Machine Learning Models for Coastal Hazards Predictions, or What I Learned on My Sabbatical

JC Dietrich[1]

[1]Dep't of Civil, Construction, and Environmental Engineering, NC State Univ

EWC Seminar Series
NC State Univ, 4 Dec 2023

Motivation

When did everyone learn this? ...

GREEK ALPHABET

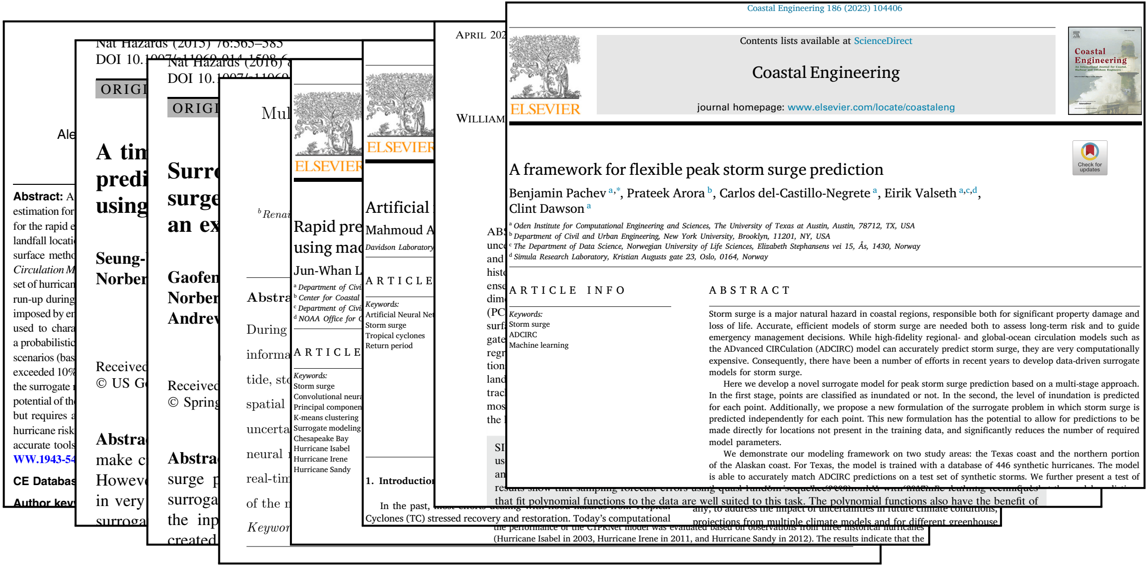
By Ben Crowder • bencrowder.net • Last modified 2 May 2012

Αα	Ββ	Γγ	Δδ	Εε	Ζζ
ALPHA [a] *ἄλφα*	**BETA** [b] *βῆτα*	**GAMMA** [g] *γάμμα*	**DELTA** [d] *δέλτα*	**EPSILON** [e] *ἒ ψιλόν*	**ZETA** [dz] *ζῆτα*
Ηη	Θθ	Ιι	Κκ	Λλ	Μμ
ETA [ɛː] *ἦτα*	**THETA** [tʰ] *θῆτα*	**IOTA** [i] *ἰῶτα*	**KAPPA** [k] *κάππα*	**LAMBDA** [l] *λάμβδα*	**MU** [m] *μῦ*
Νν	Ξξ	Οο	Ππ	Ρρ	Σσς
NU [n] *νῦ*	**XI** [ks] *ξεῖ*	**OMICRON** [o] *ὂ μικρόν*	**PI** [p] *πεῖ*	**RHO** [r] *ῥῶ*	**SIGMA** [s] *σῖγμα*
Ττ	Υυ	Φφ	Χχ	Ψψ	Ωω
TAU [t] *ταῦ*	**UPSILON** [ʉ] *ὖ ψιλόν*	**PHI** [pʰ] *φεῖ*	**CHI** [kʰ] *χεῖ*	**PSI** [ps] *ψεῖ*	**OMEGA** [ɔː] *ὦ μέγα*

Crowder (2012)

Motivation

… or all of this?



Coastal Engineering 186 (2023) 104406

Contents lists available at ScienceDirect

Coastal Engineering

journal homepage: www.elsevier.com/locate/coastaleng

A framework for flexible peak storm surge prediction

Benjamin Pachev [a,*], Prateek Arora [b], Carlos del-Castillo-Negrete [a], Eirik Valseth [a,c,d], Clint Dawson [a]

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[b] Department of Civil and Urban Engineering, New York University, Brooklyn, 11201, NY, USA
[c] The Department of Data Science, Norwegian University of Life Sciences, Elizabeth Stephansens vei 15, Ås, 1430, Norway
[d] Simula Research Laboratory, Kristian Augusts gate 23, Oslo, 0164, Norway

ARTICLE INFO

Keywords:
Storm surge
ADCIRC
Machine learning

ABSTRACT

Storm surge is a major natural hazard in coastal regions, responsible both for significant property damage and loss of life. Accurate, efficient models of storm surge are needed both to assess long-term risk and to guide emergency management decisions. While high-fidelity regional- and global-ocean circulation models such as the ADvanced CIRCulation (ADCIRC) model can accurately predict storm surge, they are very computationally expensive. Consequently, there have been a number of efforts in recent years to develop data-driven surrogate models for storm surge.

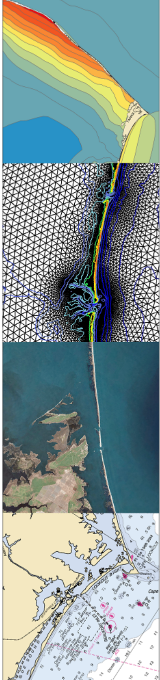
Here we develop a novel surrogate model for peak storm surge prediction based on a multi-stage approach. In the first stage, points are classified as inundated or not. In the second, the level of inundation is predicted for each point. Additionally, we propose a new formulation of the surrogate problem in which storm surge is predicted independently for each point. This new formulation has the potential to allow for predictions to be made directly for locations not present in the training data, and significantly reduces the number of required model parameters.

We demonstrate our modeling framework on two study areas: the Texas coast and the northern portion of the Alaskan coast. For Texas, the model is trained with a database of 446 synthetic hurricanes. The model is able to accurately match ADCIRC predictions on a test set of synthetic storms. We further present a test of

Plans for scholarly reassignment

1. Certificate in deep learning specialization
   - Five courses that introduce neural networks and deep learning
   - Estimated at 4–5 months
2. Develop a neural network for coastal flooding predictions
   - Led by my MS student Tomás Cuevas López
3. Submit proposal on machine learning
   - Supplemental funds from DHS Coastal Resilience Center
   - Collaborated on proposal to DOD ESTCP


WELL, IT WAS TOUGH FOR ME
SO BACK OFF
quickmeme.com



ADvanced CIRCulation (ADCIRC) solves modified forms of the shallow water equations ...

We use ADCIRC to represent the long waves of tides and storm surge

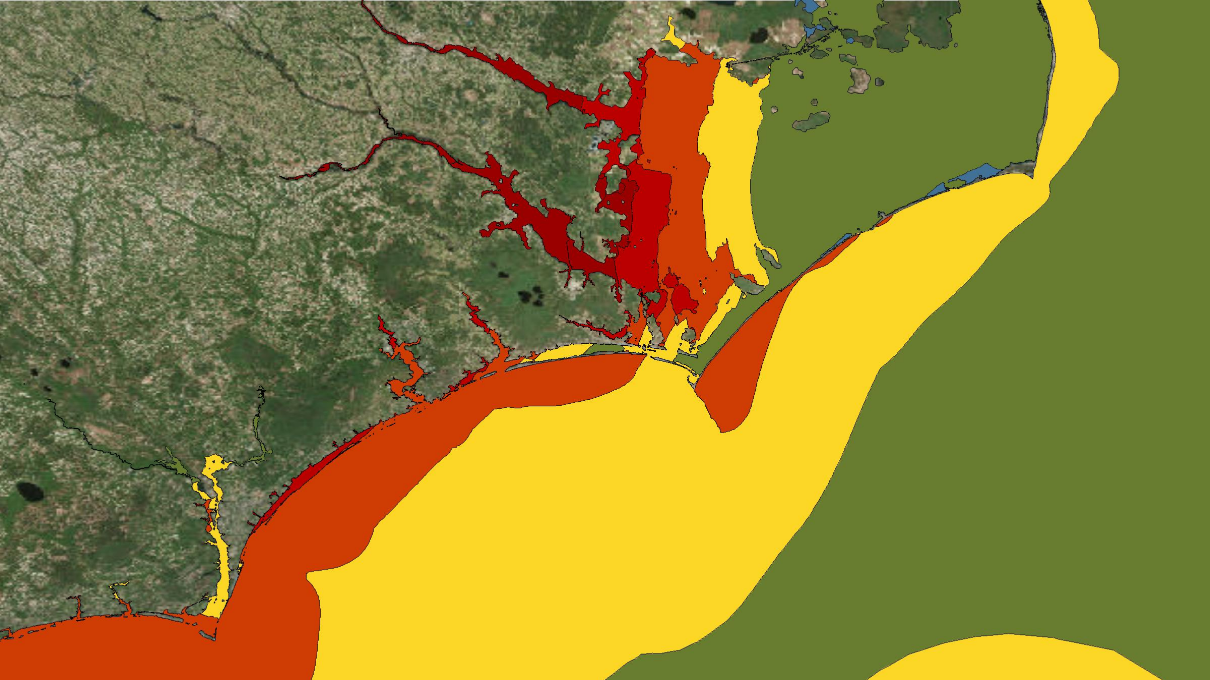
- Solves the generalized wave continuity equation (GWCE) for water levels (ζ):

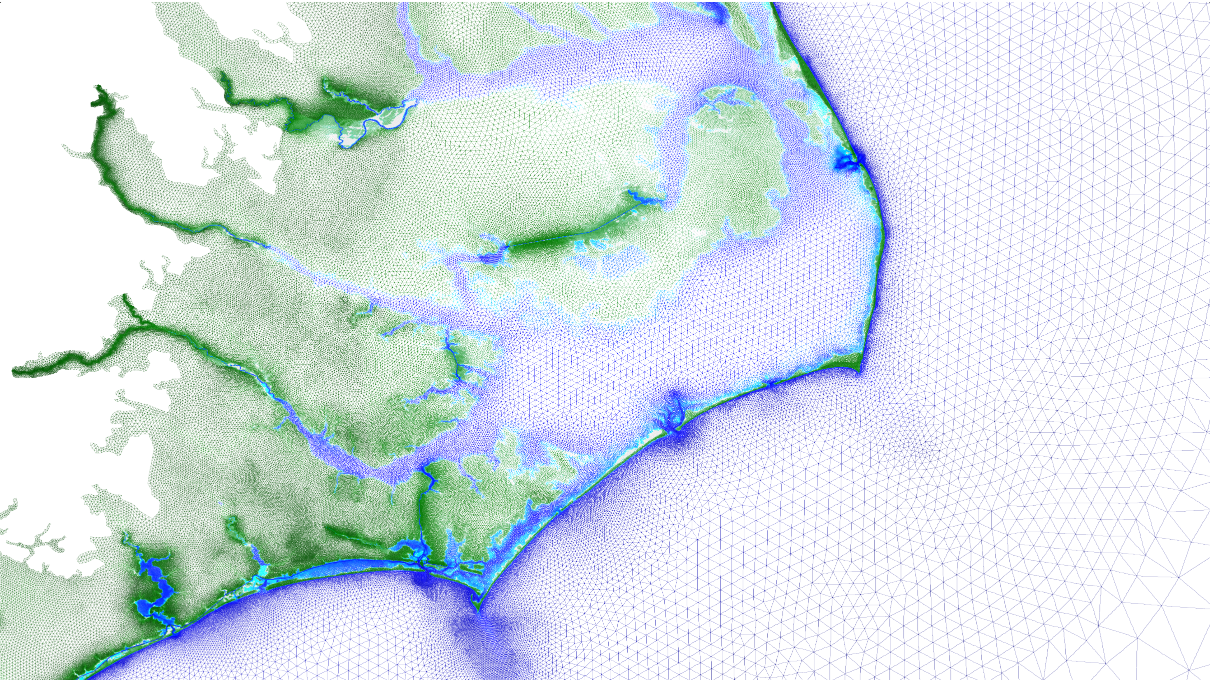
$$\frac{\partial^2 \zeta}{\partial t^2} + \tau_0 \frac{\partial \zeta}{\partial t} + \frac{\partial \tilde{J}_x}{\partial x} + \frac{\partial \tilde{J}_y}{\partial y} - UH\frac{\partial \tau_0}{\partial x} - VH\frac{\partial \tau_0}{\partial y} = 0$$

- Solves the depth-averaged momentum equations for currents (U, V):

$$\frac{\mathrm{D}U}{\mathrm{D}t} - fV = -g\frac{\partial}{\partial x}\left[\zeta + \frac{p_s}{g\rho_0} - \alpha\eta\right] + \frac{\tau_{sx} + \tau_{bx}}{\rho_0 H} + \frac{M_x - D_x}{H}$$

$$\frac{\mathrm{D}V}{\mathrm{D}t} + fU = -g\frac{\partial}{\partial y}\left[\zeta + \frac{p_s}{g\rho_0} - \alpha\eta\right] + \frac{\tau_{sy} + \tau_{by}}{\rho_0 H} + \frac{M_y - D_y}{H}$$

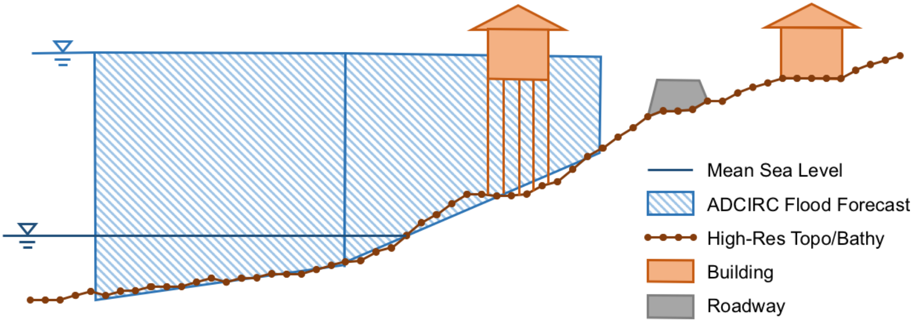




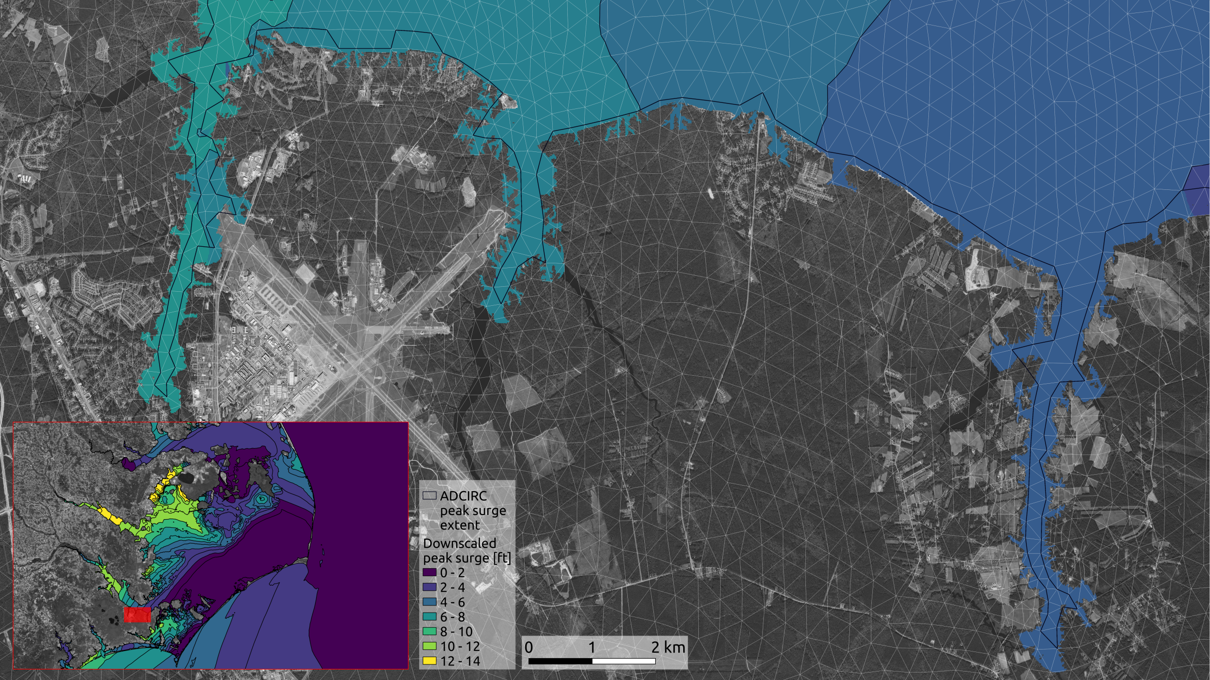
… and we can downscale the flood maps by using Kalpana

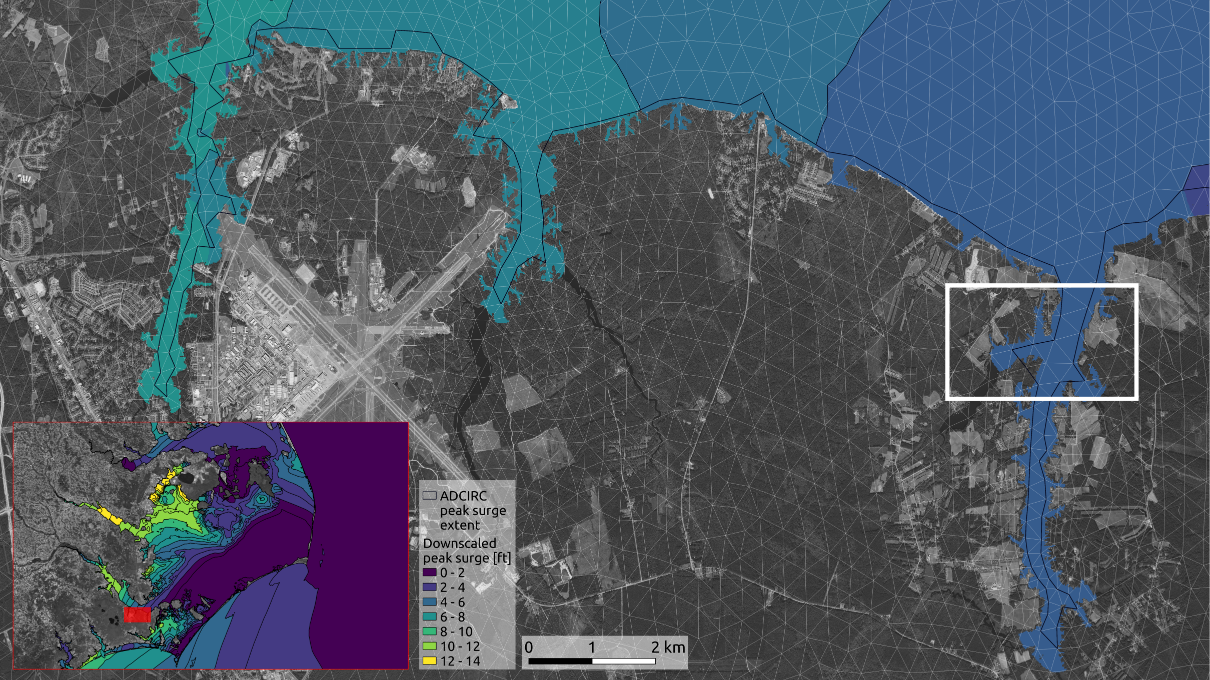
Even the smallest elements can be large compared to coastal infrastructure

- Use a geospatial post-processor to downscale to the ground surface in the DEM



Rucker (2021)


ADCIRC peak surge extent
Downscaled peak surge [ft]
0 - 2
2 - 4
4 - 6
6 - 8
8 - 10
10 - 12
12 - 14
0
1
2 km


ADCIRC
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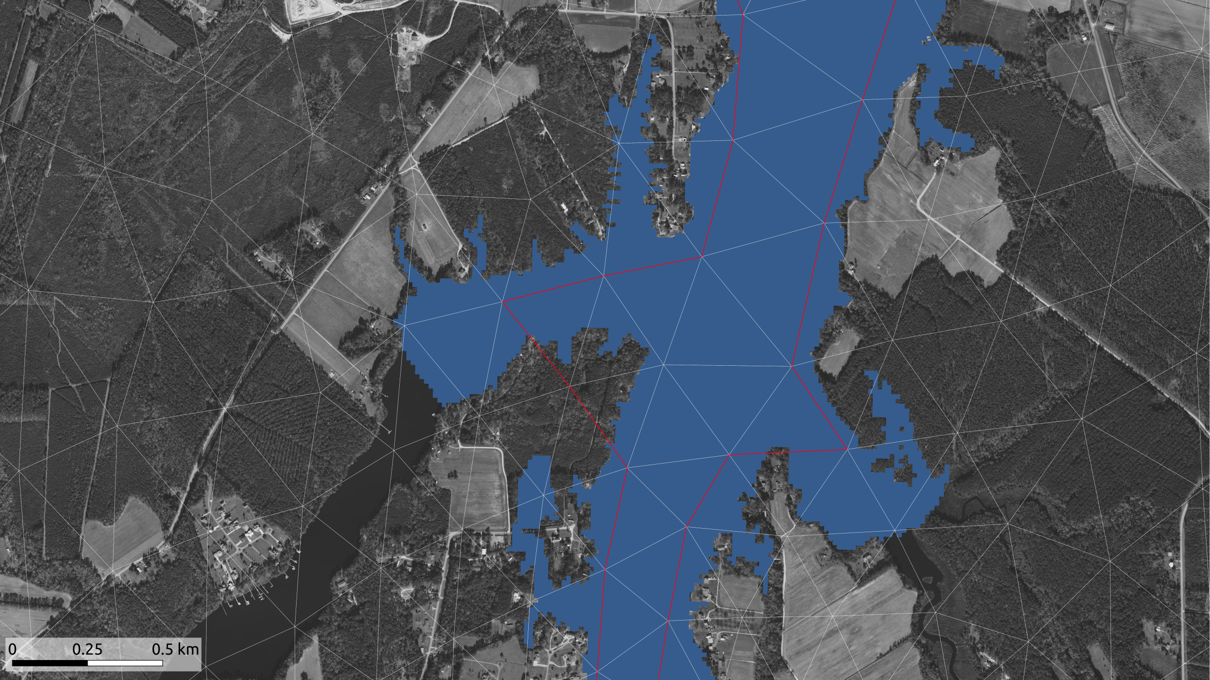
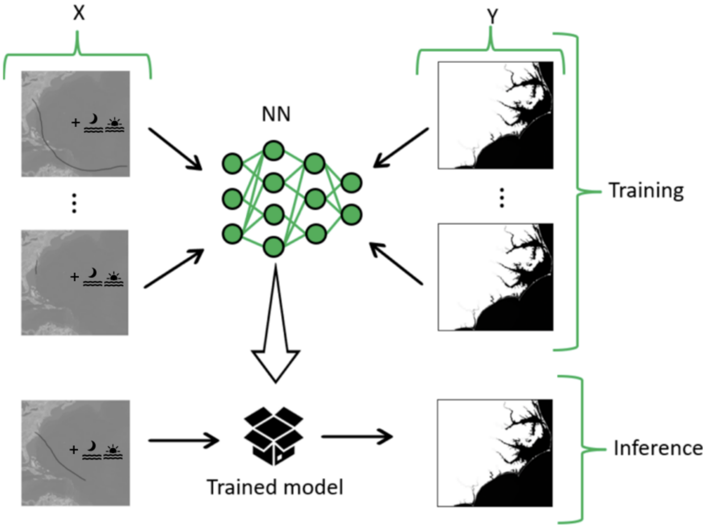

0
0.25
0.5 km

We can generate downscaled flood maps as rasters (grayscale images) ...

… so can we leverage machine learning techniques that are aimed at images?



Recent studies have predicted only at specific locations along the coast ...

Multi-Output Artificial Neural Network for Storm Surge Prediction in North Carolina

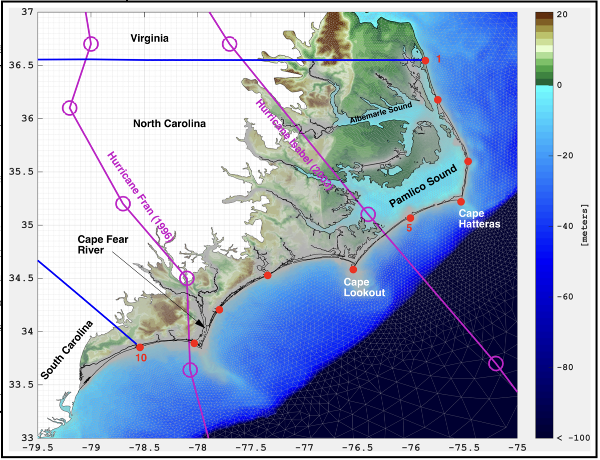
Anton Bezuglov[a,*], Brian Blanton[b], Reinaldo Santiago[a]

[a]*Math and Computer Science Dept, Benedict College, 1600 Harden St., Columbia, SC, 2*
[b]*Renaissance Computing Institute, The University of North Carolina at Chapel Hill, 100 Europa Dr.,*
27517

Abstract

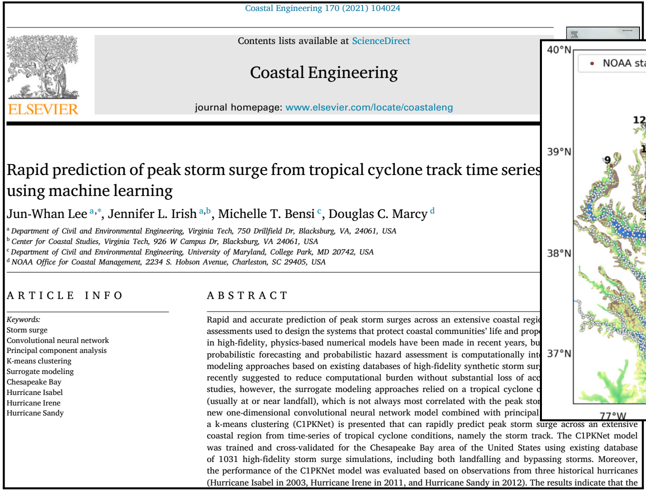
During hurricane seasons, emergency managers and other decision makers need accura
information on potential storm surge impacts. Fully dynamical computer models, such
tide, storm surge, and wind-wave model take several hours to complete a forecast when c
spatial resolution. Additionally, statically meaningful ensembles of high-resolution mo
uncertainty estimation) cannot easily be computed in near real-time. This paper disc
neural network model for storm surge prediction in North Carolina. The network mo
real-time storm surge estimates at coastal locations in North Carolina. The paper studies
of the neural network model vs. other models on synthetic and real hurricane data.

Keywords: feedforward artificial neural network, storm surge, hurricane, regression



Recent Studies and Motivation

... or predict only at specific locations along the coast ...



Coastal Engineering 170 (2021) 104024

Contents lists available at ScienceDirect

Coastal Engineering

journal homepage: www.elsevier.com/locate/coastaleng

ELSEVIER

Rapid prediction of peak storm surge from tropical cyclone track time series using machine learning

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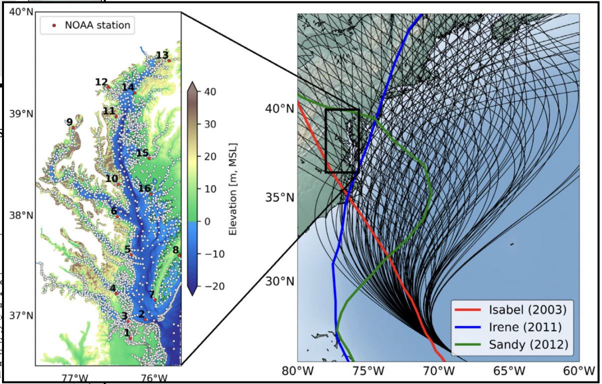
ARTICLE INFO

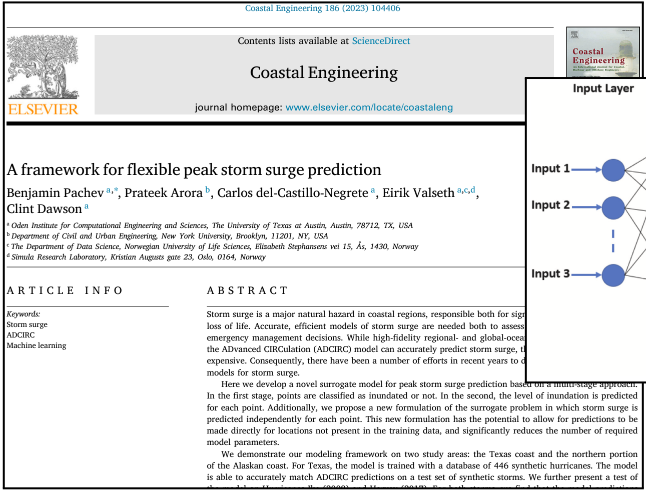
Keywords:
Storm surge
Convolutional neural network
Principal component analysis
K-means clustering
Surrogate modeling
Chesapeake Bay
Hurricane Isabel
Hurricane Irene
Hurricane Sandy

ABSTRACT

Rapid and accurate prediction of peak storm surges across an extensive coastal regi
assessments used to design the systems that protect coastal communities' life and prop
in high-fidelity, physics-based numerical models have been made in recent years, bu
probabilistic forecasting and probabilistic hazard assessment is computationally int
modeling approaches based on existing databases of high-fidelity synthetic storm sur
recently suggested to reduce computational burden without substantial loss of acc
studies, however, the surrogate modeling approaches relied on a tropical cyclone c
(usually at or near landfall), which is not always most correlated with the peak stor
new one-dimensional convolutional neural network model combined with principal
a k-means clustering (C1PKNet) is presented that can rapidly predict peak storm surge across an extensive coastal region from time-series of tropical cyclone conditions, namely the storm track. The C1PKNet model was trained and cross-validated for the Chesapeake Bay area of the United States using existing database of 1031 high-fidelity storm surge simulations, including both landfalling and bypassing storms. Moreover, the performance of the C1PKNet model was evaluated based on observations from three historical hurricanes (Hurricane Isabel in 2003, Hurricane Irene in 2011, and Hurricane Sandy in 2012). The results indicate that the



… or predict without using all of the geospatial connectivity



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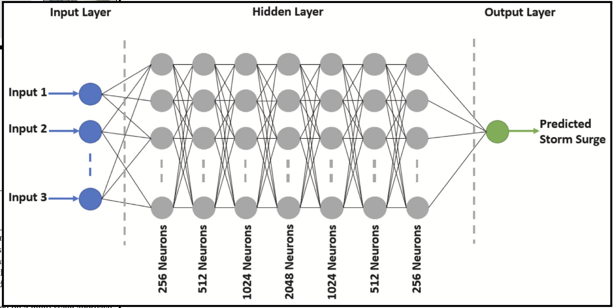

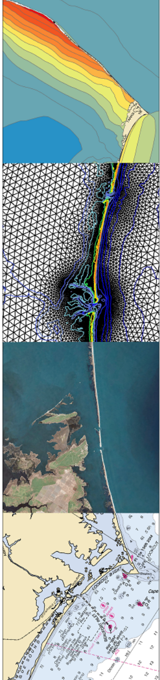

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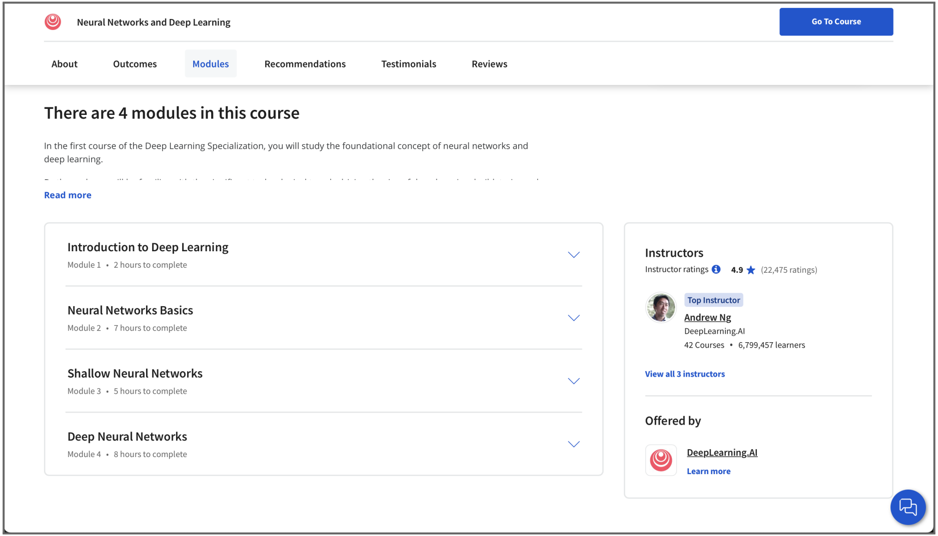
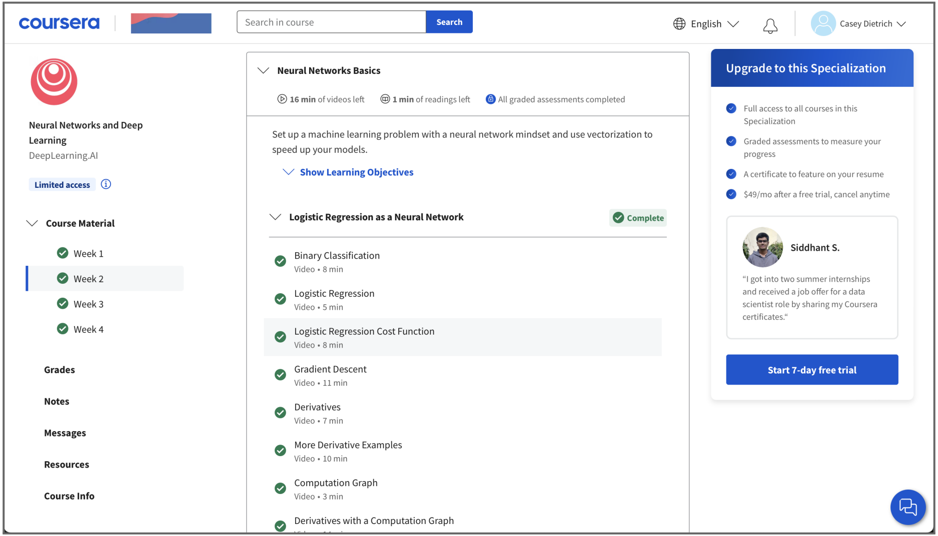
Structure and Content

… and each course has 3-5 modules …



Structure and Content

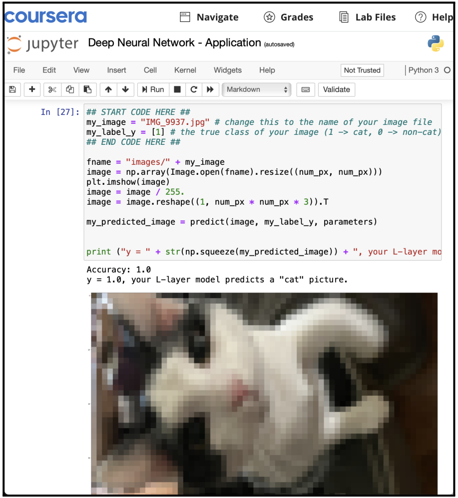
… and each module has videos, a quiz, and 1-2 programming assignments



Structure and Content

I earned certificates!

Fun assignments included a cat identifier ...



… creating art in the style of Impressionists …

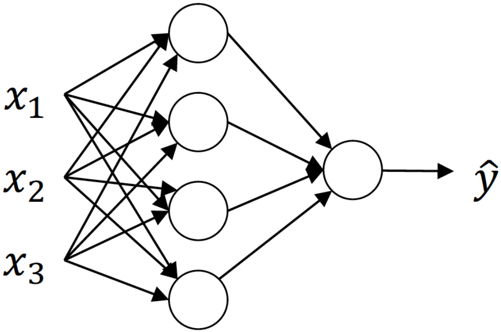
… writing poetry in the style of Shakespeare …

In [61]:
```
# Run this cell to try with different inputs without having to re-train the model
generate_output()
```

```
Write the beginning of your poem, the Shakespeare machine will complete it. Your input is: To be or not to be


Here is your poem:

To be or not to be,
co truth i gonling wheh more faip on shank,
that sicentangor edis manl's reclime a seem,
lowe's sreartunge thone thy sich thee be:
and do wo ad botily such adoudes anjeding state,
foo shime my heald of is why a todder, ling wascices lard.

the wistery eardss shomol unos nod his furell.
 :
cnaved buth in thy wist ountorted, thou to  memacpy:
so eactr winth to boreow miring fached,
though you so w
```

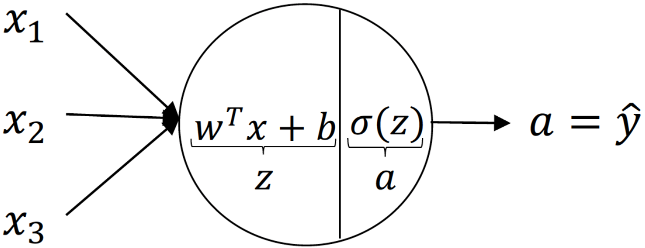
… and generating music in the style of Jazz

Neural networks are composed of one or more layers ...



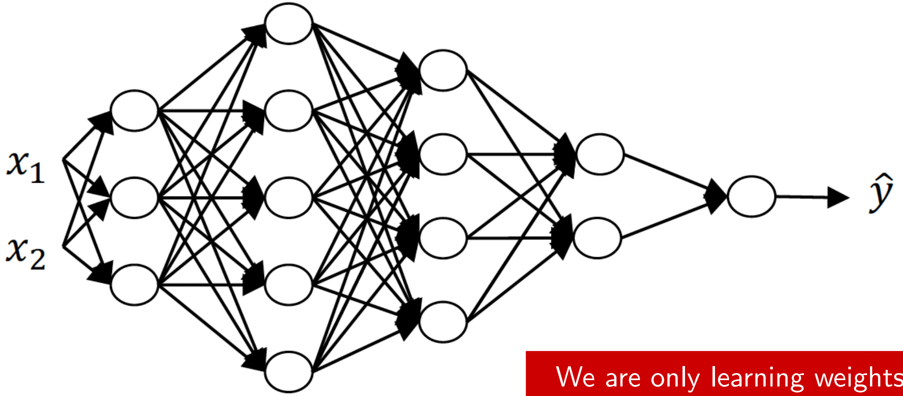
Ng (2021)

… with each layer having matrix operations with learn-able parameters …



Ng (2021)

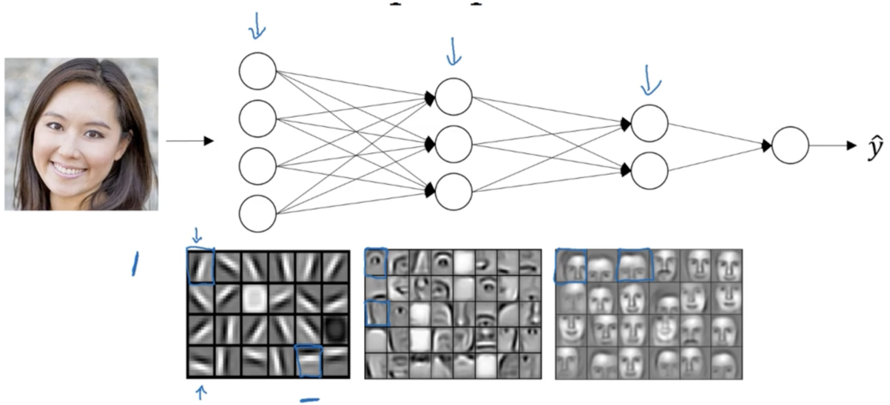
… so any complexity just adds more parameters to learn



We are only learning weights for matrix operations!

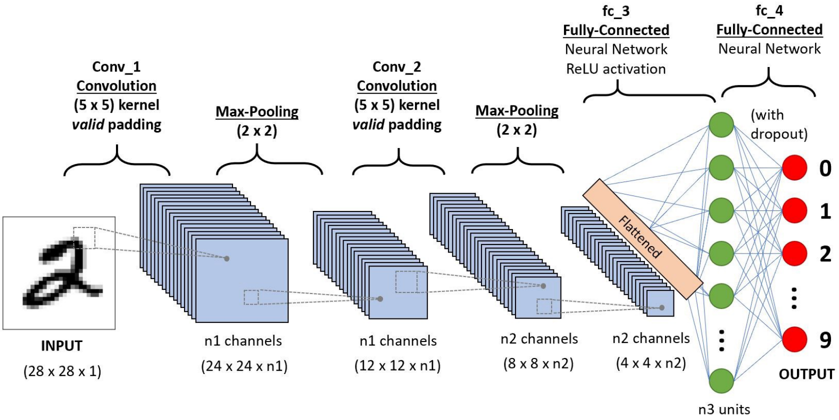
Ng (2021)

We can add convolutions to recognize spatial patterns in images ...



Ng (2021)

… and thus reduce an image to a small number of outputs



Ratan (2023)

Deterministic Models for Coastal Flooding

- ADCIRC & Kalpana
- Recent Studies and Motivation

Deep Learning Specialization on Coursera

- Structure and Content
- Convolutional Neural Networks

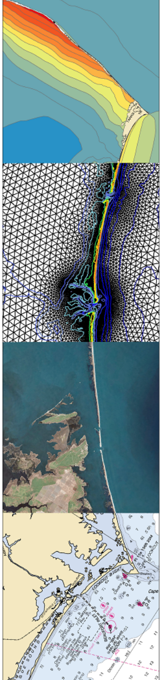
Proof of Concept

- Hurricane Irene (2011)
- Deep Neural Network

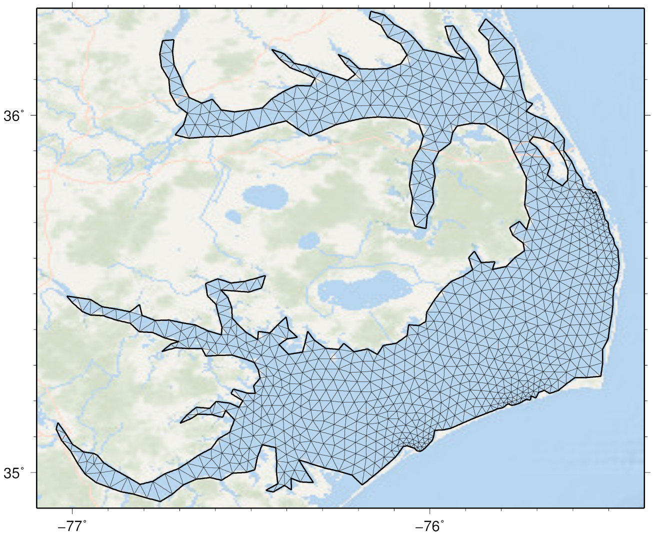
Current Research

- Library of Storm Simulations
- Preliminary Results

Conclusions and Future Work



Start with a coarse model for the NC estuaries/sounds ...



… and use a simple vortex model to represent the storm …

Parametric vortex model from Holland (1980) and modified by Gao (2018):

$$V(r) = \sqrt{V_{\max}^2 \left(1 + 1/R_o\right) e^{\psi\left(1-\left(R_{\max}/r\right)^B\right)} \left(R_{\max}/r\right)^B + \left(rf/2\right)^2} - \left(rf/2\right)$$

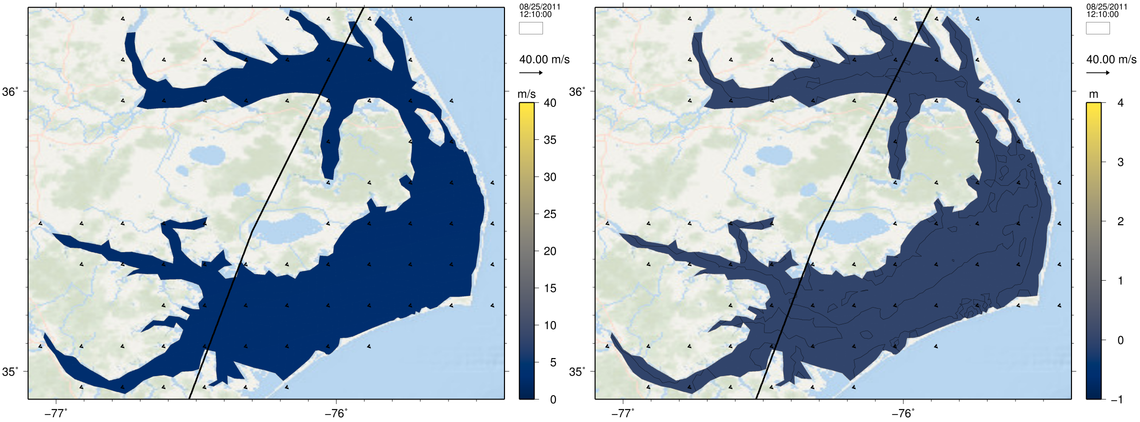
in which:

- $V_{\max}$ and $R_{\max}$ are the maximum wind speed and the radius to it
- R_o is the Rossby number (ratio of nonlinear and Coriolis accelerations)
- f is the Coriolis parameter (function of latitude)
- ψ and B are scaling factors

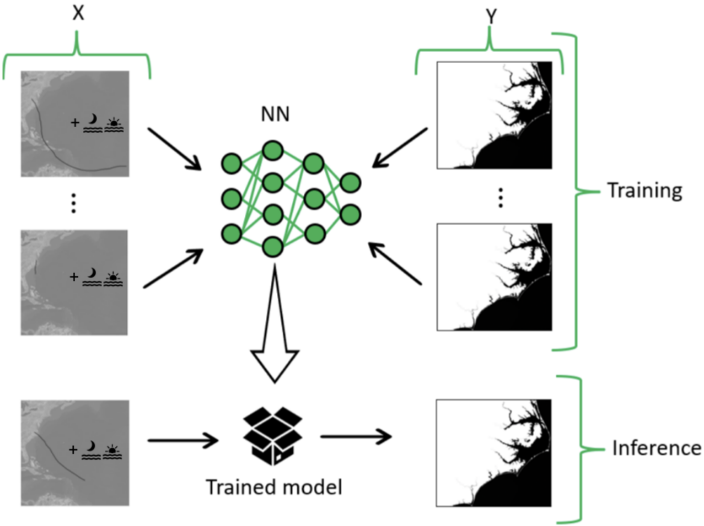
Holland (1980); Gao (2018)

Hurricane Irene (2011)

… and compute its effects on winds and water levels …



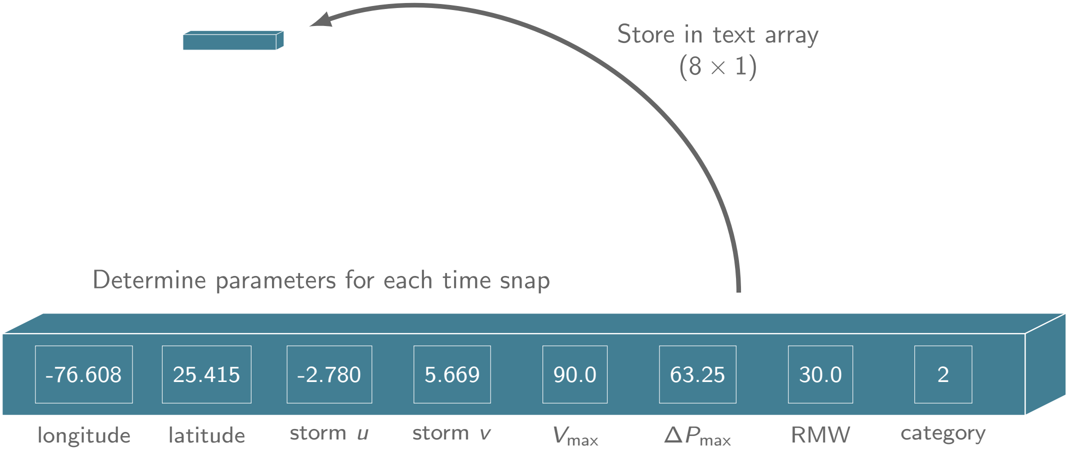
... so can we also use the storm parameters to predict with a deep neural network?



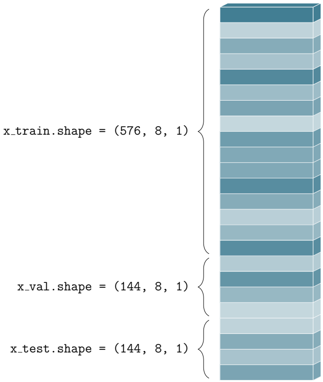
For the inputs, we can use available information about the storm ...

AL	09	2011082512		BEST	0	254N	766W	90	950		34	NEQ	250	200	100
AL	09	2011082512		BEST	0	254N	766W	90	950		50	NEQ	100	100	50
AL	09	2011082512		BEST	0	254N	766W	90	950		64	NEQ	60	60	25
AL	09	2011082518		BEST	6	265N	772W	90	950		34	NEQ	250	200	125
AL	09	2011082518		BEST	6	265N	772W	90	950		50	NEQ	110	100	50
AL	09	2011082518		BEST	6	265N	772W	90	950		64	NEQ	70	60	25
AL	09	2011082600		BEST	12	277N	773W	90	946		34	NEQ	250	200	125
AL	09	2011082600		BEST	12	277N	773W	90	946		50	NEQ	110	100	50
AL	09	2011082600		BEST	12	277N	773W	90	946		64	NEQ	70	60	25
AL	09	2011082606		BEST	18	288N	773W	90	942		34	NEQ	250	200	130
AL	09	2011082606		BEST	18	288N	773W	90	942		50	NEQ	125	105	75
AL	09	2011082606		BEST	18	288N	773W	90	942		64	NEQ	80	80	50
AL	09	2011082612		BEST	24	300N	774W	85	947		34	NEQ	250	200	130
AL	09	2011082612		BEST	24	300N	774W	85	947		50	NEQ	125	105	75
AL	09	2011082612		BEST	24	300N	774W	85	947		64	NEQ	80	80	50
AL	09	2011082618		BEST	30	311N	775W	80	950		34	NEQ	250	225	140
AL	09	2011082618		BEST	30	311N	775W	80	950		50	NEQ	125	125	80
AL	09	2011082618		BEST	30	311N	775W	80	950		64	NEQ	80	80	50
AL	09	2011082700		BEST	36	321N	771W	75	952		34	NEQ	225	225	140
AL	09	2011082700		BEST	36	321N	771W	75	952		50	NEQ	125	125	90
AL	09	2011082700		BEST	36	321N	771W	75	952		64	NEQ	80	80	40
AL	09	2011082706		BEST	42	334N	768W	75	952		34	NEQ	225	225	140
AL	09	2011082706		BEST	42	334N	768W	75	952		50	NEQ	125	125	90
AL	09	2011082706		BEST	42	334N	768W	75	952		64	NEQ	80	80	40

… to develop the inputs (storm parameters) …

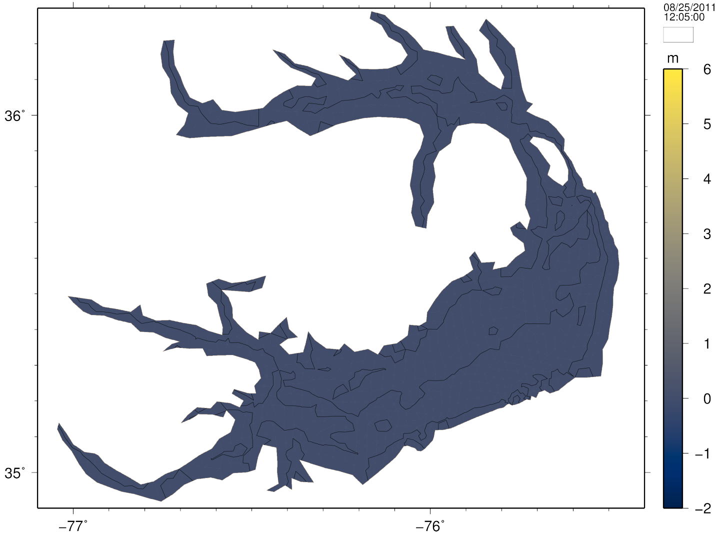


… and randomize the time snaps



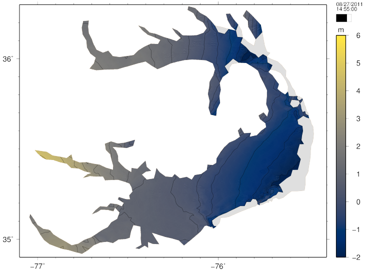
Deep Neural Network

For the outputs, we want to predict maps of water levels during the storm ...

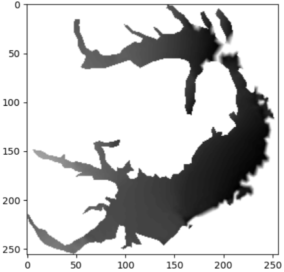


… so we convert each map to a grayscale image …

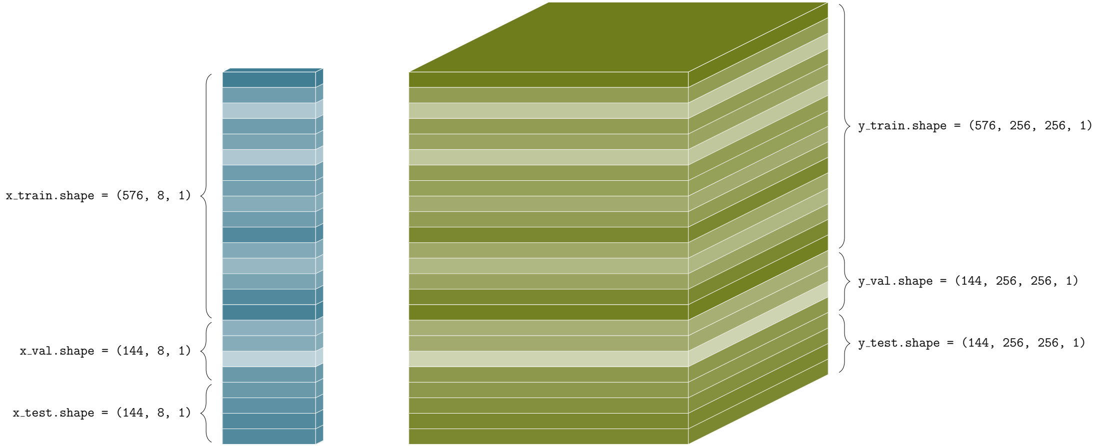
Store in text array
$(256 \times 256 \times 1)$



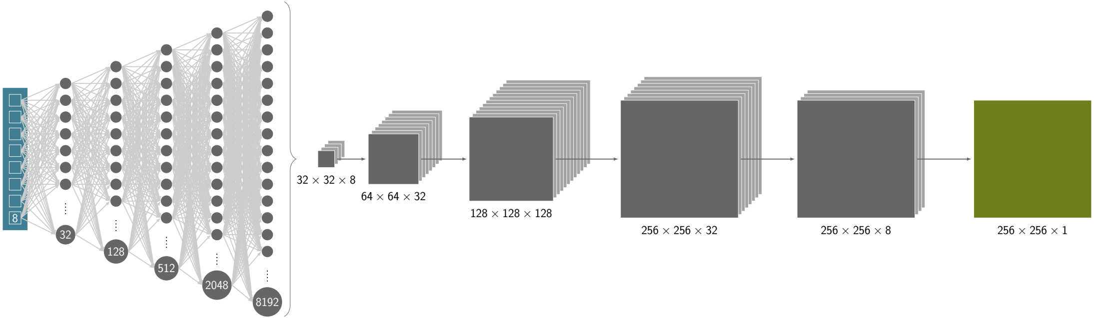
Convert to grayscale image
(water levels = 0–200;
dry pixels = 255)



… and then combine the inputs (storm parameters) and outputs (water-level maps)



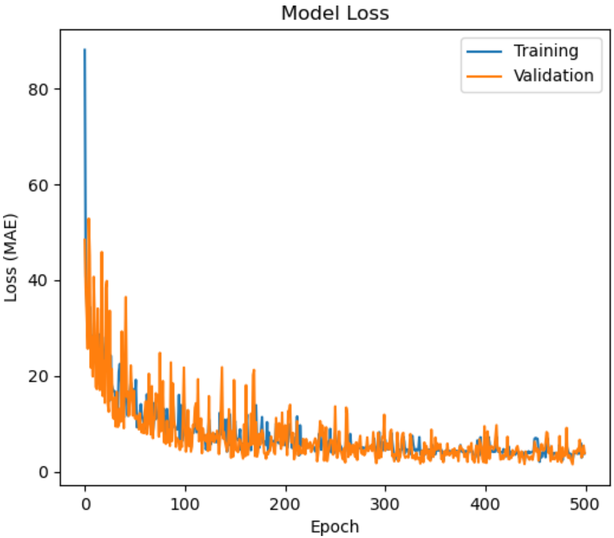
Use a network with fully connected and reverse convolution layers ...



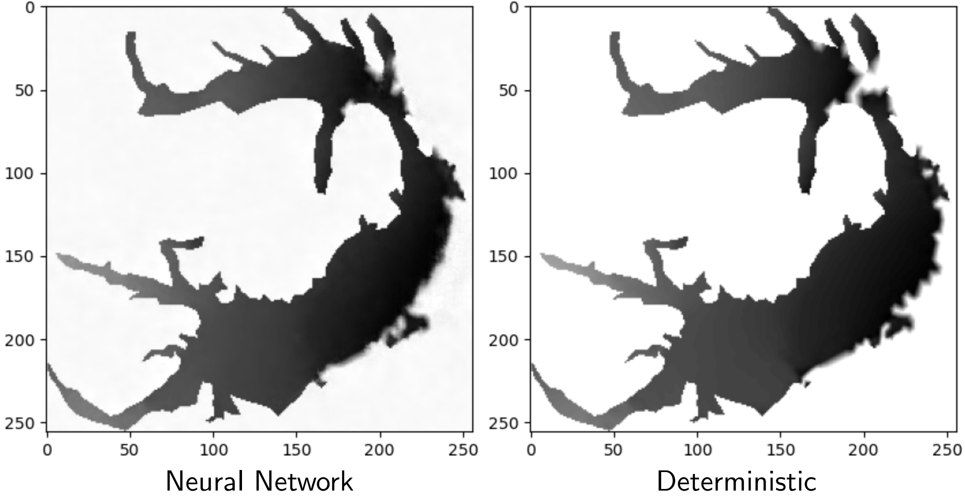
Trainable parameters: 18,326,865

Deep Neural Network

… and train it

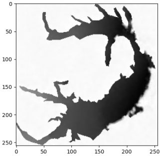


Predicted flood maps are good overall ...



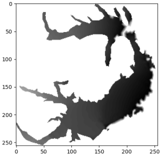
Deep Neural Network

… but have errors near the wet/dry front



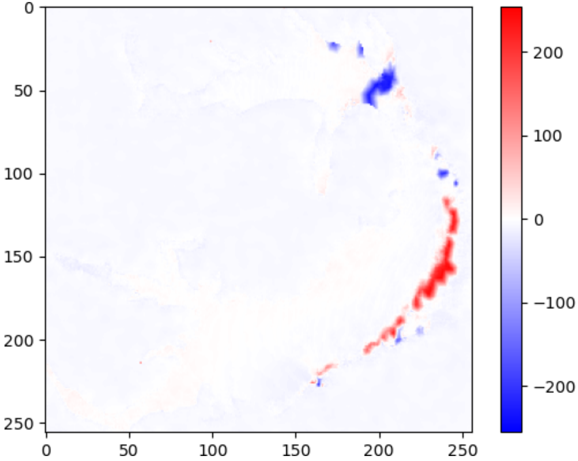
Neural Network

−



Deterministic

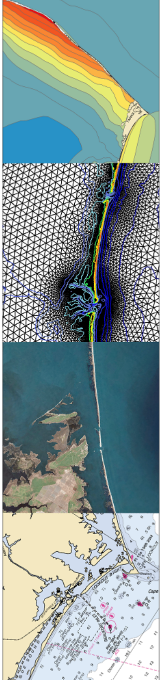
=



Differences

Mean error $= 0.09$ m

Median error $= -0.04$ m



Prediction of High-Resolution Maps of Storm-Driven Coastal Flooding using Deep Learning

TA Cuevas López[1], BJ Tucker[1], JC Dietrich[1], DL Anderson[2]

[1]Dep't of Civil, Construction, and Environmental Engineering, NC State Univ
[2]Coastal and Hydraulics Lab, U.S. Army Engineer Research and Development Center

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Gobierno de Chile

We have spent most of our time in developing a training library

Step 1

Data Collection

- Dataset of synthetic tropical cyclones
- Select impactful tracks

Step 2

Flood Map Library

- Deterministic simulations
- Downscaling to grayscale raster images

Step 3

Deep Learning

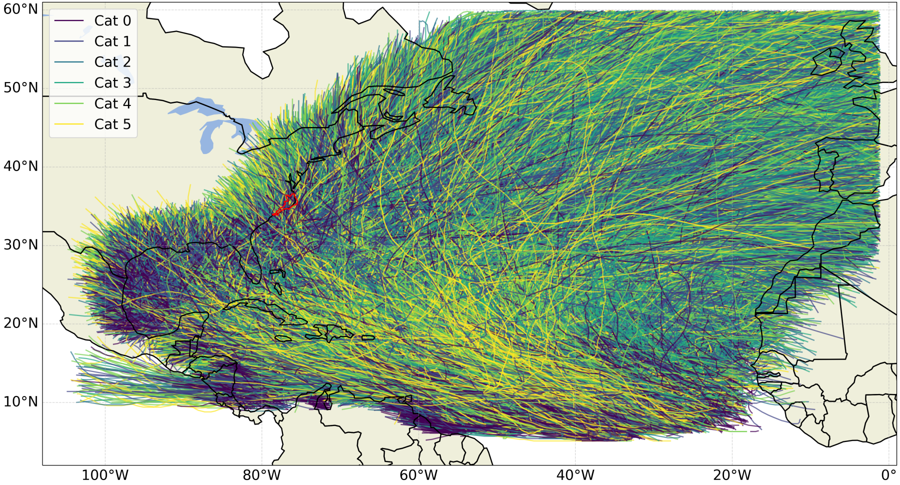
- Sequential and convolutional layers
- Train / test / validate

Step 4

Final Validation

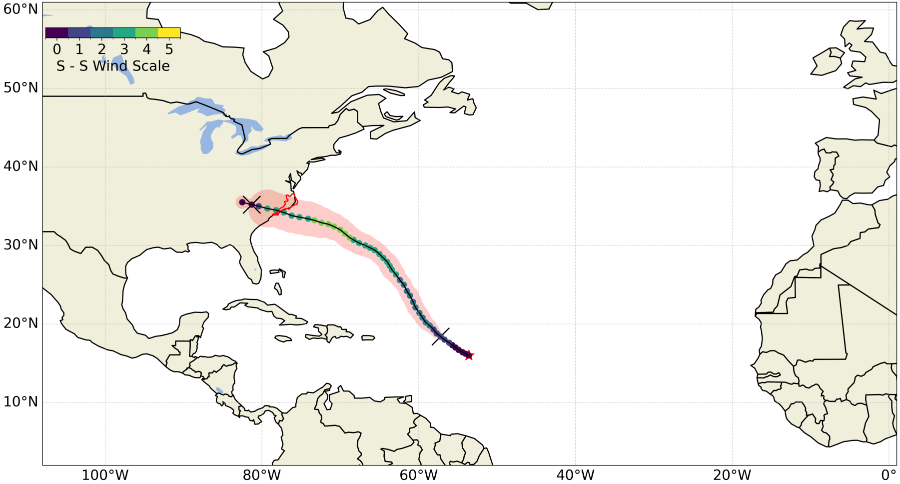
- Compare neural network to deterministic hindcasts

Start with a database of 100,000 synthetic storms ...



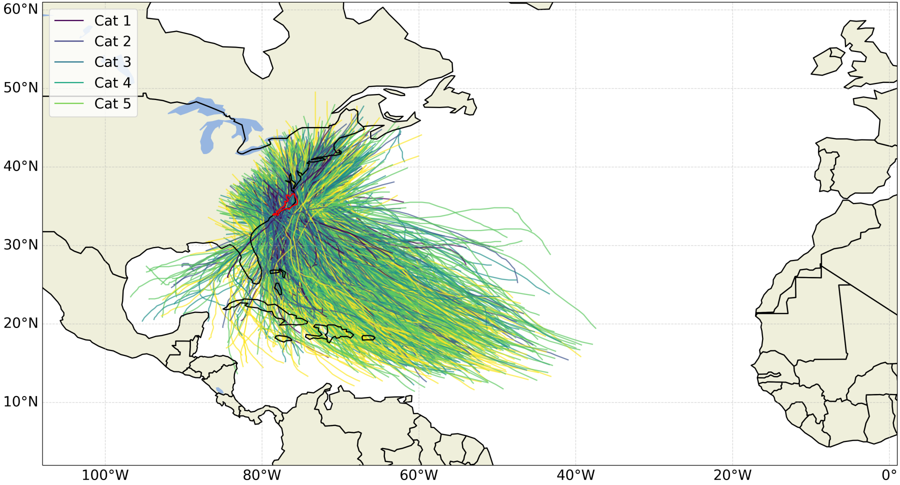
Bloemendaal (2020)

… for each storm, define an area of influence …

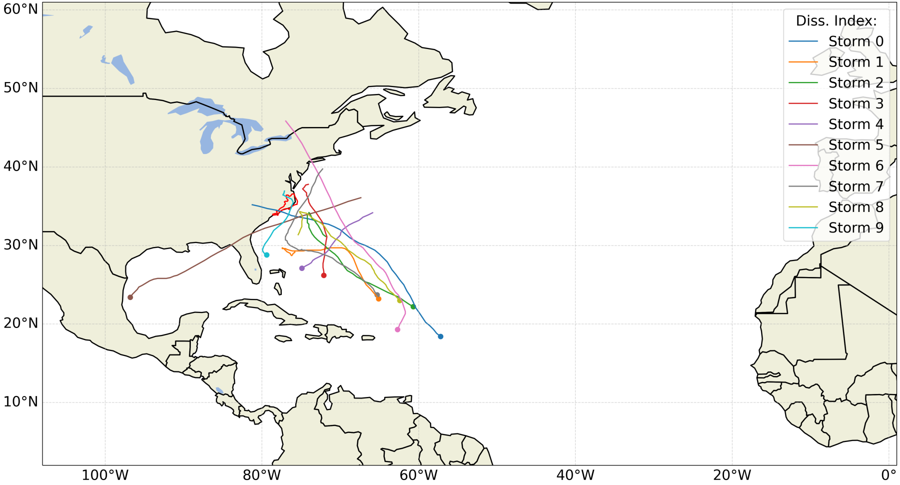


Holland (1980)

… identify the 1813 storms that influence North Carolina …



… and rank the storms by dissimilarity



Camus (2011)

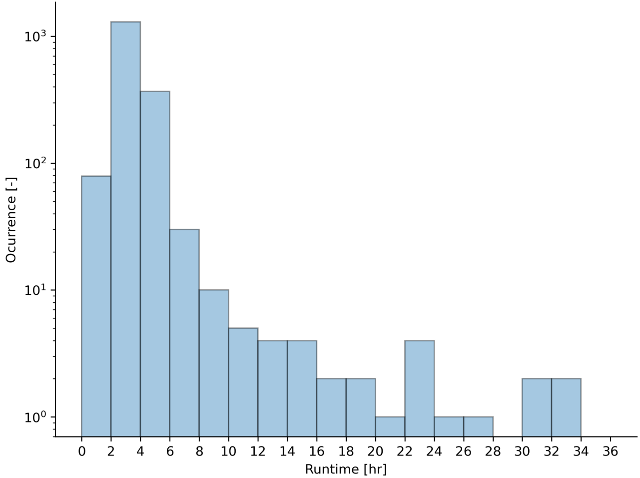
These storm simulations were a LOT of work

HPC systems:

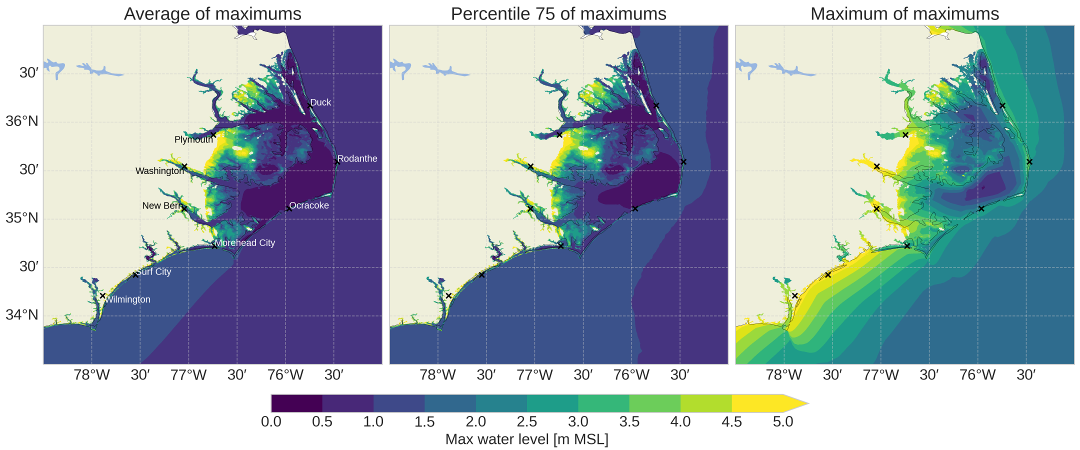
- NCSU Hazel
- Purdue Anvil
- TACC Stampede 2

Simulation stats:

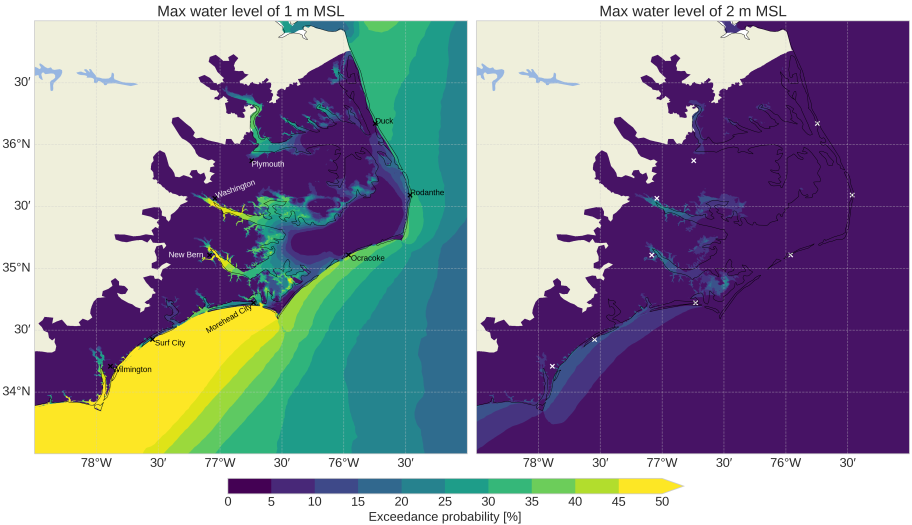
- Total of **1813 storms**
- **1.3M** CPU-hours
- Mean wall-clock time of **3.7 hr**
- **1.7T** of data



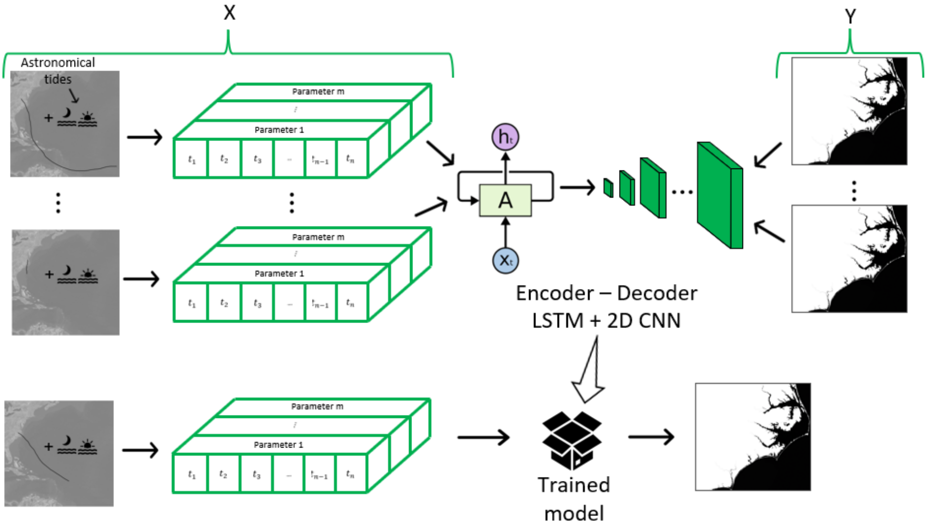
Simulations show the potential for large storm surges ...



… but the largest storm surges are unlikely

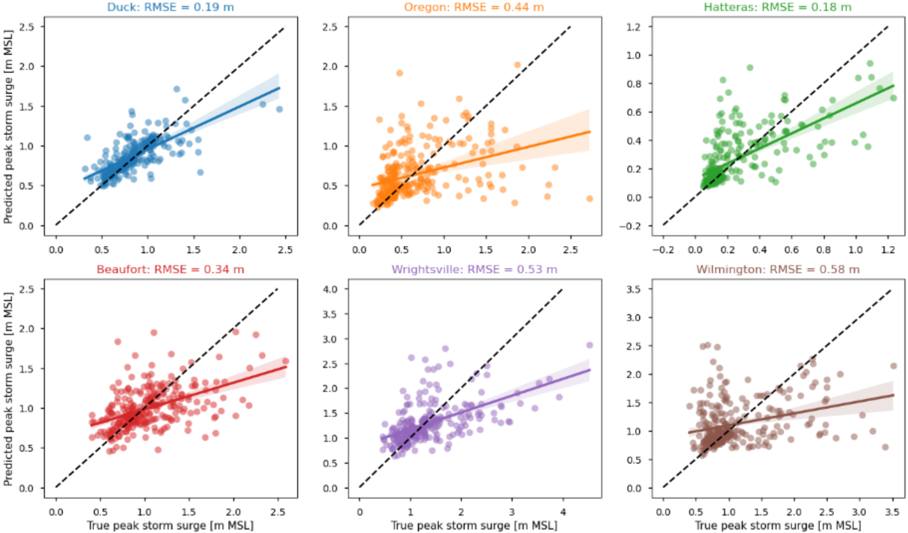


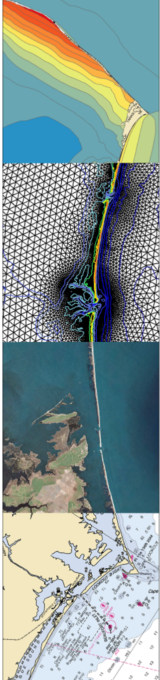
Tomás has designed a neural network with sequential and convolutional layers ...



Preliminary Results

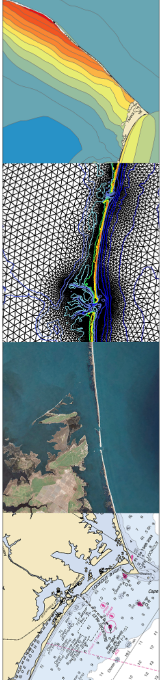
… and it is encouraging for predictions at single locations

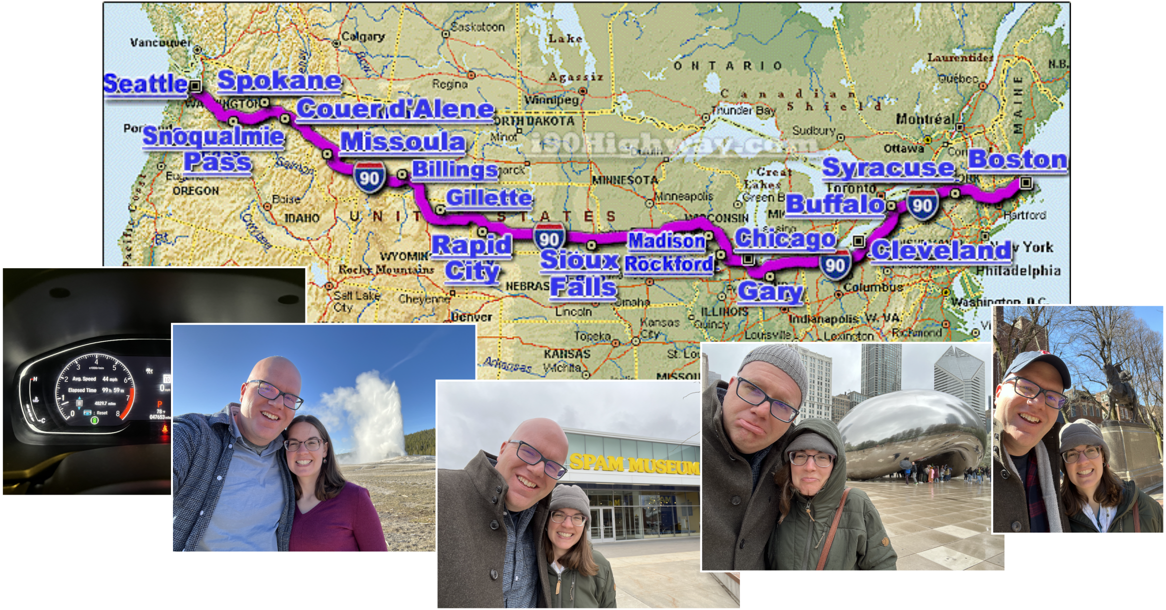




Machine learning models for coastal hazards predictions

1. Sabbaticals are fun!
2. Coursera can be a good introduction to a new topic
   - Still not an expert in machine learning (and never will be?)
   - But much more familiar with concepts and model development
3. **Promising preliminary results with deep neural networks**
   - Proof-of-concept shows we can predict grayscale raster maps
   - Now adding complexity in storms, resolution, network design
   - Ongoing work to improve performance
4. Must be extremely careful with training data
   - Synthetic storm simulations were a LOT of work
   - Compounds the challenges of deterministic models





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Richmond
ILLINOIS
Quincy
Kansas City
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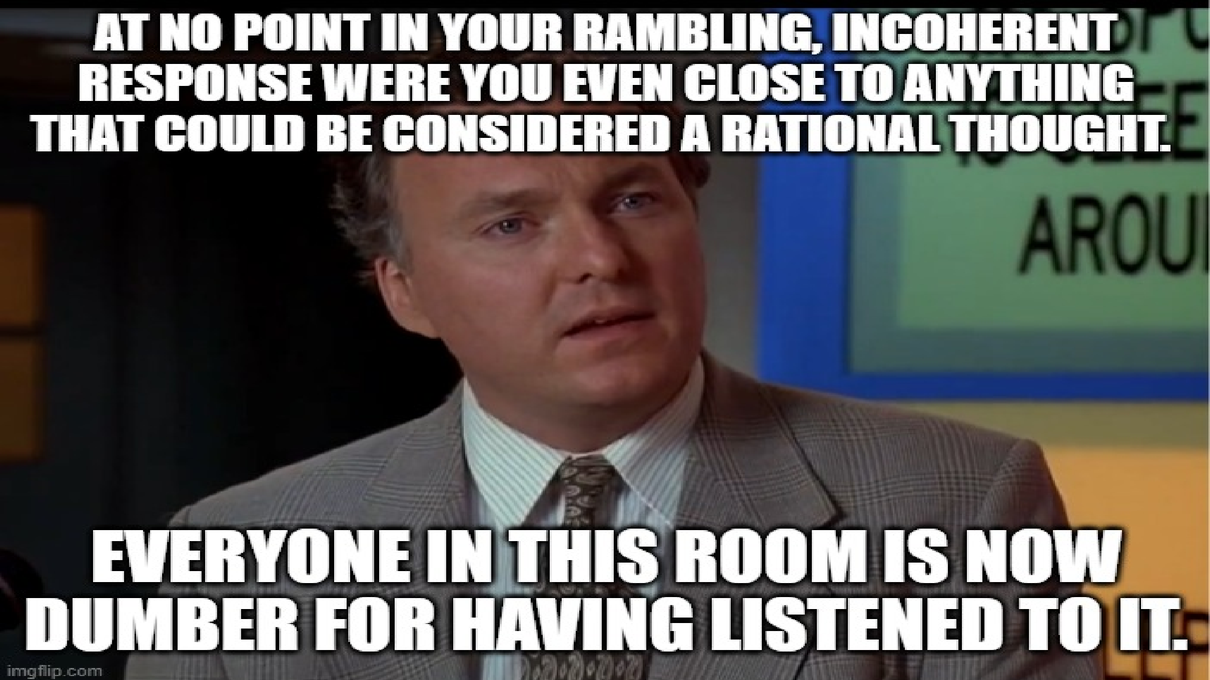
KANSAS
Wichita
Lincoln
Omaha
Avg. Speed 44 mph
Elapsed Time 99 h 59 m
4829.7 miles
SPAM MUSEUM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