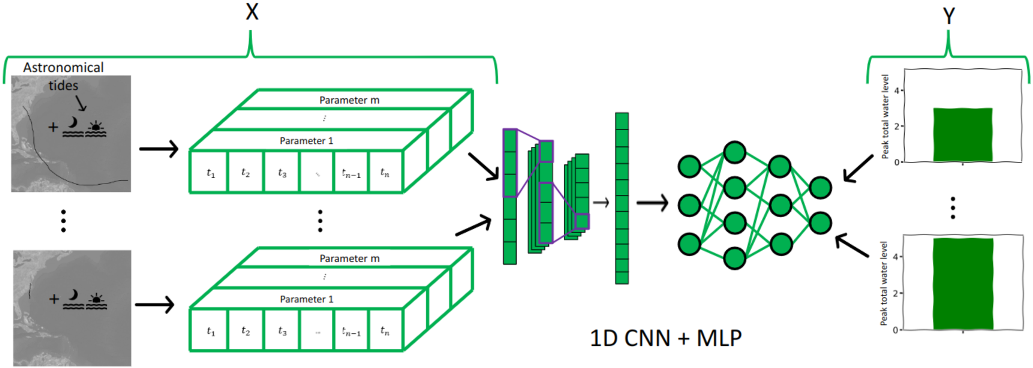
Neural network architecture: 1D CNNs and dense layers

Step 3: Deep learning

Neural network architecture: 1D CNNs and dense layers

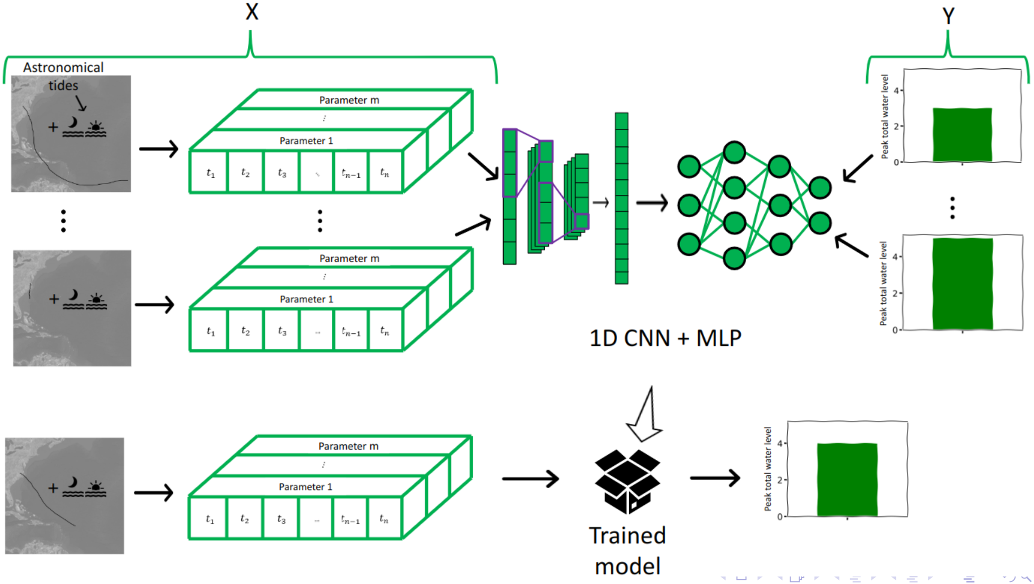
Step 3: Deep learning

Neural network architecture: 1D CNNs and dense layers



Step 3: Deep learning

Neural network architecture: 1D CNNs and dense layers



Step 3: Deep learning

Summary of hyperparameters, data & architecture

- Hyperparameters
  - Loss: Huber
  - Optimizer: RMSProp
  - Learning rate: 10^{-4}
  - Epochs: 1,000
  - Batch size: 100
- Data
  - 20 input time series
  - 9 time-constant outputs
  - 15% for testing
  - 80% of remaining 85% for training
  - 20% of remaining 85% for validation
  - Standard scaling
- Architecture
  - 3 blocks of 1D CNNs (16, 32 & 64 channels)
  - Batch normalization
  - Max pooling (size 2)
  - 4 blocks of dense layers (1728, 64, 32 & 9 neurons)
  - ReLU activation function
  - Dropout 20%
  - **Many-to-one**

Step 3: Deep learning
Metrics

Mean bias error

$$\text{MBE} = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i) \tag{1}$$

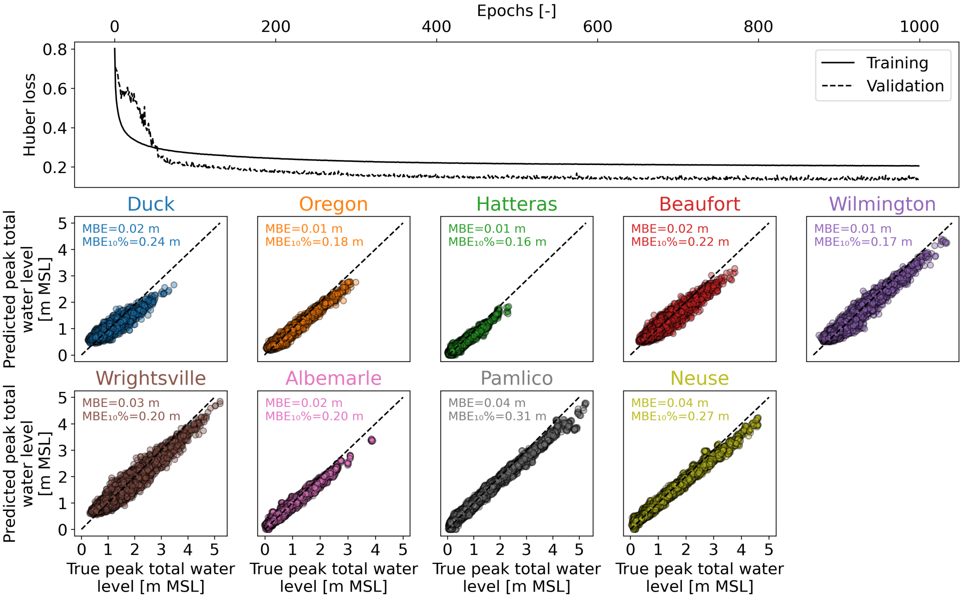
MBE of largest 10%

$$\text{MBE}_{10\%} = \frac{1}{N}\sum_{i=0.9\times N}^{N}(Y_i - \hat{Y}_i) \tag{2}$$

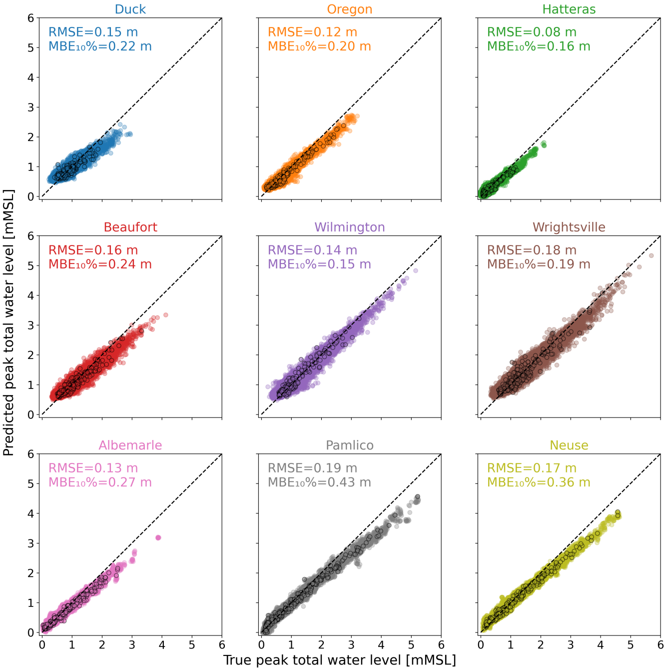
Root mean squared error

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}{N}} \tag{3}$$

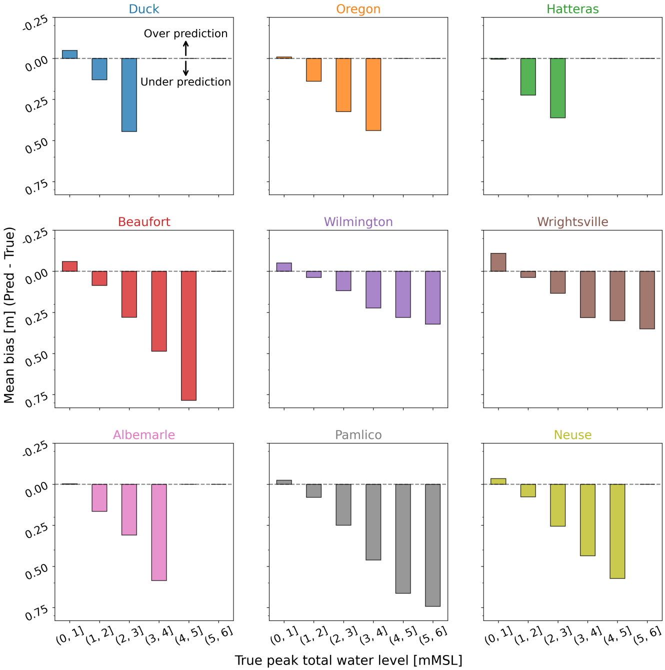
Step 3: Neural network validation



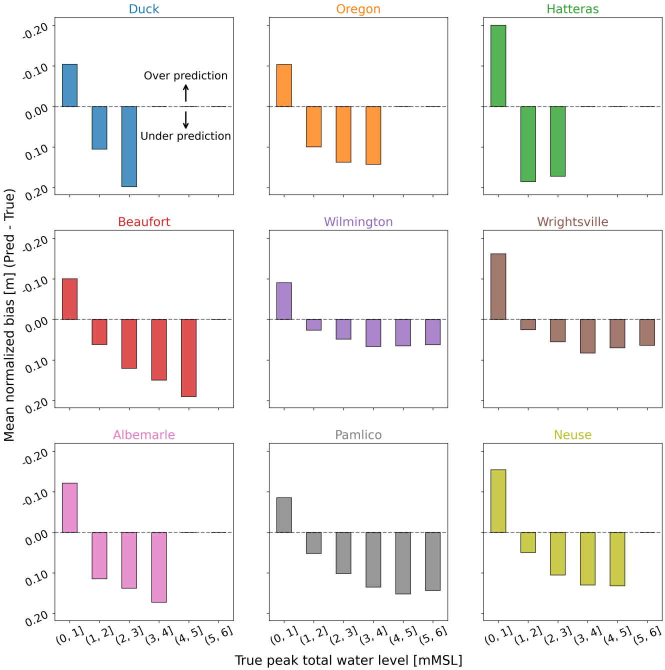
Step 3:
Neural network testing



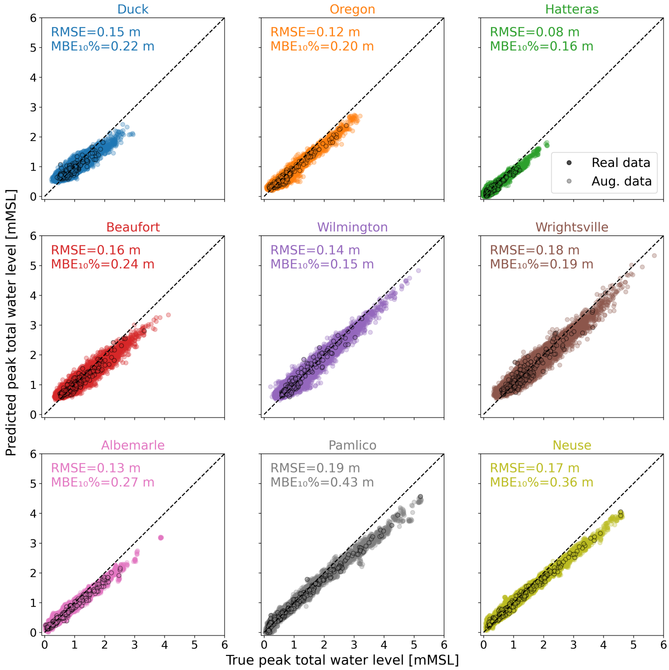
Step 3:
Neural network testing



Step 3:
Neural network testing

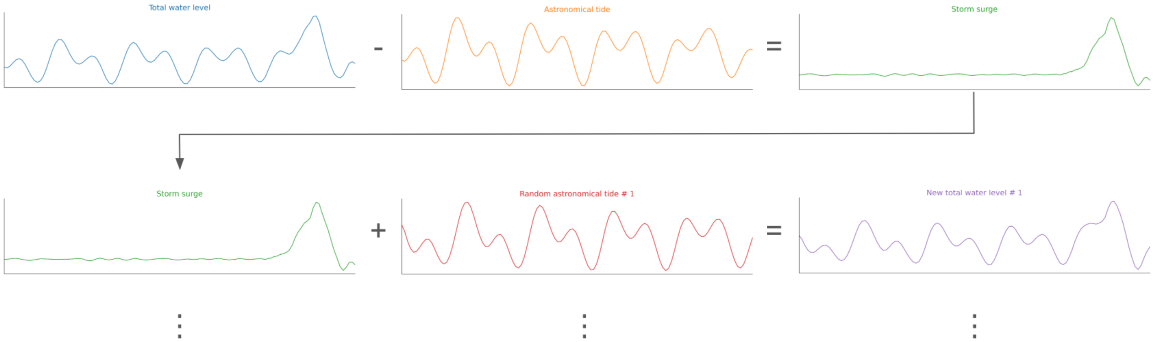


Step 3:
Neural network testing



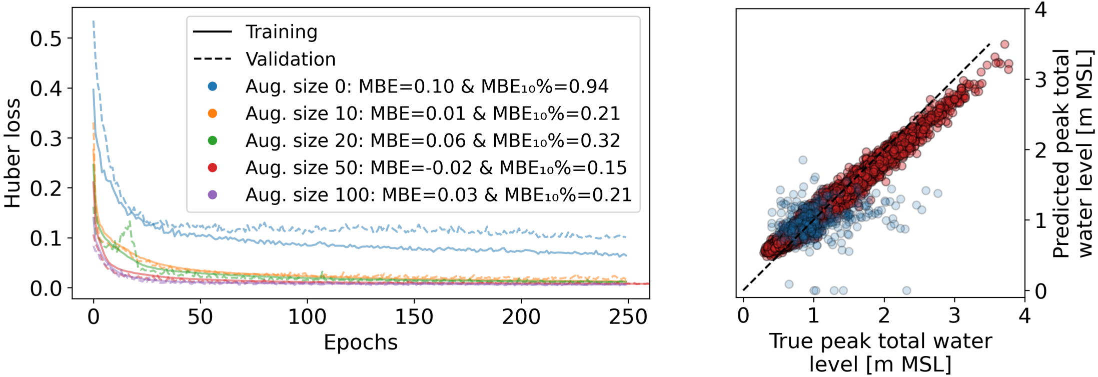
Step 3: Data augmentation methodology

Key assumption 3 – Storm surge and astronomical tides are independent



Step 3: Augmentation size validation

Simpler NN at Beaufort



Step 1

Data Collection

- Dataset of synthetic tropical cyclones
- Select impactful tracks

→

Step 2

ADCIRC Library

- Hydrodynamic modeling
- Downscaling

→

Step 3

Deep Learning

- 1D CNNs
- MLP
- Train/Test/Validate

→

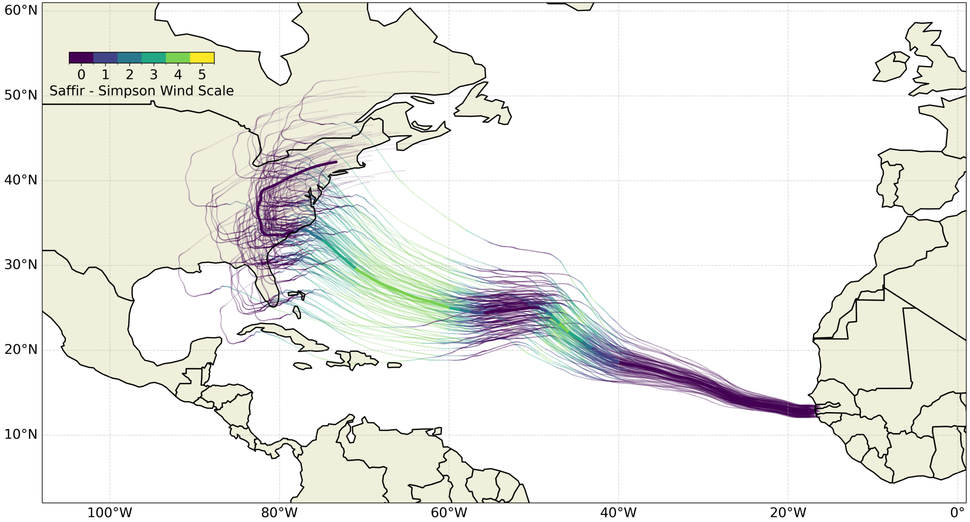
Step 4

Probabilistic prediction

- Observed tracks
- Perturbations

Step 4: Probabilistic prediction

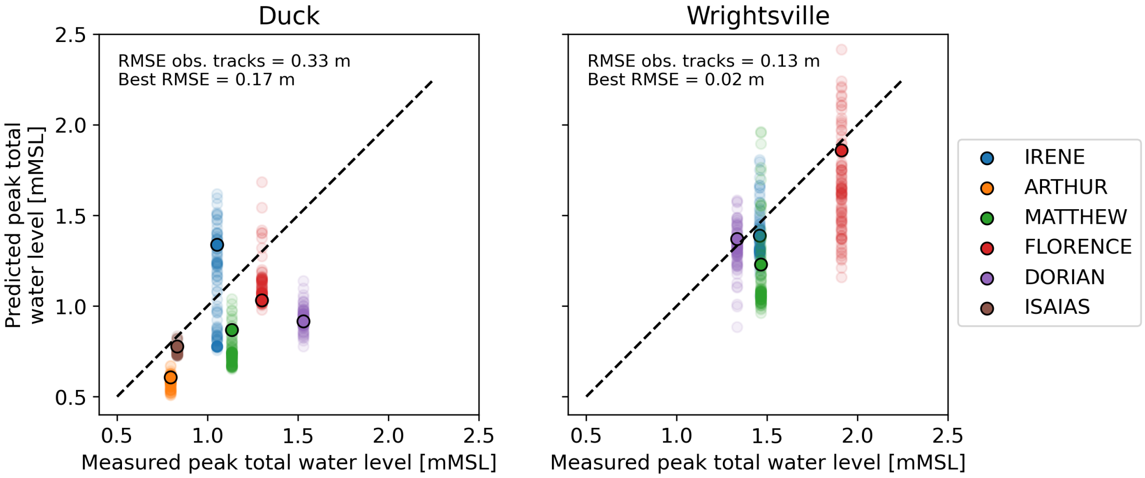
Florence (2018) perturbations with CLIMADA



Aznar-Siguan et al. (2023)

Step 4: Probabilistic prediction

Comparison with measured peak water levels

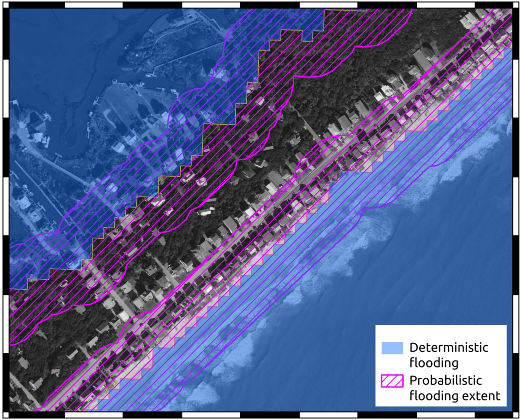


National Centers for Environmental Information (2023)

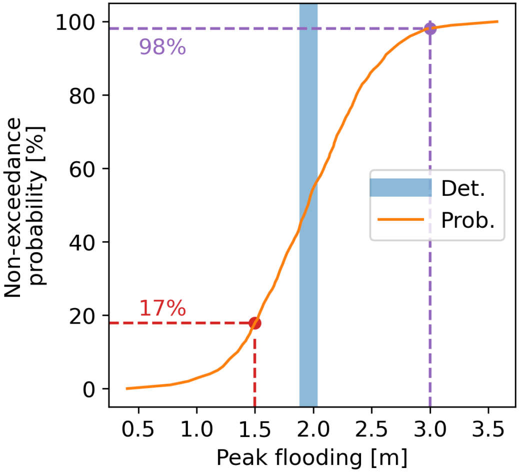
Step 4: Probabilistic prediction

Possible outcomes of a probabilistic prediction framework

Probabilistic 2D results



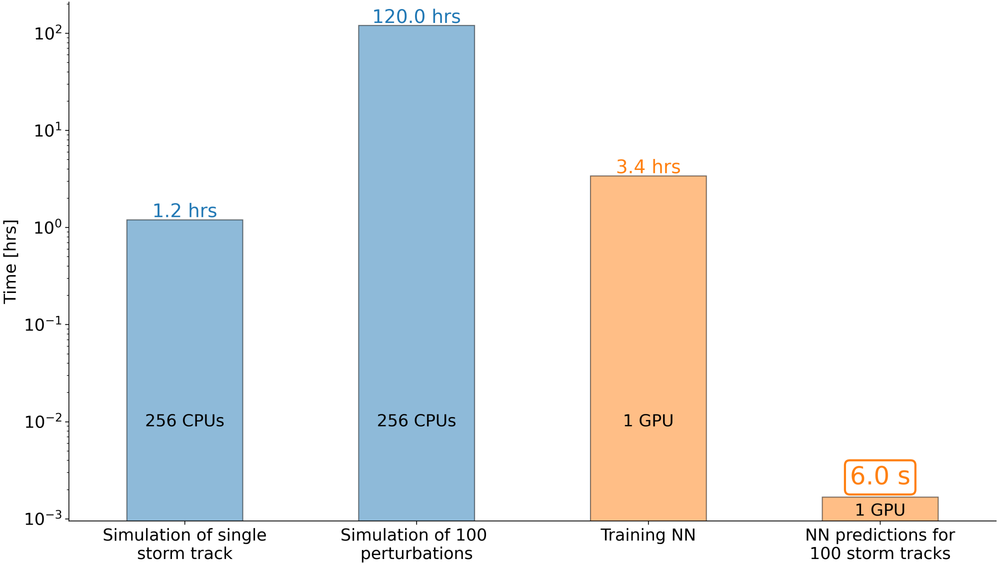
Probabilistic results at stations



Plots made with synthetic data

Step 4: Probabilistic prediction

Runtimes comparison



Step 1

Data Collection

- Dataset of synthetic tropical cyclones
- Select impactful tracks

→

Step 2

ADCIRC Library

- Hydrodynamic modeling
- Downscaling

→

Step 3

Deep Learning

- 1D CNNs
- MLP
- Train/Test/Validate

→

Step 4

Probabilistic prediction

- Observed tracks
- Perturbations

Step 1

Data Collection

- Dataset of synthetic tropical cyclones
- Select impactful tracks

→

Step 2

ADCIRC Library

- Hydrodynamic modeling
- Downscaling

→

Step 3

Deep Learning

- 1D CNNs
- MLP
- Train/Test/Validate

→

Step 4

Probabilistic prediction

- Observed tracks
- Perturbations

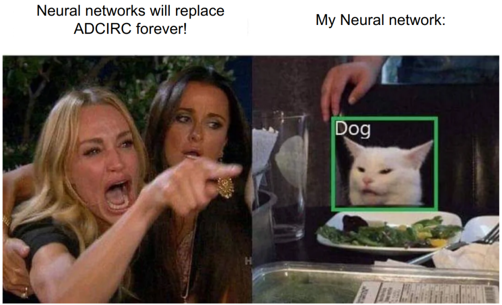
Our NN is a few steps closer to process-based models!

Takeaways

1. The NN required a lot of data for training.
2. The assumption that storm surge and astronomical tides are independent allowed us to increase the training dataset 50 times.
3. The NN performed well; the stations-averaged RMSE was 15 cm.
4. The extremes were underestimated; the NN's bias increased linearly with the magnitude of the true peak total water level.
5. The NN's prediction time allowed us to implement a probabilistic prediction framework.

Future work

1. Improve the NN's performance for extremes by trying other augmentation methodologies or creating more data.
2. Extend the NN framework to predict 2D spatially continuous maps of peak total water level for the NC coast by replacing the dense layers with transpose 2D CNNs.
3. Use a more sophisticated tool to perturb observed tracks so the performance of the probabilistic prediction framework can be quantified.



Acknowledgments





HOME
"If you're having FUN

Thank you – Gracias!

github.com/ccht-ncsu/Kalpana

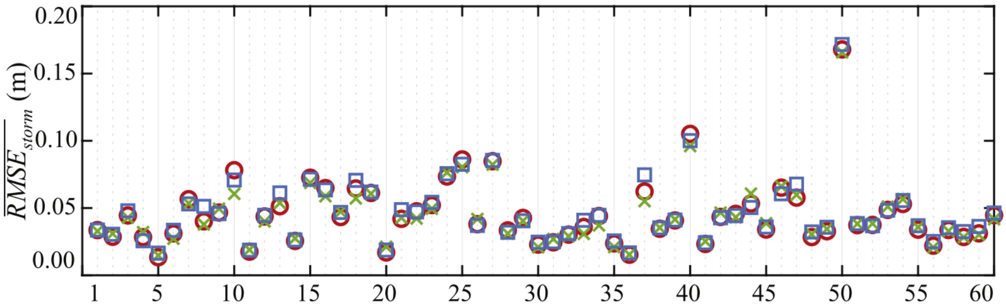
Statistical learning methods to predict storm surge

Started many years ago

- Moving least squared applied to waves and surge risk assessment (Taflanidis et al. 2012)

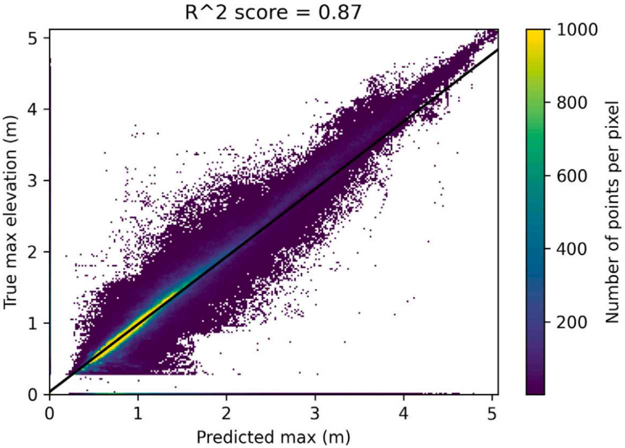
  ⋮

- Gaussian-processes for spatio-temporal emulation of storm surge (Kyprioti et al. 2023)



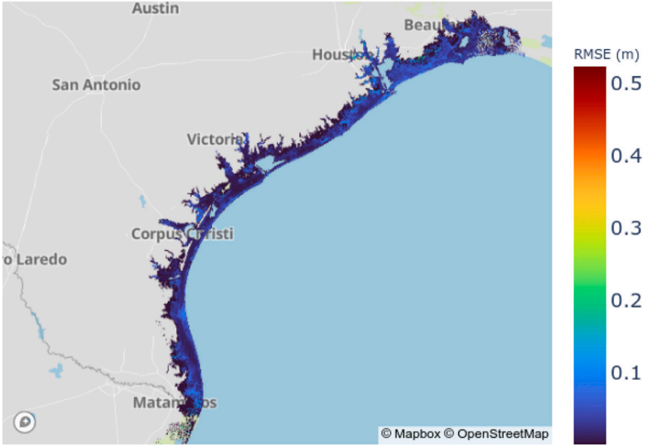
Peak storm surge from wind field at Texas & Alaska (Pachev et al. 2023)

- 446 synthetic tracks (TX)
- Peak storm surge at mesh vertex
- Wind field interpolated to the mesh
- Statistics to represent the temporal component
- Point-wise formulation (X_i, y_i)
- One-to-one neural network



Peak storm surge from wind field at Texas & Alaska (Pachev et al. 2023)

- 446 synthetic tracks (TX)
- Peak storm surge at mesh vertex
- Wind field interpolated to the mesh
- Statistics to represent the temporal component
- Point-wise formulation (X_i, y_i)
- One-to-one neural network

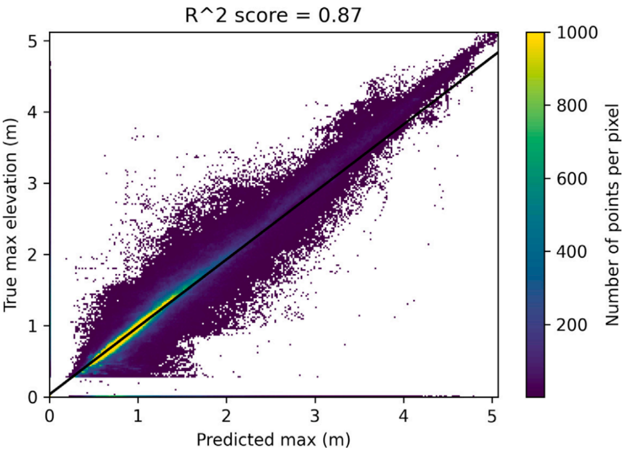


Deep learning to predict storm surge

Neural networks and storm surge process-based simulations

Peak storm surge from wind field at Texas & Alaska (Pachev et al. 2023)

- 446 ADCIRC simulations of synthetic storms (TX)
- Wind field interpolated to the mesh
- Peak storm surge at mesh vertex
- One-to-one neural network
- **No astronomical tide**
- **No temporal component**
- **Data tailored for extremes**

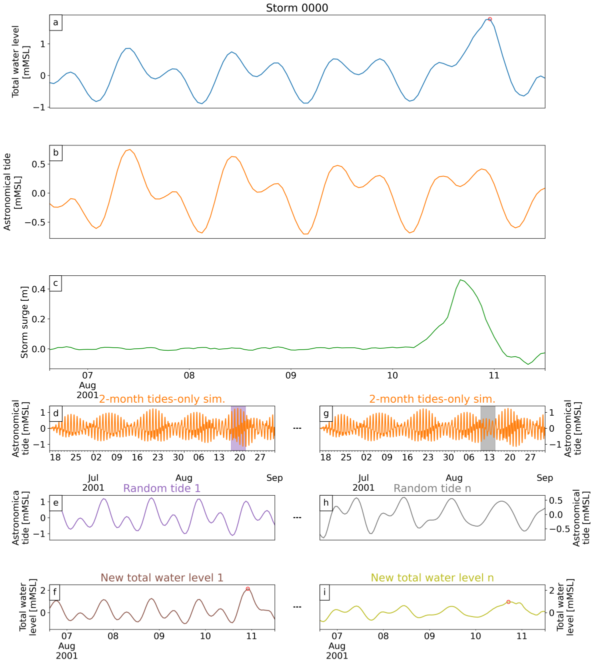


Statistical learning vs deep learning

	Pros	Cons
Statistical learning	o High interpretability o Easy implementation o Cheap to train	o Bad generalization o Bad for non-linearities o Cheap to train
Deep learning	o Great for non-linearities o Good generalization	o Bad interpretability o Hard implementation o Expensive to train

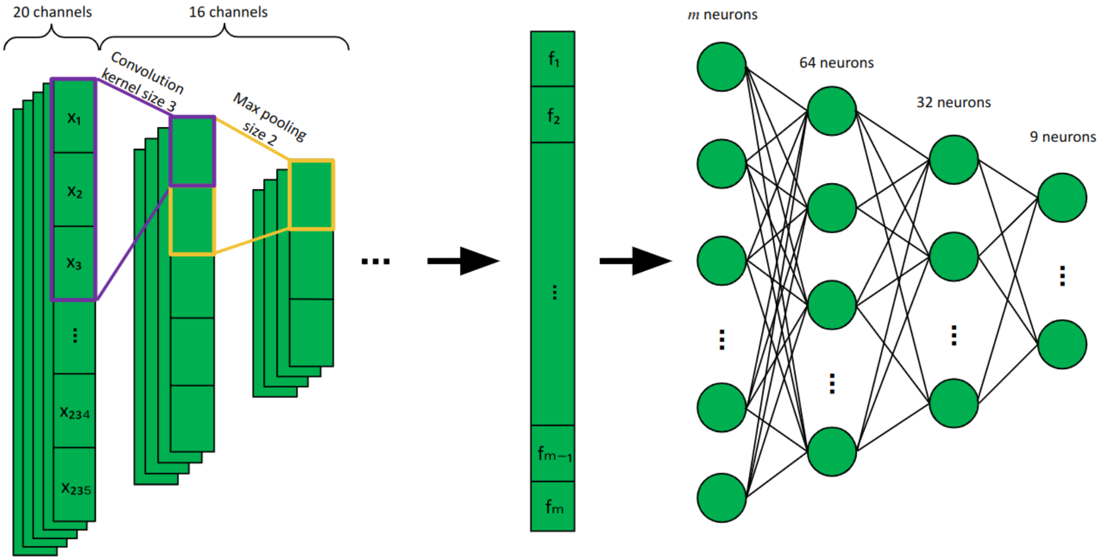
	Pros	Cons
Storm surge observations	o Global coverage o No need for models	o Not full track o Obs. are scarce o Eye is not captured
Process-based models	o Full track o Eye dynamics o Large domains	o A lot of data o Models are expensive

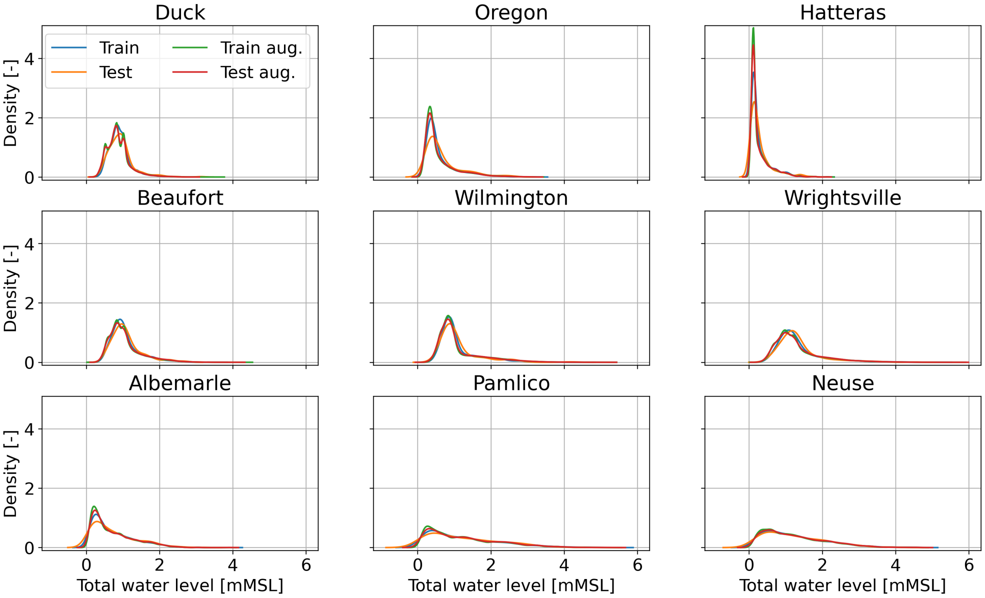
- Decomposed total water level
- Assumed surge and tides are independent
- Computed storm surge time series
- Add random tides to the storm surge time series
- Repeat *n* times per storm

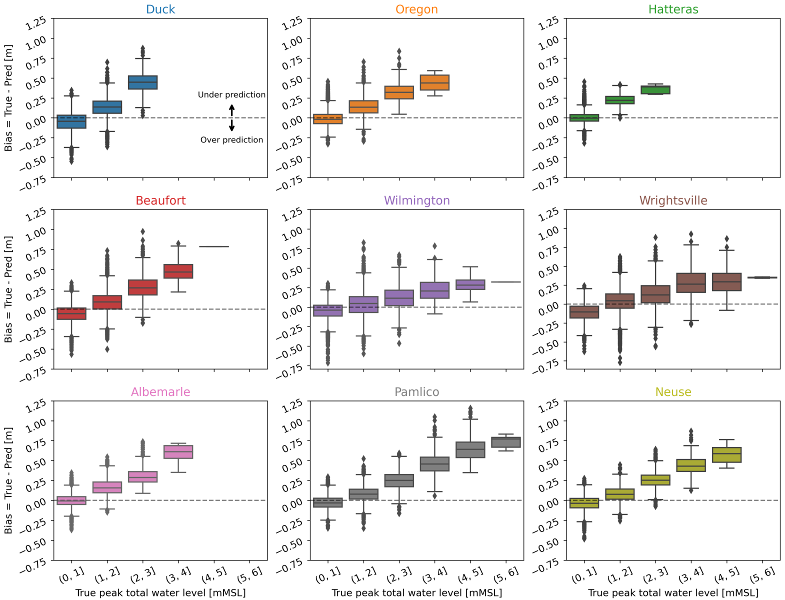


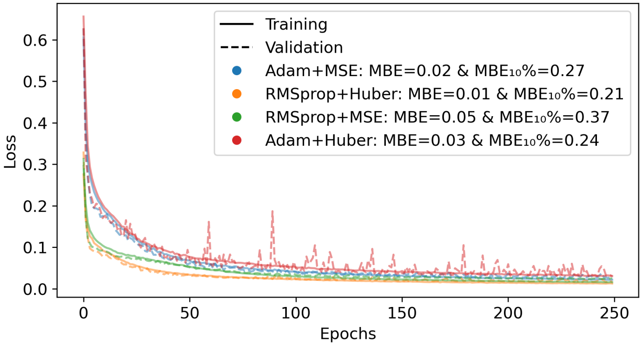
Step 3: Deep learning

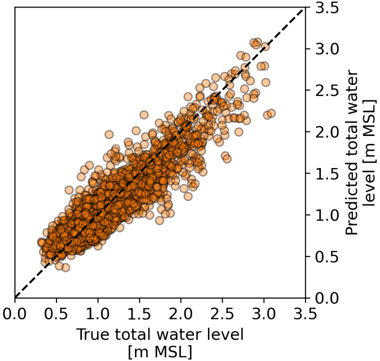
Neural network architecture: 1D CNNs and dense layers

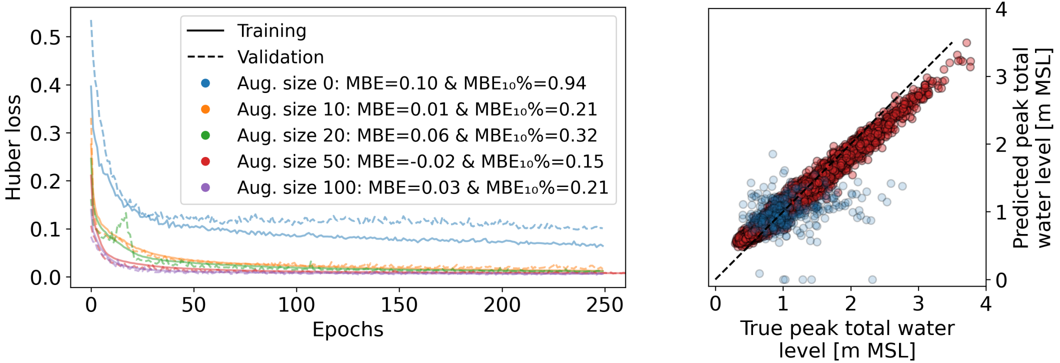


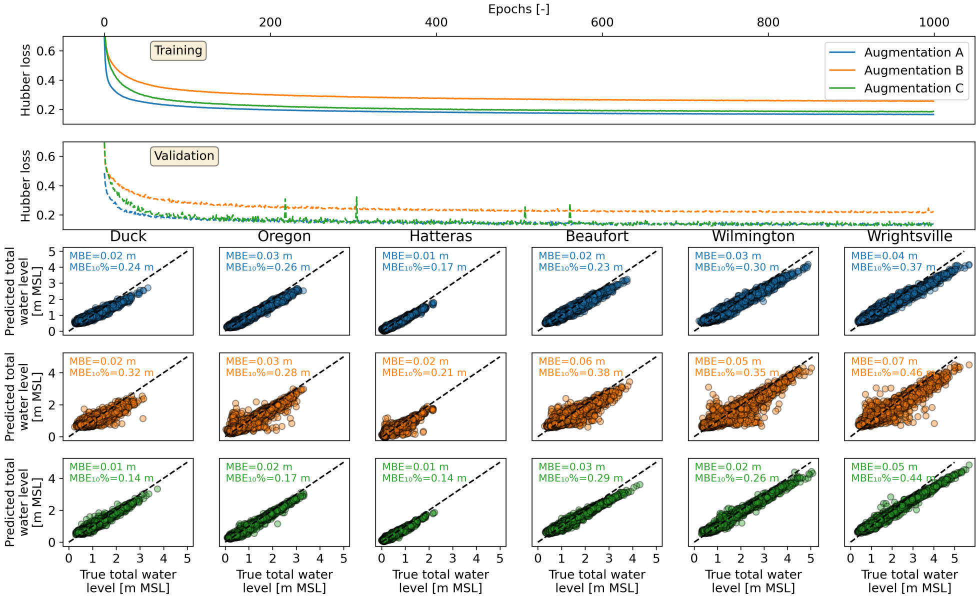

Duck
Oregon
Hatteras
Beaufort
Wilmington
Wrightsville
Albemarle
Pamlico
Neuse
Train
Test
Train aug.
Test aug.
Density [-]
Total water level [mMSL]
0
2
4
6


Duck
Oregon
Hatteras
Beaufort
Wilmington
Wrightsville
Albemarle
Pamlico
Neuse
Bias = True - Pred [m]
Under prediction
Over prediction
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
(0, 1]
(1, 2]
(2, 3]
(3, 4]
(4, 5]
(5, 6]
True peak total water level [mMSL]

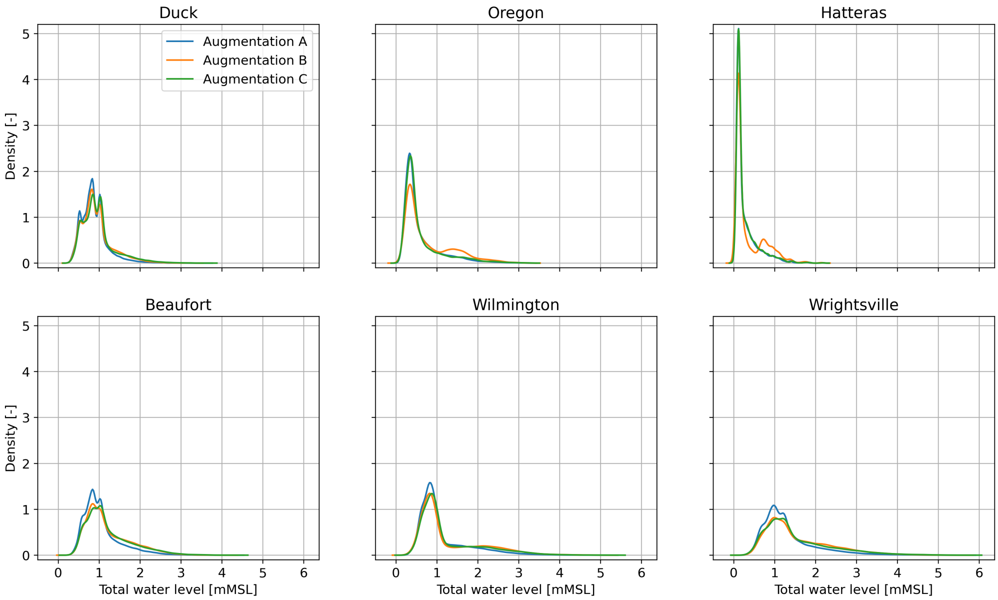

Training
Validation
Adam+MSE: MBE=0.02 & MBE$_{10}$%=0.27
RMSprop+Huber: MBE=0.01 & MBE$_{10}$%=0.21
RMSprop+MSE: MBE=0.05 & MBE$_{10}$%=0.37
Adam+Huber: MBE=0.03 & MBE$_{10}$%=0.24
Loss
Epochs

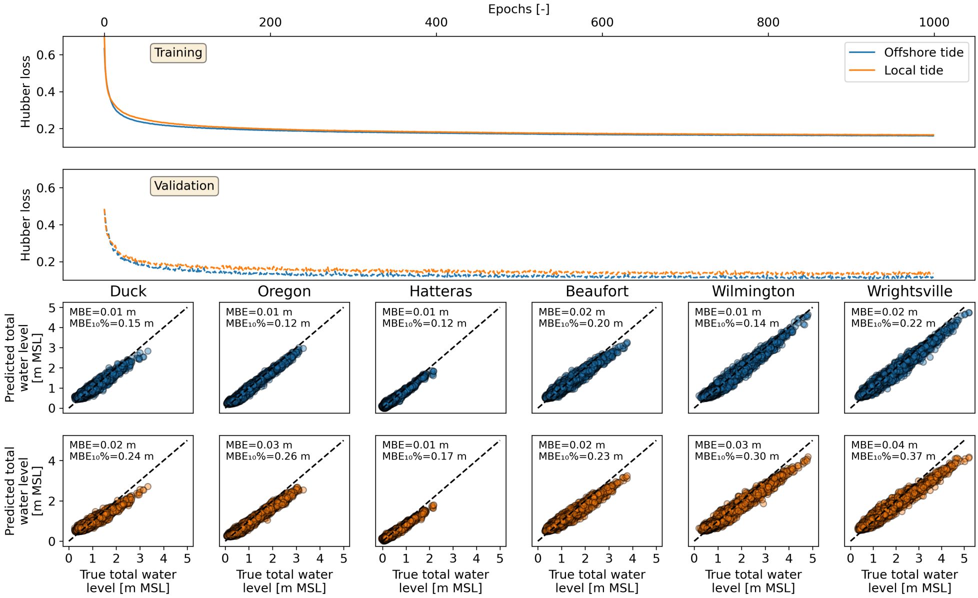

Predicted total water level [m MSL]
True total water level [m MSL]


Training
Validation
Aug. size 0: MBE=0.10 & MBE₁₀%=0.94
Aug. size 10: MBE=0.01 & MBE₁₀%=0.21
Aug. size 20: MBE=0.06 & MBE₁₀%=0.32
Aug. size 50: MBE=-0.02 & MBE₁₀%=0.15
Aug. size 100: MBE=0.03 & MBE₁₀%=0.21
Huber loss
Epochs
True peak total water level [m MSL]
Predicted peak total water level [m MSL]

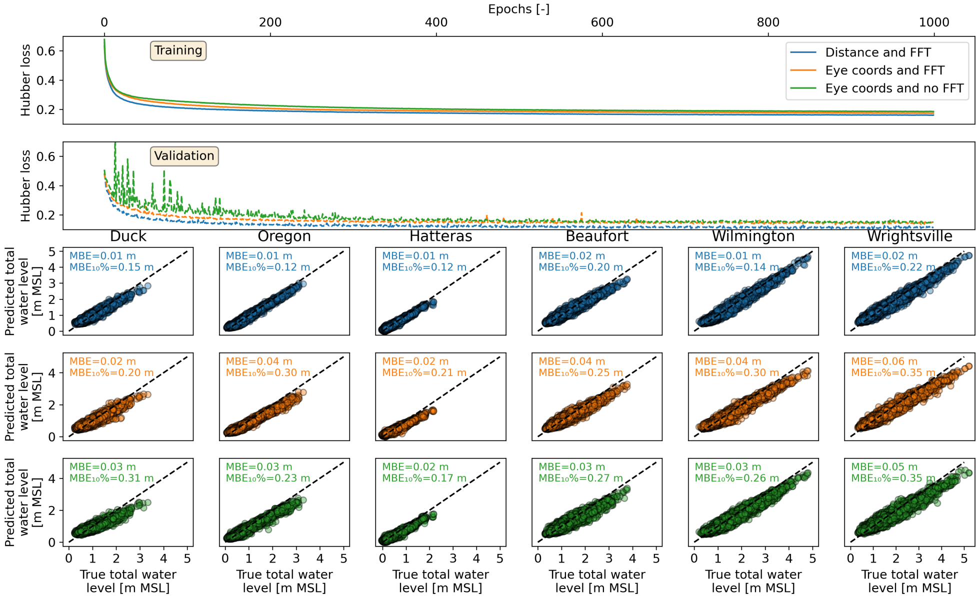


Epochs [-]
0
200
400
600
800
1000
Hubber loss
0.6
0.4
0.2
Training
Augmentation A
Augmentation B
Augmentation C
Hubber loss
0.6
0.4
0.2
Validation
Duck
Oregon
Hatteras
Beaufort
Wilmington
Wrightsville
Predicted total water level [m MSL]
MBE=0.02 m
MBE10%=0.24 m
MBE=0.03 m
MBE10%=0.26 m
MBE=0.01 m
MBE10%=0.17 m
MBE=0.02 m
MBE10%=0.23 m
MBE=0.03 m
MBE10%=0.30 m
MBE=0.04 m
MBE10%=0.37 m
MBE=0.02 m
MBE10%=0.32 m
MBE=0.03 m
MBE10%=0.28 m
MBE=0.02 m
MBE10%=0.21 m
MBE=0.06 m
MBE10%=0.38 m
MBE=0.05 m
MBE10%=0.35 m
MBE=0.07 m
MBE10%=0.46 m
MBE=0.01 m
MBE10%=0.14 m
MBE=0.02 m
MBE10%=0.17 m
MBE=0.01 m
MBE10%=0.14 m
MBE=0.03 m
MBE10%=0.29 m
MBE=0.02 m
MBE10%=0.26 m
MBE=0.05 m
MBE10%=0.44 m
True total water level [m MSL]


Duck
Oregon
Hatteras
Beaufort
Wilmington
Wrightsville
Augmentation A
Augmentation B
Augmentation C
Density [-]
Total water level [mMSL]



Epochs [-]
Training
Validation
Hubber loss
Offshore tide
Local tide
Duck
Oregon
Hatteras
Beaufort
Wilmington
Wrightsville
MBE=0.01 m
MBE10%=0.15 m
MBE=0.01 m
MBE10%=0.12 m
MBE=0.01 m
MBE10%=0.12 m
MBE=0.02 m
MBE10%=0.20 m
MBE=0.01 m
MBE10%=0.14 m
MBE=0.02 m
MBE10%=0.22 m
MBE=0.02 m
MBE10%=0.24 m
MBE=0.03 m
MBE10%=0.26 m
MBE=0.01 m
MBE10%=0.17 m
MBE=0.02 m
MBE10%=0.23 m
MBE=0.03 m
MBE10%=0.30 m
MBE=0.04 m
MBE10%=0.37 m
Predicted total water level [m MSL]
True total water level [m MSL]


Epochs [-]
0
200
400
600
800
1000
Hubber loss
0.6
0.4
0.2
Training
Distance and FFT
Eye coords and FFT
Eye coords and no FFT
Hubber loss
Validation
Duck
Oregon
Hatteras
Beaufort
Wilmington
Wrightsville
Predicted total water level [m MSL]
MBE=0.01 m
MBE10%=0.15 m
MBE=0.01 m
MBE10%=0.12 m
MBE=0.01 m
MBE10%=0.12 m
MBE=0.02 m
MBE10%=0.20 m
MBE=0.01 m
MBE10%=0.14 m
MBE=0.02 m
MBE10%=0.22 m
MBE=0.02 m
MBE10%=0.20 m
MBE=0.04 m
MBE10%=0.30 m
MBE=0.02 m
MBE10%=0.21 m
MBE=0.04 m
MBE10%=0.25 m
MBE=0.04 m
MBE10%=0.30 m
MBE=0.06 m
MBE10%=0.35 m
MBE=0.03 m
MBE10%=0.31 m
MBE=0.03 m
MBE10%=0.23 m
MBE=0.02 m
MBE10%=0.17 m
MBE=0.03 m
MBE10%=0.27 m
MBE=0.03 m
MBE10%=0.26 m
MBE=0.05 m
MBE10%=0.35 m
True total water level [m MSL]