Hurri-GAN: Bias Correction with Spatiotemporal Extrapolation using GenAI

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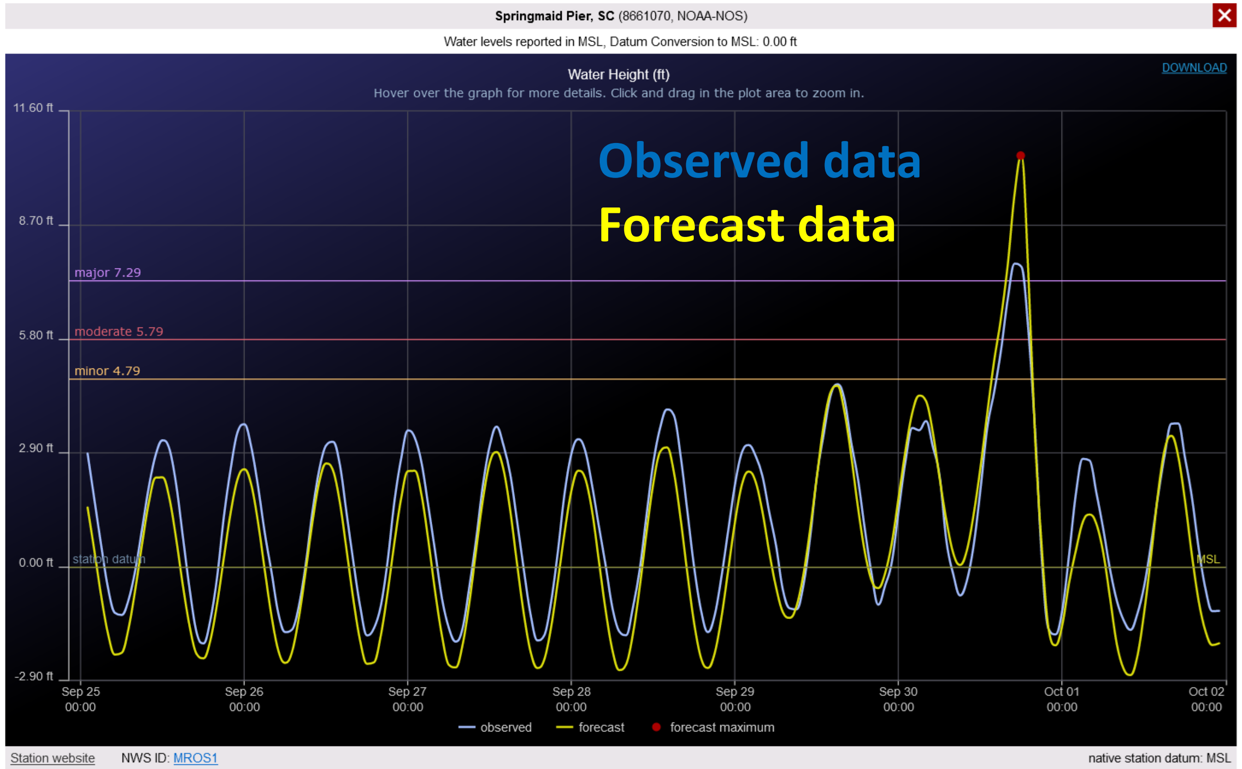
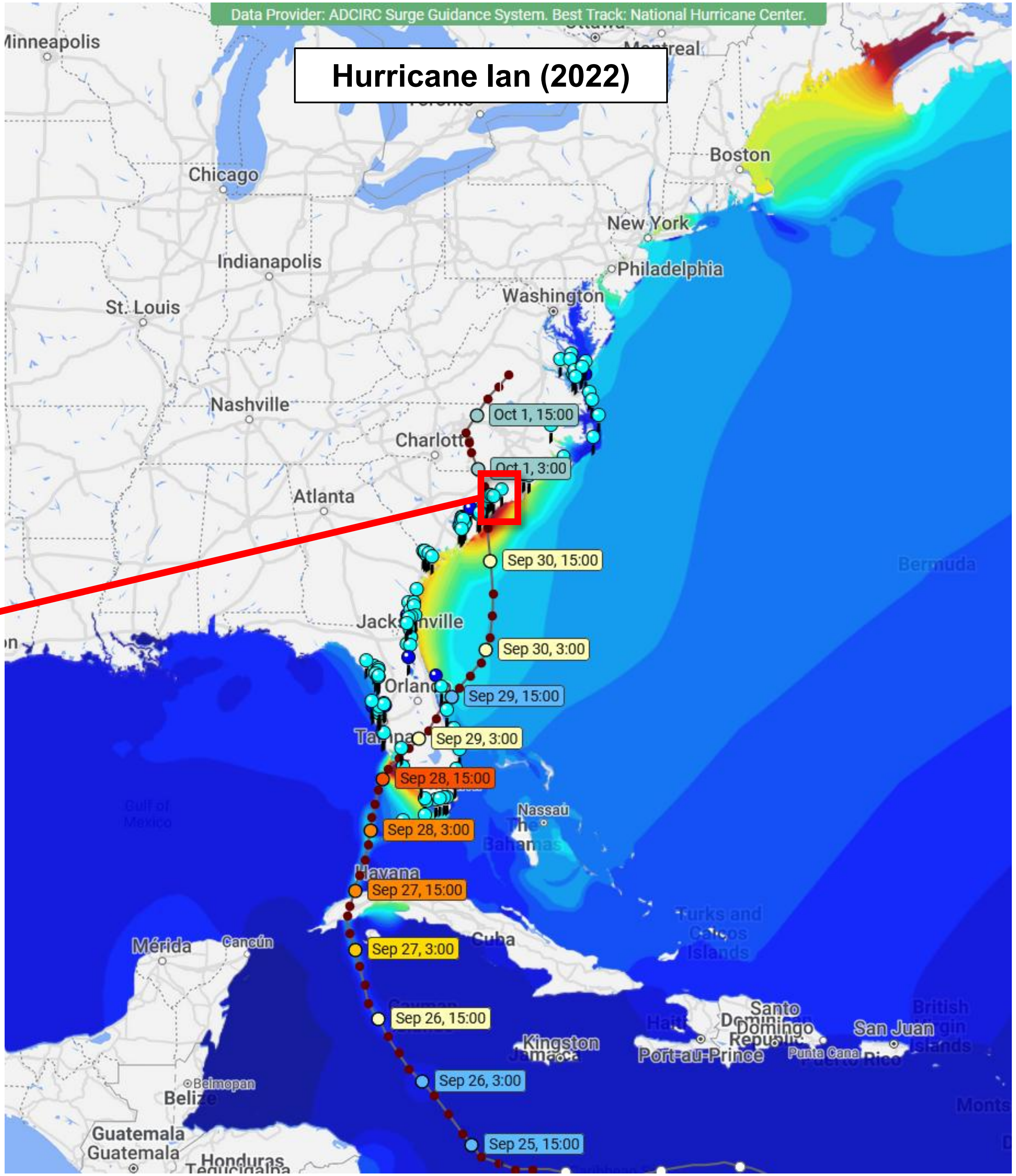
Coastal Emergency Risks Assessment
STORM SURGE – WIND – WAVE – FLOOD GUIDANCE

USJ 1875 Université Saint-Joseph de Beyrouth
ARISTOTLE UNIVERSITY OF THESSALONIKI
LSU Center for Computation & Technology
STE||AR GROUP

Background

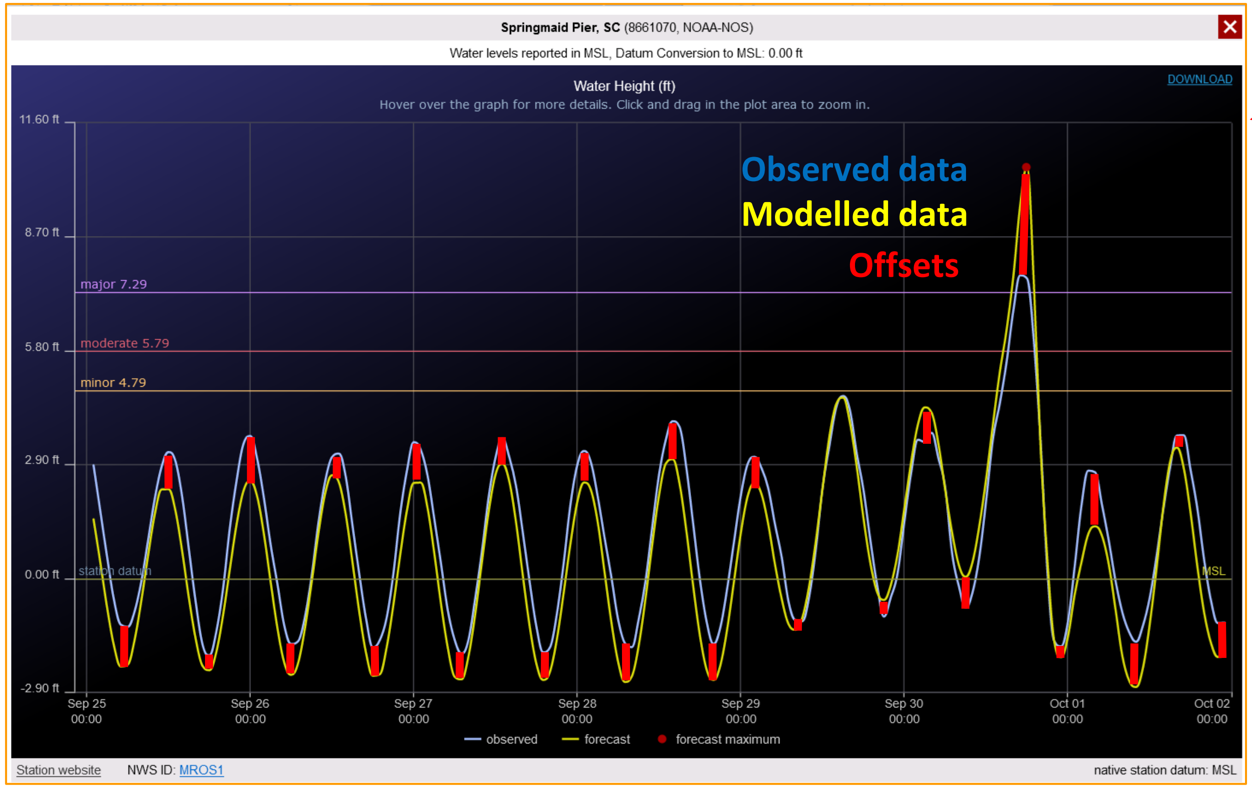
- **CERA website (cera.coastalrisk.live):** Real time measurements of water level, wind etc
- **Water level data:**
  - **Forecast data:** ADCIRC
  - **Observed data:** Gauge stations (USGS, NOAA etc.)

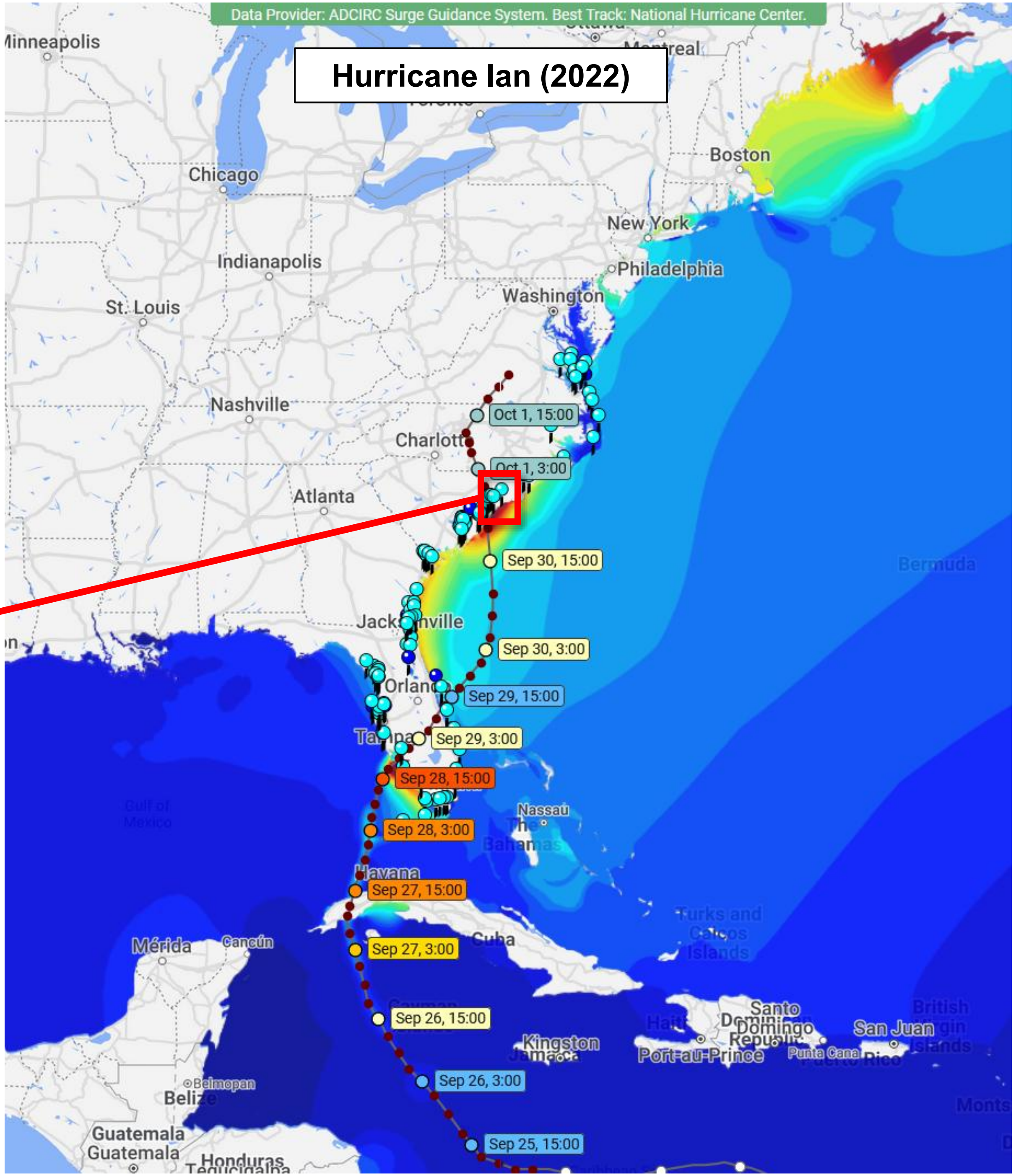




Background

Motivation: ML prediction of the **offsets** between **observed** and ADCIRC **forecast water height** for post-simulation mitigation of the systemic model errors during storms





Historical Storm Archive

historicalstorms.coastalrisk.live

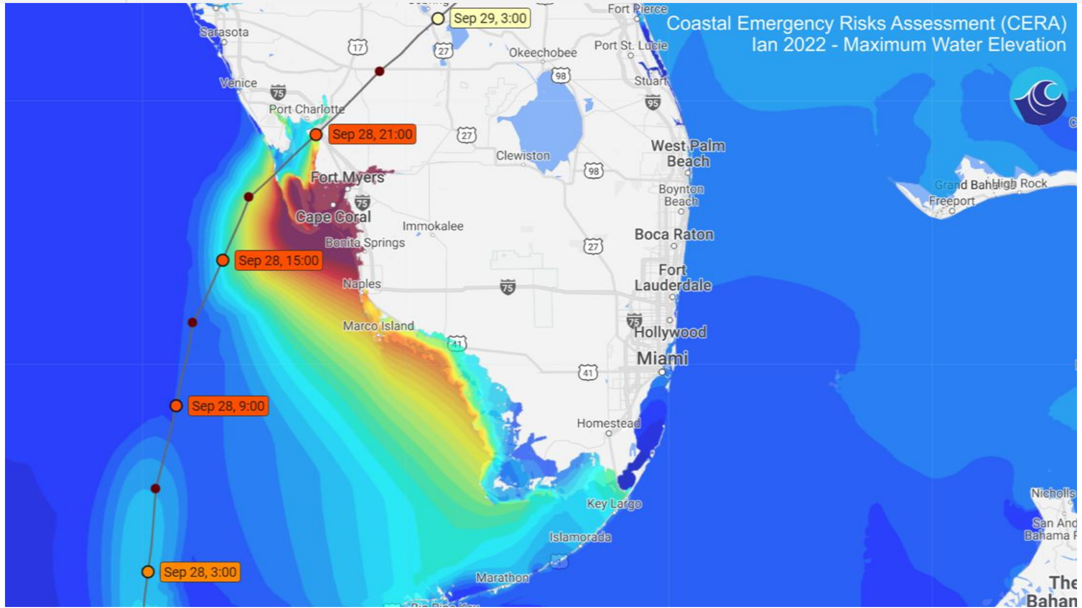
- User-friendly archive with water levels from 60+ **U.S. tropical storms** from the past 20 years, interfaced to the CERA website

Hurricane IAN 2022

Sep 25 2022 - Oct 2 2022

NHC Storm Number	09L
Number of Advisories:	38
Category:	H4
Highest Sustained Winds:	155 mph (250.0 km/h)
Lowest Pressure:	936 mbar (hPa)
Fatalities:	157
Damage:	50.2 billion (2022 USD)
Areas affected:	Cayman Islands • Cuba • U.S. West Florida, East Florida, Georgia, South Carolina

source: *Wikimedia*



C. Kaiser, C. Dawson, E. Nikidis, J. Fleming. (2023) "ADCIRC/SWAN Hindcasts for Historical Storms 2003-2022", in *CERA / ADCIRC Storm Surge Hindcasts: Historical Storms 2003-2022*. DesignSafe-CI. https://doi.org/10.17603/ds2-b5gh-ce94 v1

Background

Previous work:

- LSTM-based approach for bias correcting water levels in gauge stations
- Model trained on biases from observed and ADCIRC simulated historical storm water level data

ELSEVIER

Coastal Engineering

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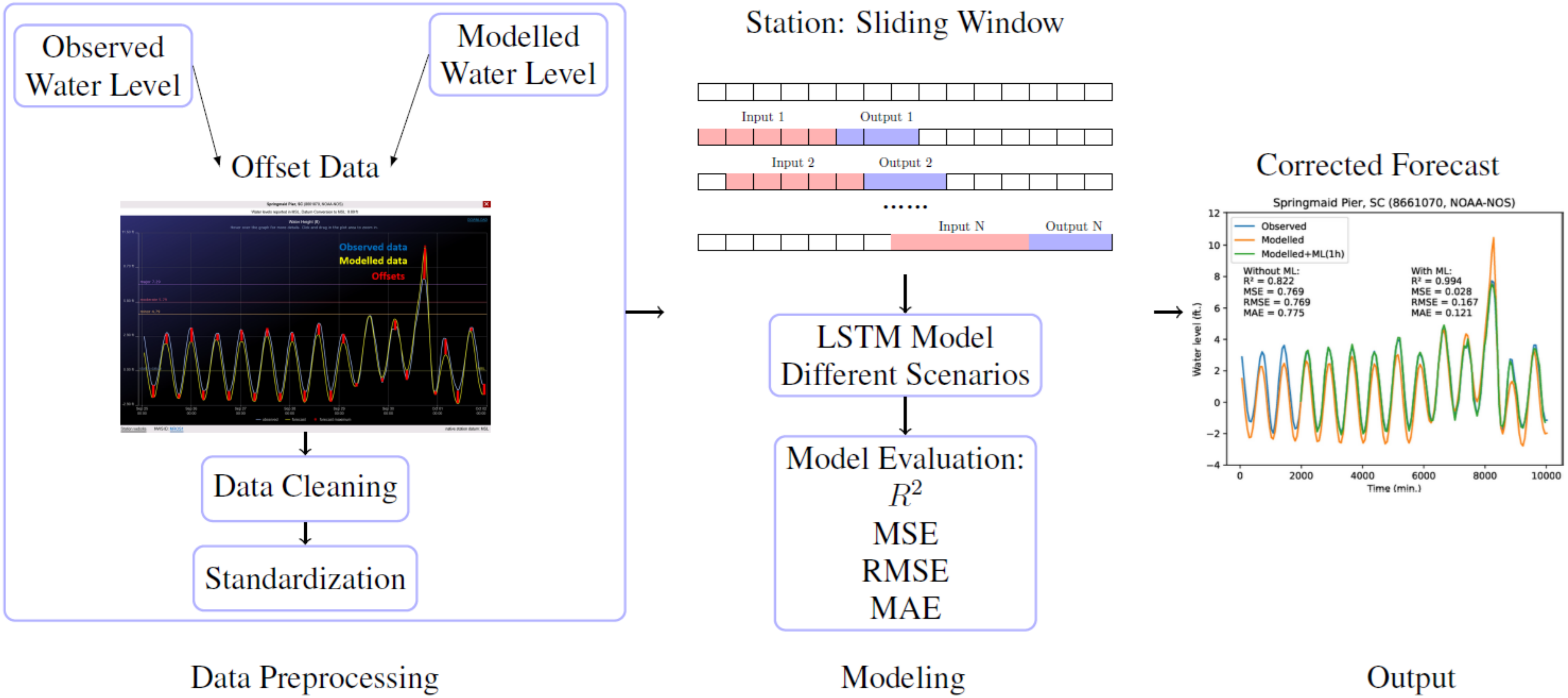
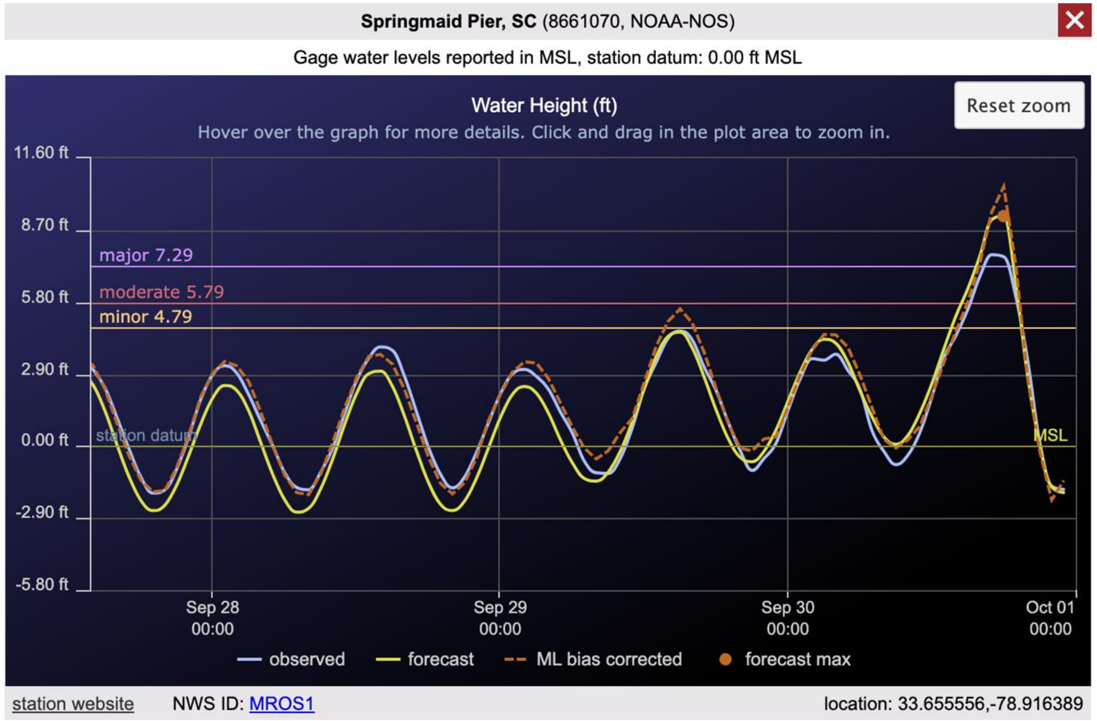
Storm surge modeling in the AI era: Using LSTM-based machine learning for enhancing forecasting accuracy

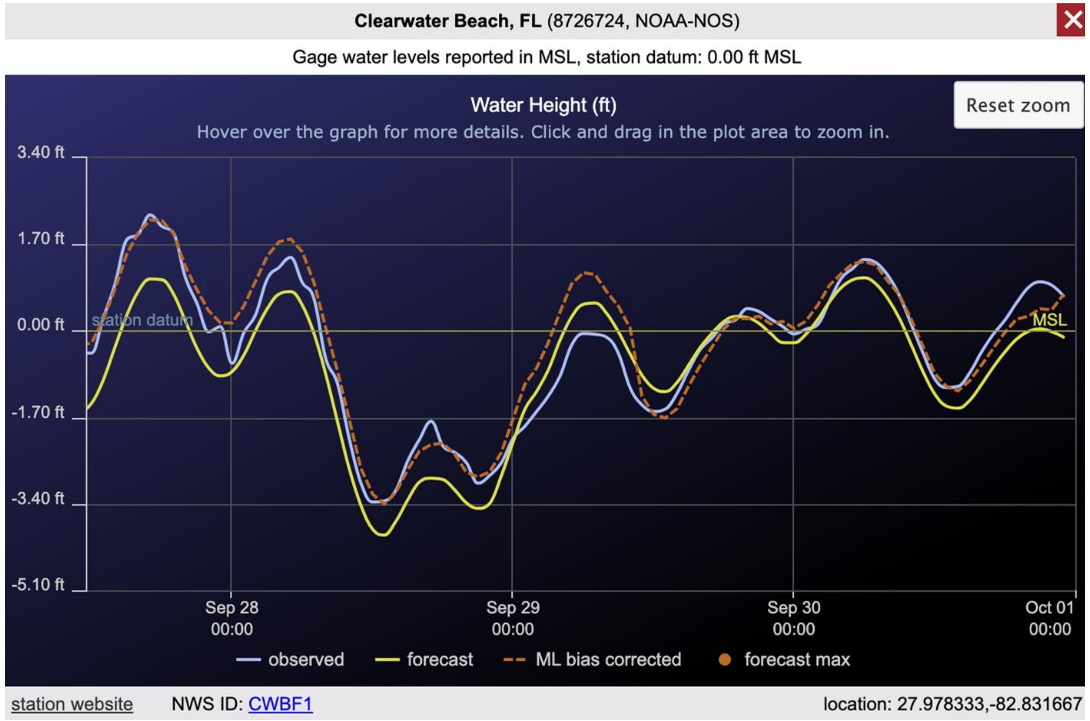
Stefanos Giaremis [a], Noujoud Nader [b], Clint Dawson [c], Carola Kaiser [b], Efstratios Nikidis [a], Hartmut Kaiser [b]



Background

CERA implementation:





(Hurricane Ian, 2022)

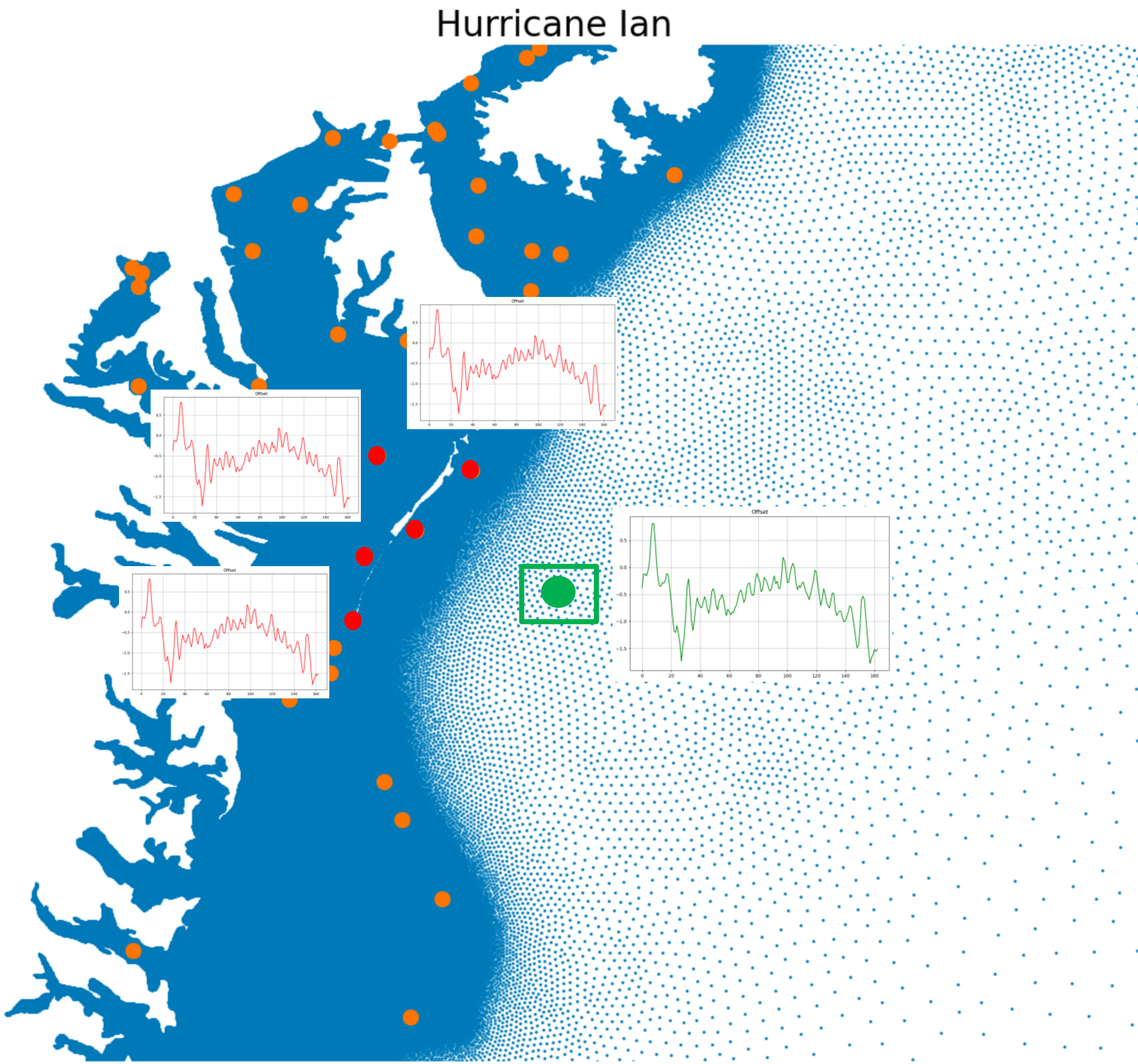
Scope

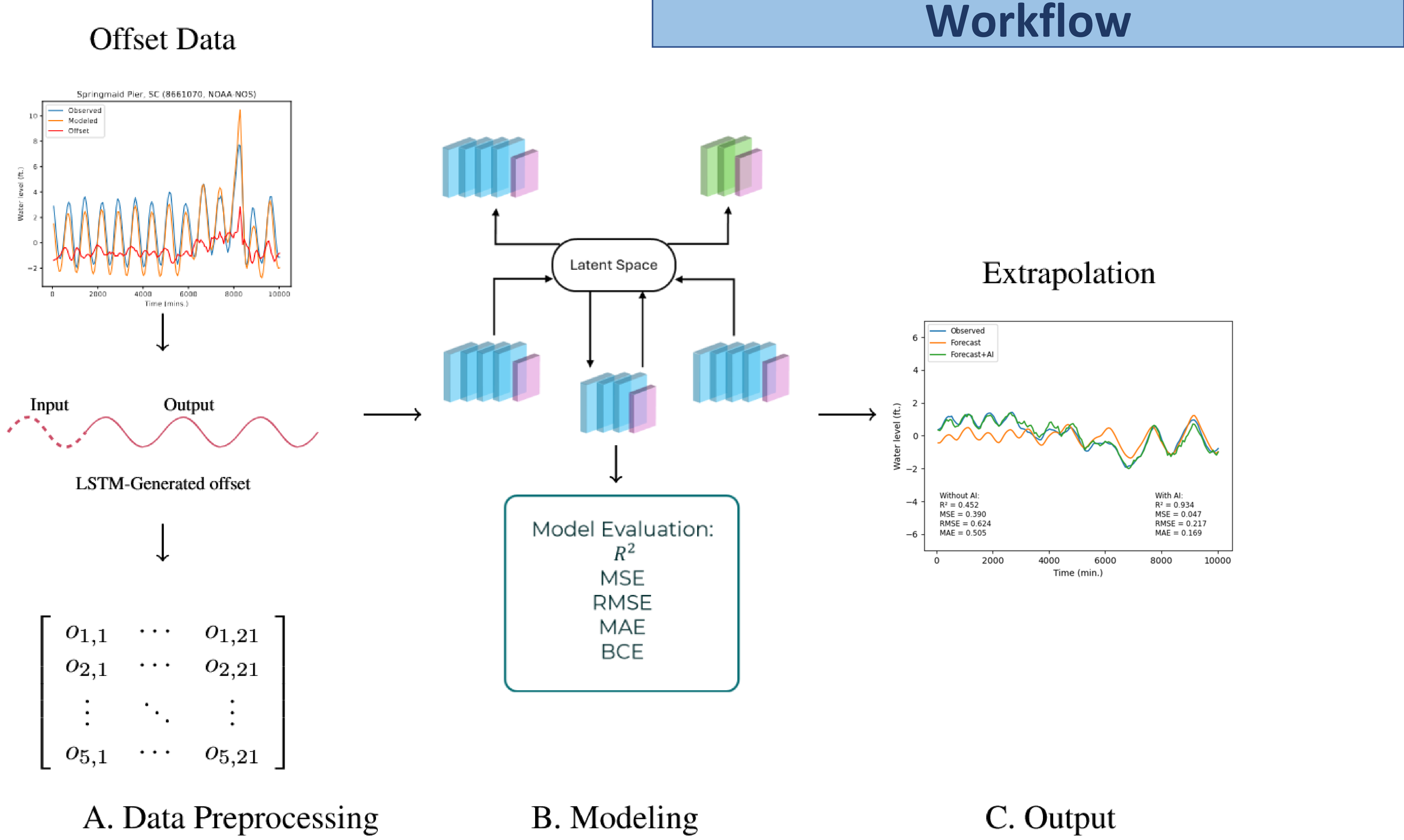
Generating extrapolated offsets beyond the gauge stations

→ Predict biases on arbitrary grid points

- **Learn:** known offsets from gauge stations
- **Predict:** offsets at desired coordinates

→ **Generative AI**




Workflow
Offset Data
Springmaid Pier, SC (8661070, NOAA-NOS)
Observed
Modeled
Offset
Water level (ft.)
Time (mins.)
Input
Output
LSTM-Generated offset
$\begin{bmatrix} o_{1,1} & \cdots & o_{1,21} \\ o_{2,1} & \cdots & o_{2,21} \\ \vdots & \ddots & \vdots \\ o_{5,1} & \cdots & o_{5,21} \end{bmatrix}$
A. Data Preprocessing
Latent Space
Model Evaluation:
R^2
MSE
RMSE
MAE
BCE
B. Modeling
Extrapolation
Observed
Forecast
Forecast+AI
Water level (ft.)
Without AI:
R² = 0.452
MSE = 0.390
RMSE = 0.624
MAE = 0.505
With AI:
R² = 0.934
MSE = 0.047
RMSE = 0.217
MAE = 0.169
Time (min.)
C. Output

Data

Hurricane	Category	No. of stations	No. of hourly offsets
Ian (2022)	H5	250	26250
Harvey (2017)	H4	247	25935
Ida (2021)	H4	264	18216
Idalia (2023)	H4	304	31920
Matthew (2016)	H4	236	24780
Hermine (2016)	H1	259	27195

Historical Storm Archive
historicalstorms.coastalrisk.live

Hurricane IAN 2022

Sep 19 2022 - Oct 2 2022

NHC Storm Number	09L
Number of Advisories:	38
Category:	H5
Highest Sustained Winds:	161 mph (260.0 km/h)
Lowest Pressure:	937 mbar (hPa)
Fatalities:	161
Damage:	112 billion (2022 USD)
Areas affected:	Cayman Islands • Cuba • U.S. West Florida, East Florida, Georgia, South Carolina

source: Wikimedia

Hurricane HARVEY 2017

Aug 13 2017 - Aug 31 2017

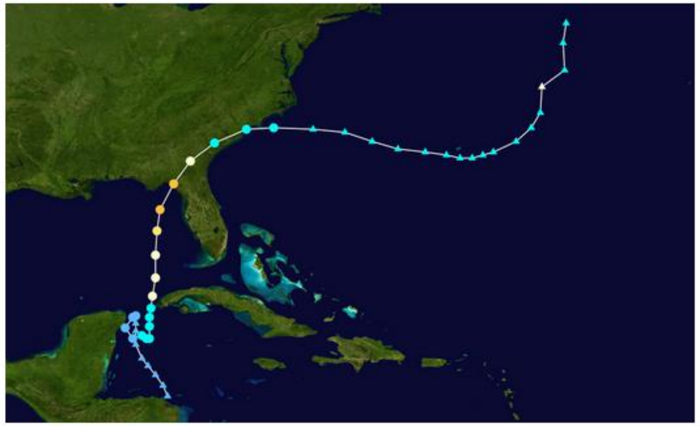
NHC Storm Number	09L
Number of Advisories:	43
Category:	H4
Highest Sustained Winds:	132 mph (213.0 km/h)
Lowest Pressure:	937 mbar (hPa)
Fatalities:	107
Damage:	125 billion (2017 USD)
Areas affected:	Belize • Mexico • U.S. Texas, Louisiana

source: Wikimedia

Hurricane IDALIA 2023

Aug 24 2023 - Sep 2 2023

NHC Storm Number	10L
Number of Advisories:	29
Category:	H4
Highest Sustained Winds:	130 mph (210.0 km/h)
Lowest Pressure:	940 mbar (hPa)
Fatalities:	10
Damage:	5 billion (2023 USD)
Areas affected:	Mexico • Cayman Islands • Cuba • U.S. South Florida, West Florida, Georgia, South Carolina, North Carolina • Bermudas

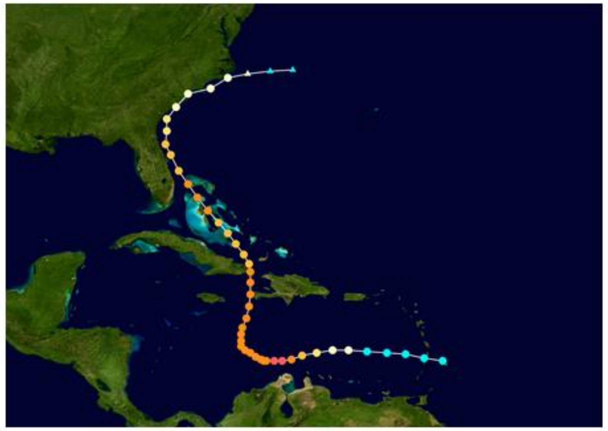


source: Wikimedia

Hurricane MATTHEW 2016

Sep 25 2016 - Oct 9 2016

NHC Storm Number	14L
Number of Advisories:	47
Category:	H4
Highest Sustained Winds:	161 mph (260.0 km/h)
Lowest Pressure:	934 mbar (hPa)
Fatalities:	603
Damage:	16.5 billion (2016 USD)
Areas affected:	Hispaniola • Jamaica • Cuba • Turks & Caicos • Bahamas • U.S. East Florida, Georgia, South Carolina, North Carolina, Virginia



source: Wikimedia

CERA Historical Storm Archive: historicalstorms.coastalrisk.live

Data

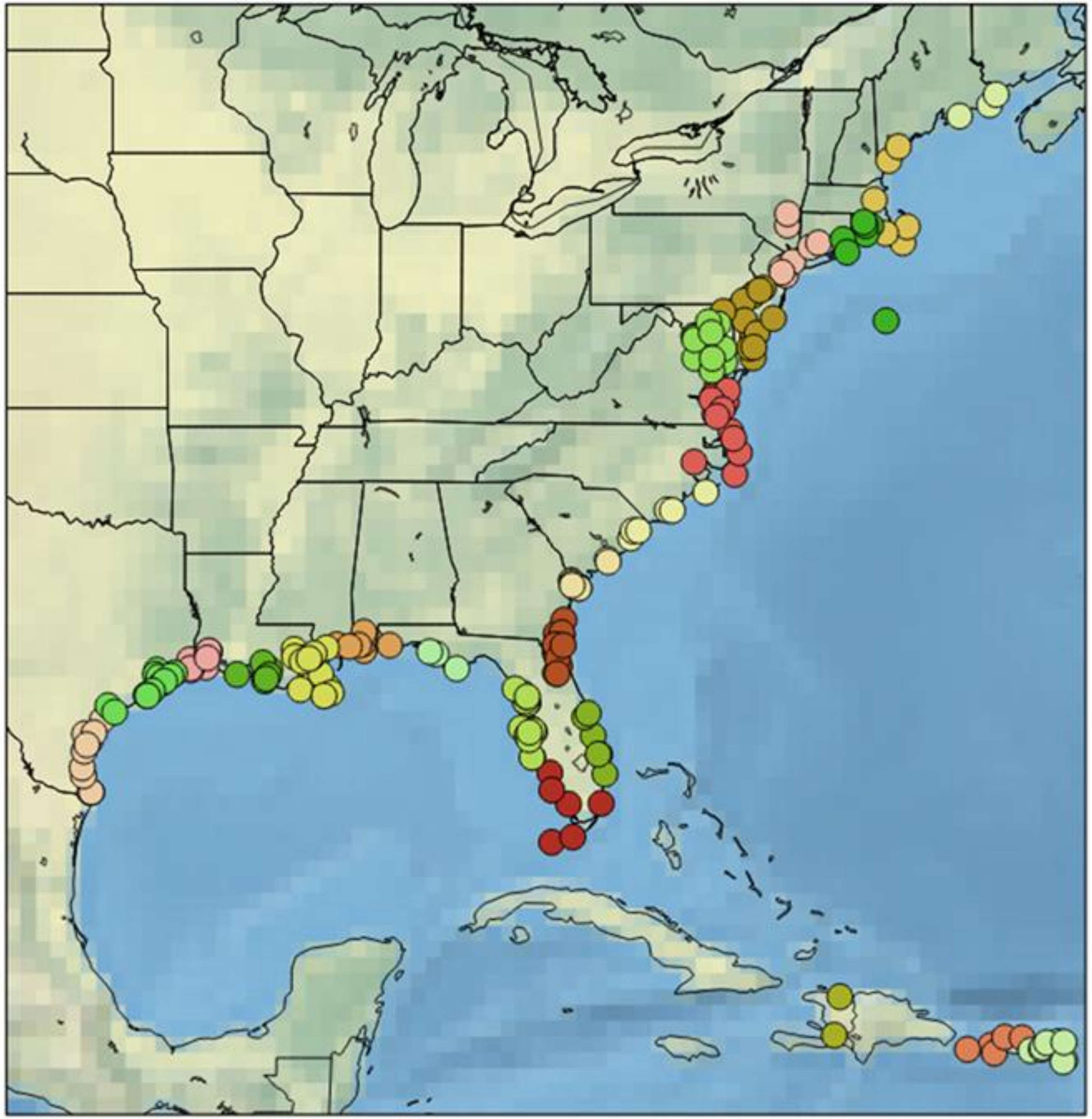
Clustering

- K-means clustering of stations based on their coordinates
- Separately for each hurricane
- No. of clusters: 10% of stations
- Training set: 90% of each cluster

Input data:

- 24h-ahead bias predictions for each training station and hurricane, generated with the LSTM-based model

Hurricane	MSE	RMSE	MAE
Ian (2022)	0.129	0.359	0.241
Harvey (2017)	0.121	0.347	0.214
Ida (2021)	0.116	0.34	0.197
Idalia (2023)	0.124	0.352	0.22
Matthew (2016)	0.066	0.257	0.169
Hermine (2016)	0.085	0.292	0.177



Generative Adversarial Networks

Main principle: Zero-sum game between two adversarial NN submodels:

- The generator: creates data by learning a distribution, starting from white noise
- The discriminator: trained on data, tries to distinguish between data from the “real” distribution and random noise (“fake” data)

Training:

- Minmax game:
  - The generator improves by minimizing the probability of “being caught” by the discriminator
  - The discriminator improves by maximizing the probability of fake detection

- The model training has converged when the discriminator can no longer distinguish whether the data from the generator are “real” or “fake” (p=0.5)

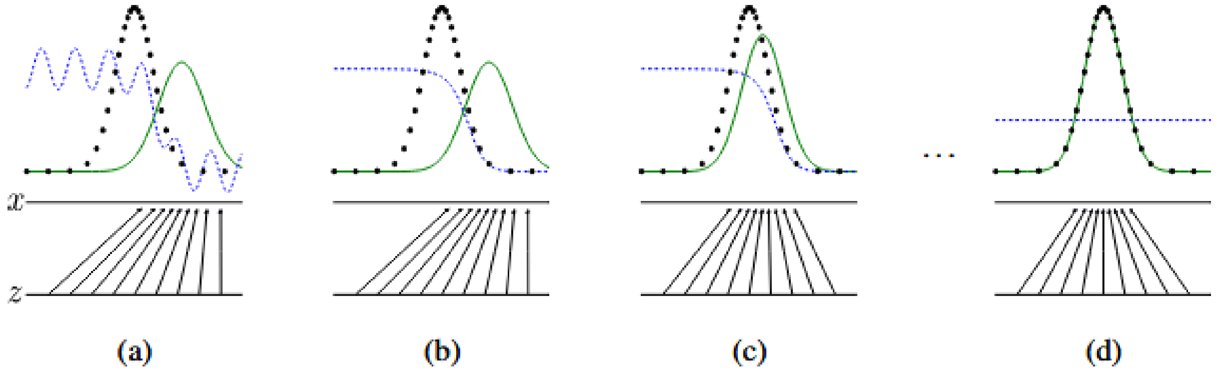
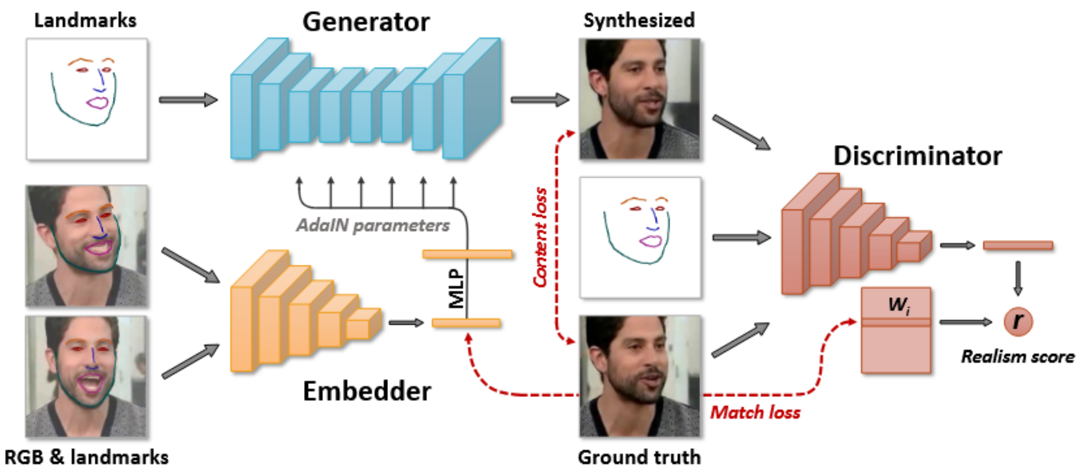


Figure 1: Generative adversarial nets are trained by simultaneously updating the discriminative distribution (D, blue, dashed line) so that it discriminates between samples from the data generating distribution (black, dotted line) p_x from those of the generative distribution p_g (G) (green, solid line). The lower horizontal line is the domain from which z is sampled, in this case uniformly. The horizontal line above is part of the domain of x. The upward arrows show how the mapping $x = G(z)$ imposes the non-uniform distribution p_g on transformed samples. G contracts in regions of high density and expands in regions of low density of p_g. (a) Consider an adversarial pair near convergence: p_g is similar to p_{data} and D is a partially accurate classifier. (b) In the inner loop of the algorithm D is trained to discriminate samples from data, converging to $D^*(x) = \frac{p_{\text{data}}(x)}{p_{\text{data}}(x)+p_g(x)}$. (c) After an update to G, gradient of D has guided $G(z)$ to flow to regions that are more likely to be classified as data. (d) After several steps of training, if G and D have enough capacity, they will reach a point at which both cannot improve because $p_g = p_{\text{data}}$. The discriminator is unable to differentiate between the two distributions, i.e. $D(x) = \frac{1}{2}$.

I.J. Goodfellow *et al.*, *Generative Adversarial Networks*, arXiv:1406.2661 (2014)

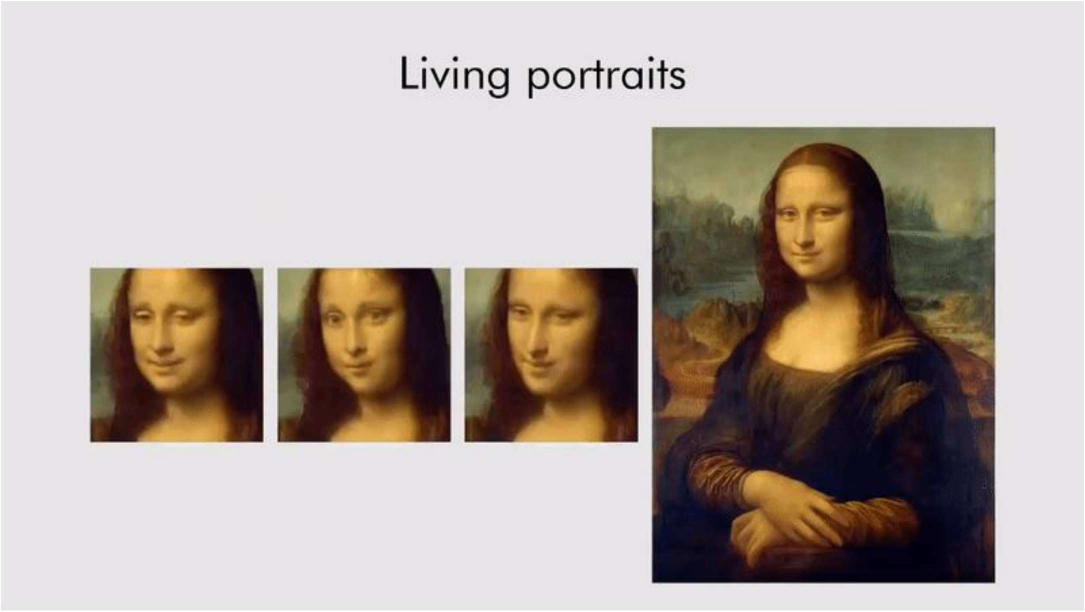
Generative Adversarial Networks



Applications

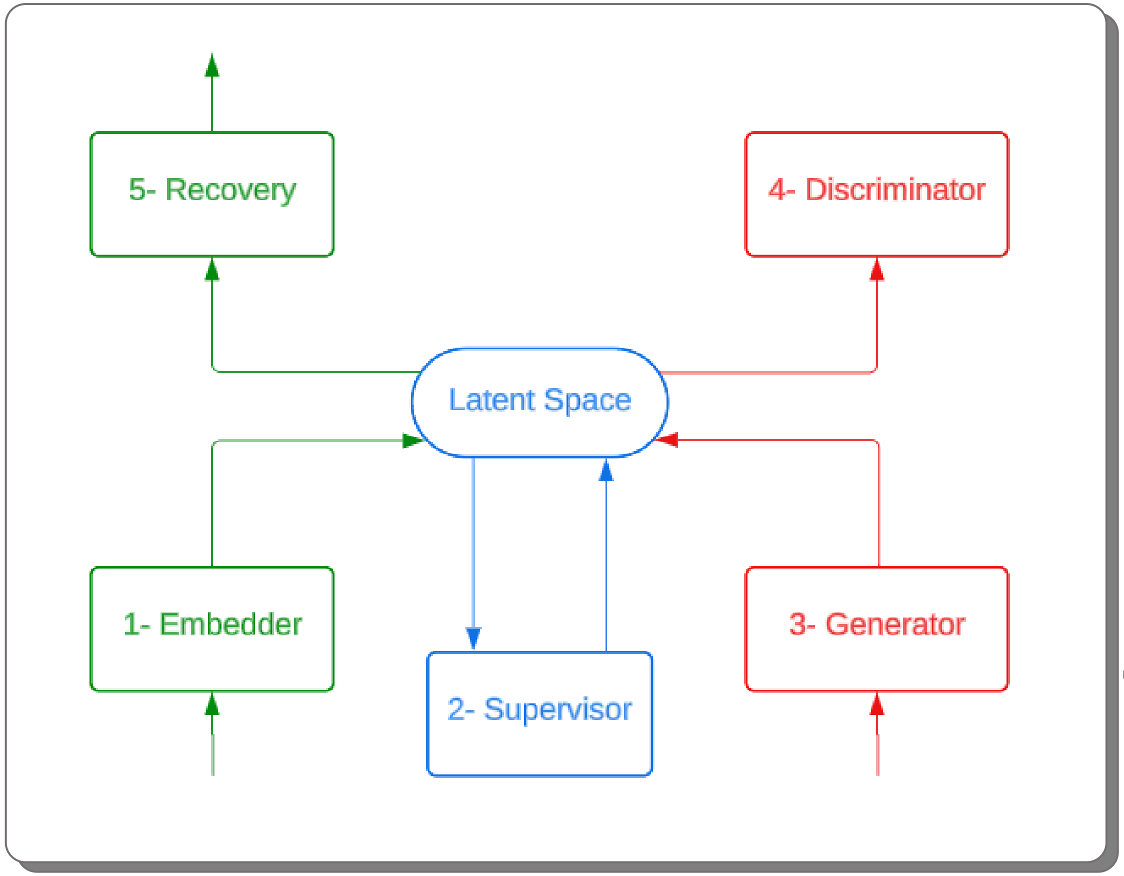
- Image/video generation/processing (enhancement, denoising, coloring)
- Synthetic dataset generation

etc.



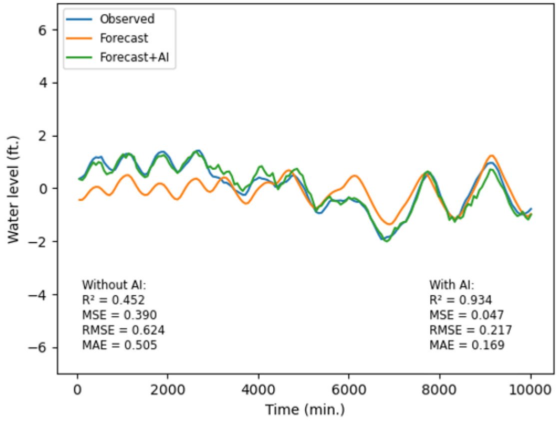
E. Zakharov *et al.*, *Few-Shot Adversarial Learning of Realistic Neural Talking Head Models*, arXiv:1905.08233 (2019)

TimeGAN for bias correction



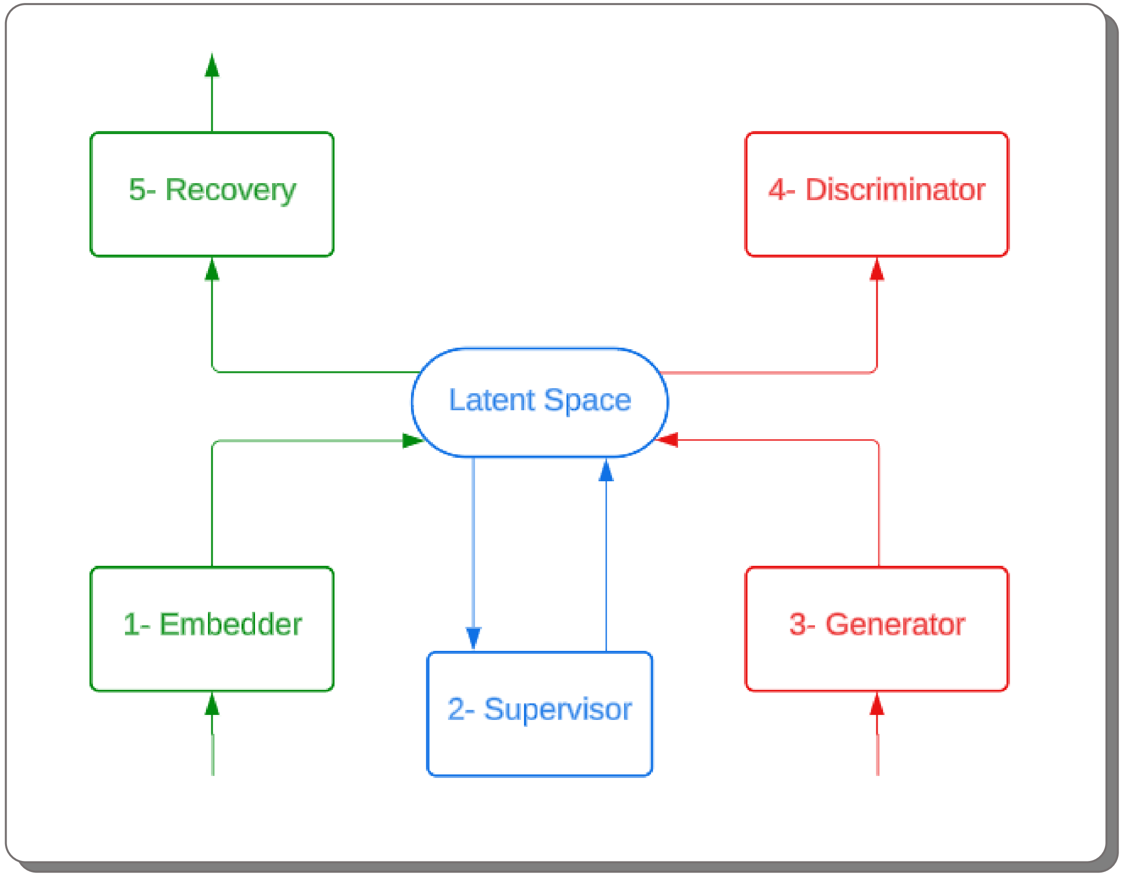
1- Maps the input time series (water level bias) and static features (coordinates) into a latent space.
2- Aims to fix the outputs of the embedder and generator
3- Generates sequences out of a uniform distribution
4- Classifies whether the data is real or synthetic
5- Reconstructs features from latent space to their original representation

Model Evaluation:
R^2
MSE
RMSE
MAE
BCE



J. Yoon *et al.*, *Time-series generative adversarial networks,* Advances in neural information processing systems, 32 (2019)

TimeGAN for bias correction



Embedder, Recovery, Generator

Layers	No. of Neurons	Activation	Output Shape
GRU	256	–	5*256
GRU	256	–	5*256
GRU	256	–	5*256
GRU	256	–	5*256
GRU	256	–	5*256
Dense	21	Sigmoid	5*21

Supervisor

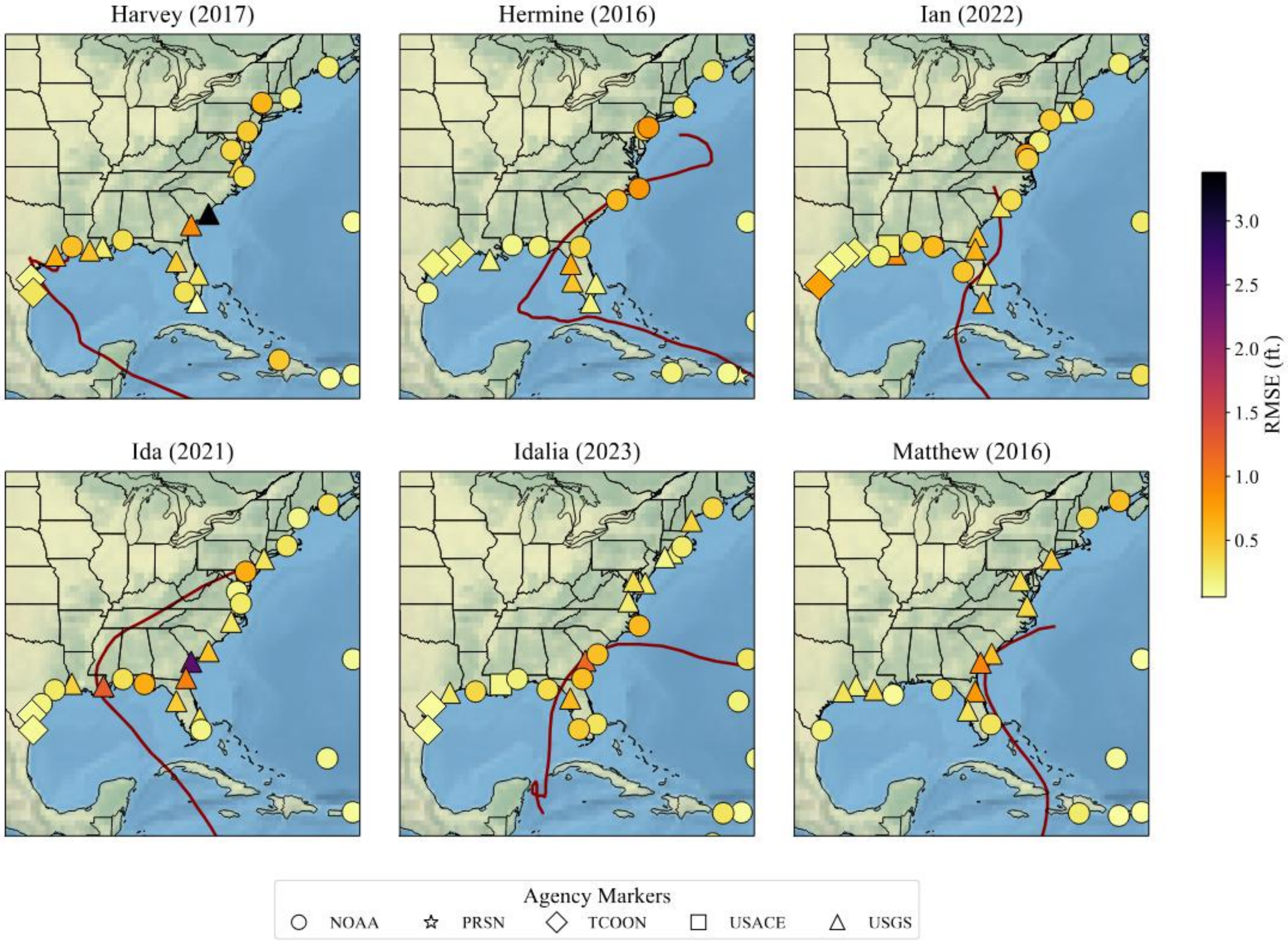
Layers	No. of Neurons	Activation	Output Shape
GRU	256	–	5*256
GRU	256	–	5*256
GRU	256	–	5*256
GRU	256	–	5*256
Dense	21	Sigmoid	5*21

Discriminator

Layers	No. of Neurons	Activation	Output Shape
Bi-GRU	256	–	5*512
Bi-GRU	256	–	1*512
Dense	1	Sigmoid	1*1

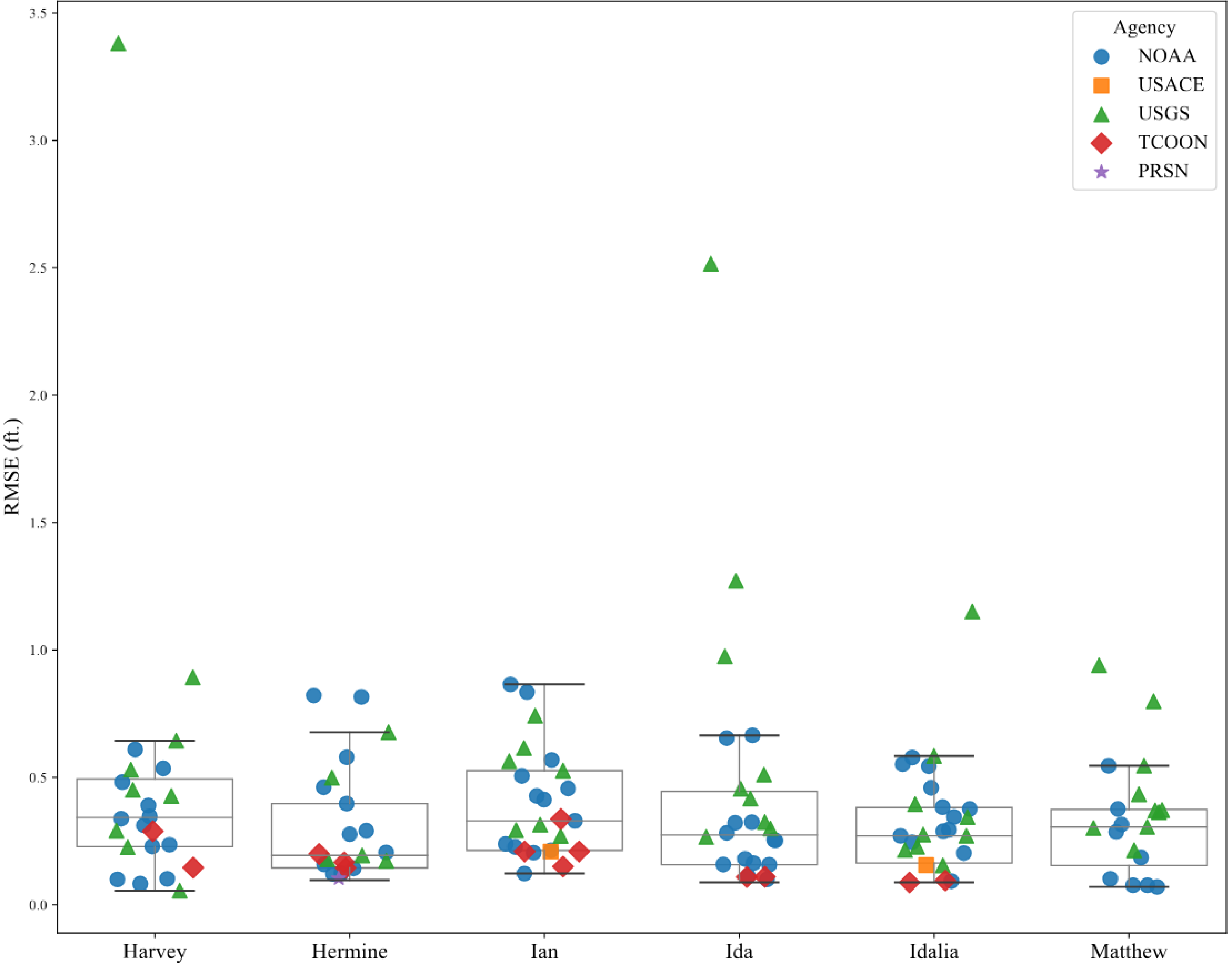
Results

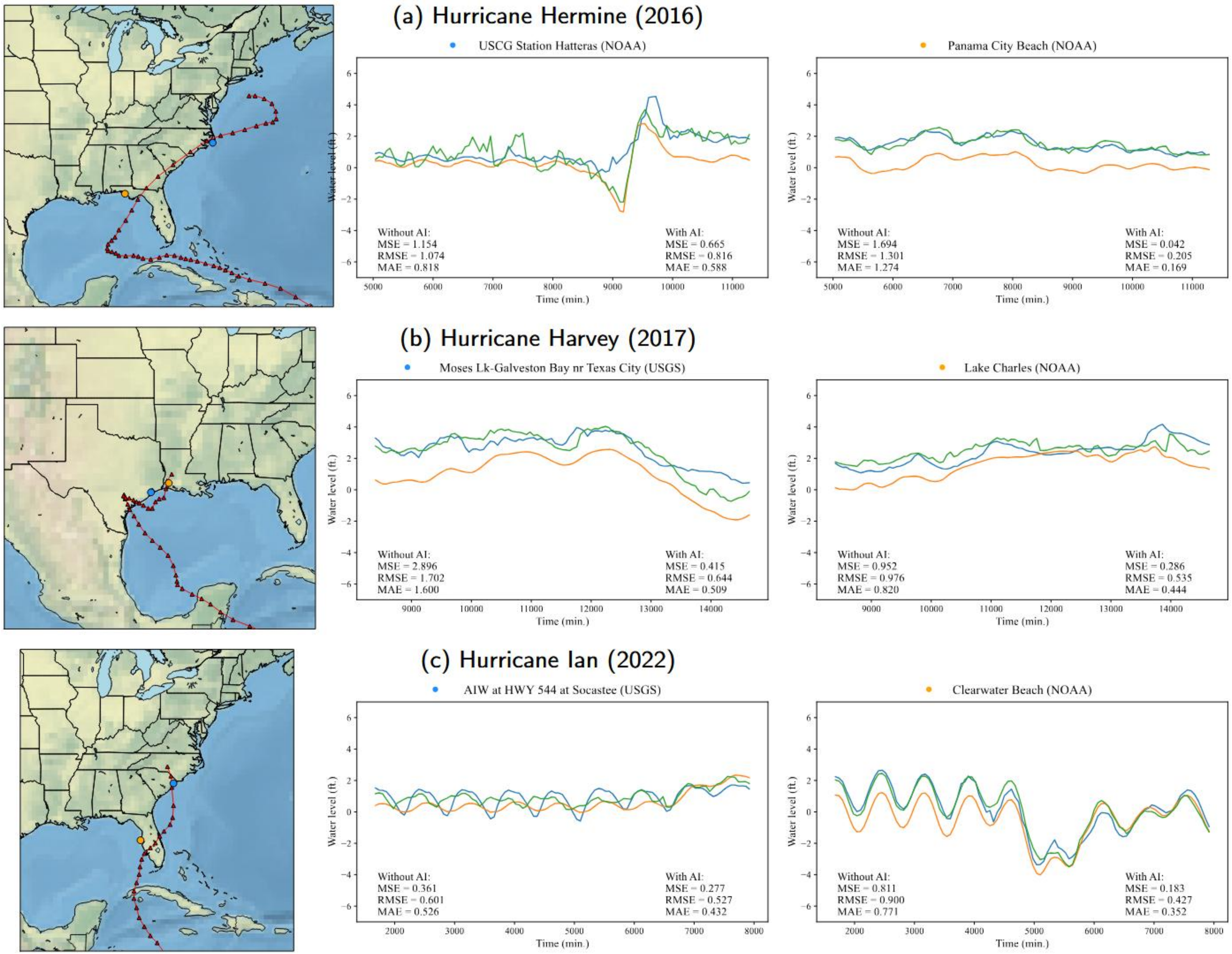
- Promising performance: Typically, low RMSE (<1.5 ft)
- Higher RMSE along storm tracks
- Few outliers



Results

- Outliers: USGS stations




(a) Hurricane Hermine (2016)
USCG Station Hatteras (NOAA)
Without AI:
MSE = 1.154
RMSE = 1.074
MAE = 0.818
With AI:
MSE = 0.665
RMSE = 0.816
MAE = 0.588
Panama City Beach (NOAA)
Without AI:
MSE = 1.694
RMSE = 1.301
MAE = 1.274
With AI:
MSE = 0.042
RMSE = 0.205
MAE = 0.169
(b) Hurricane Harvey (2017)
Moses Lk-Galveston Bay nr Texas City (USGS)
Without AI:
MSE = 2.896
RMSE = 1.702
MAE = 1.600
With AI:
MSE = 0.415
RMSE = 0.644
MAE = 0.509
Lake Charles (NOAA)
Without AI:
MSE = 0.952
RMSE = 0.976
MAE = 0.820
With AI:
MSE = 0.286
RMSE = 0.535
MAE = 0.444
(c) Hurricane Ian (2022)
AIW at HWY 544 at Socastee (USGS)
Without AI:
MSE = 0.361
RMSE = 0.601
MAE = 0.526
With AI:
MSE = 0.277
RMSE = 0.527
MAE = 0.432
Clearwater Beach (NOAA)
Without AI:
MSE = 0.811
RMSE = 0.900
MAE = 0.771
With AI:
MSE = 0.183
RMSE = 0.427
MAE = 0.352
Water level (ft.)
Time (min.)

Conclusions

- TimeGAN: Spatial extrapolation of water bias timeseries from gauge station coordinates with generative AI

- Test cases: Huricanes Ian (2022), Harvey (2017), Ida (2021), Idalia (2023), Matthew (2016), Hermine (2016)
  - Stations clustered by coordinates for each hurricane, 90/10 train/test split for each cluster

- Promising results for spatial extrapolation
- Suitable for real-time bias correction forecasting

- Future steps: Improve model robustness
  - More diverse training datasets (storms, geographic regions)

Hurri-GAN: Bias Correction with Spatiotemporal Extrapolation using GenAI

Publication (under review)**:**
HURRI-GAN: A Novel Approach for Hurricane Bias-Correction Beyond Gauge Stations using Generative Adversarial Networks
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