Assessing the systemic error of storm surge model predictions by using LSTM neural networks

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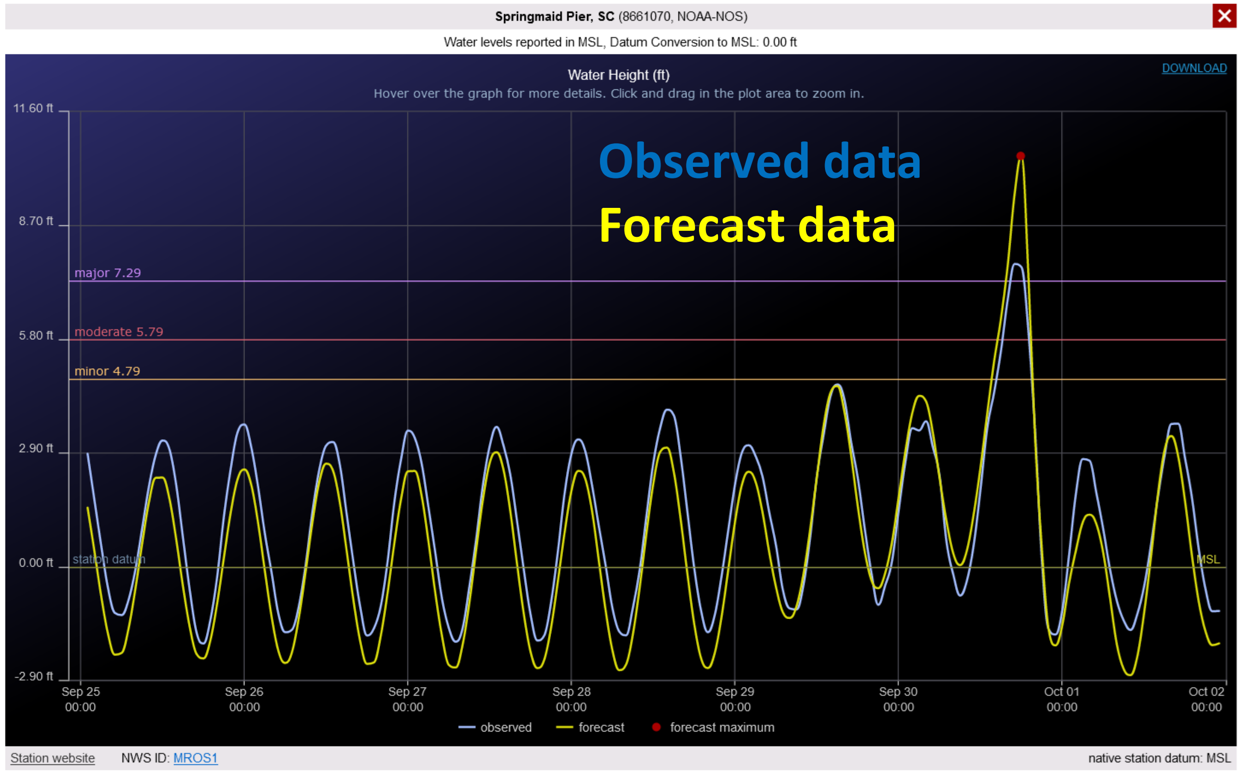
CERA - Coastal Emergency Risks Assessment

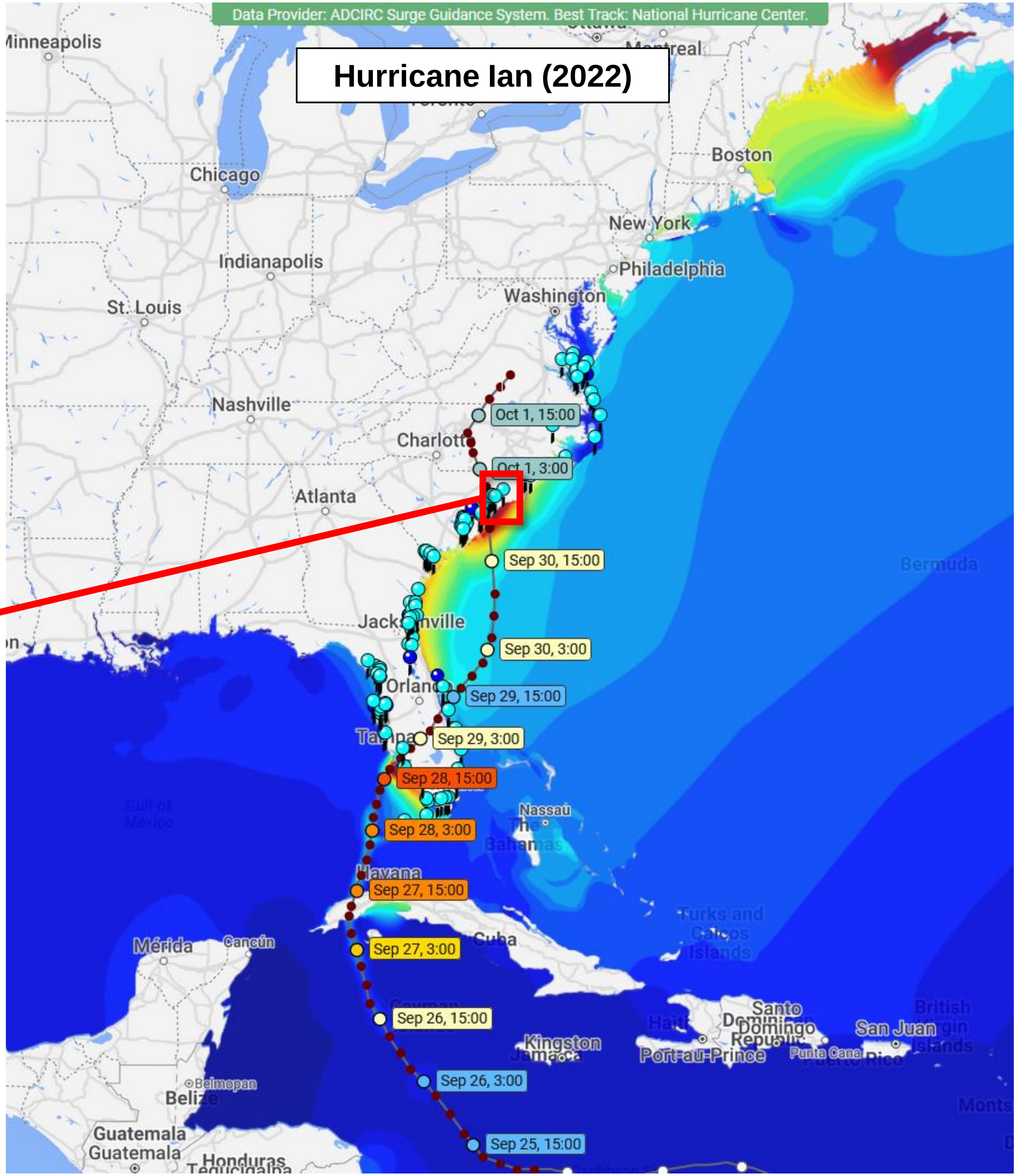
LSU | Center for Computation & Technology

STE||AR GROUP

Background

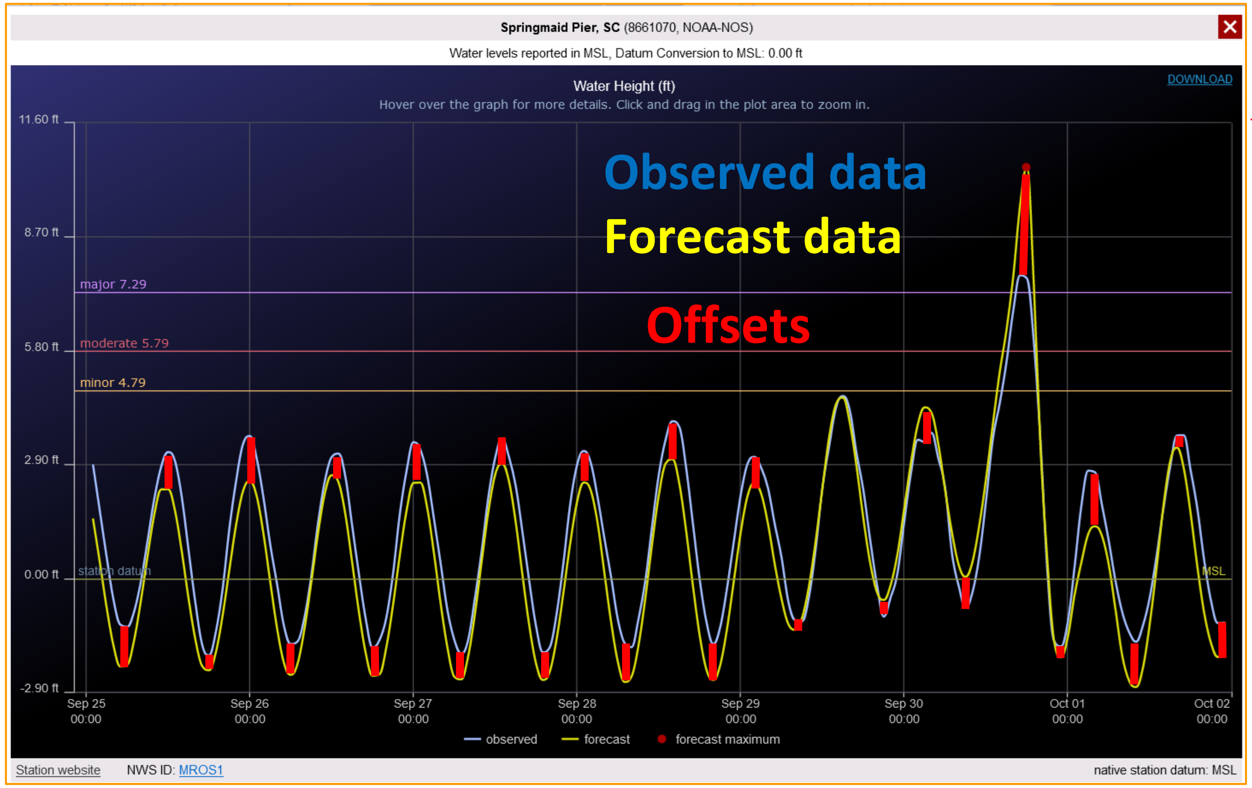
- **CERA website (cera.coastalrisk.live):** Real time measurements of water level, wind etc
- **Water level data:**
  - **Forecast data:** ADCIRC
  - **Observed data:** Gauge stations (USGS, NOAA etc.)
- **Target case:** Hurricane Ian

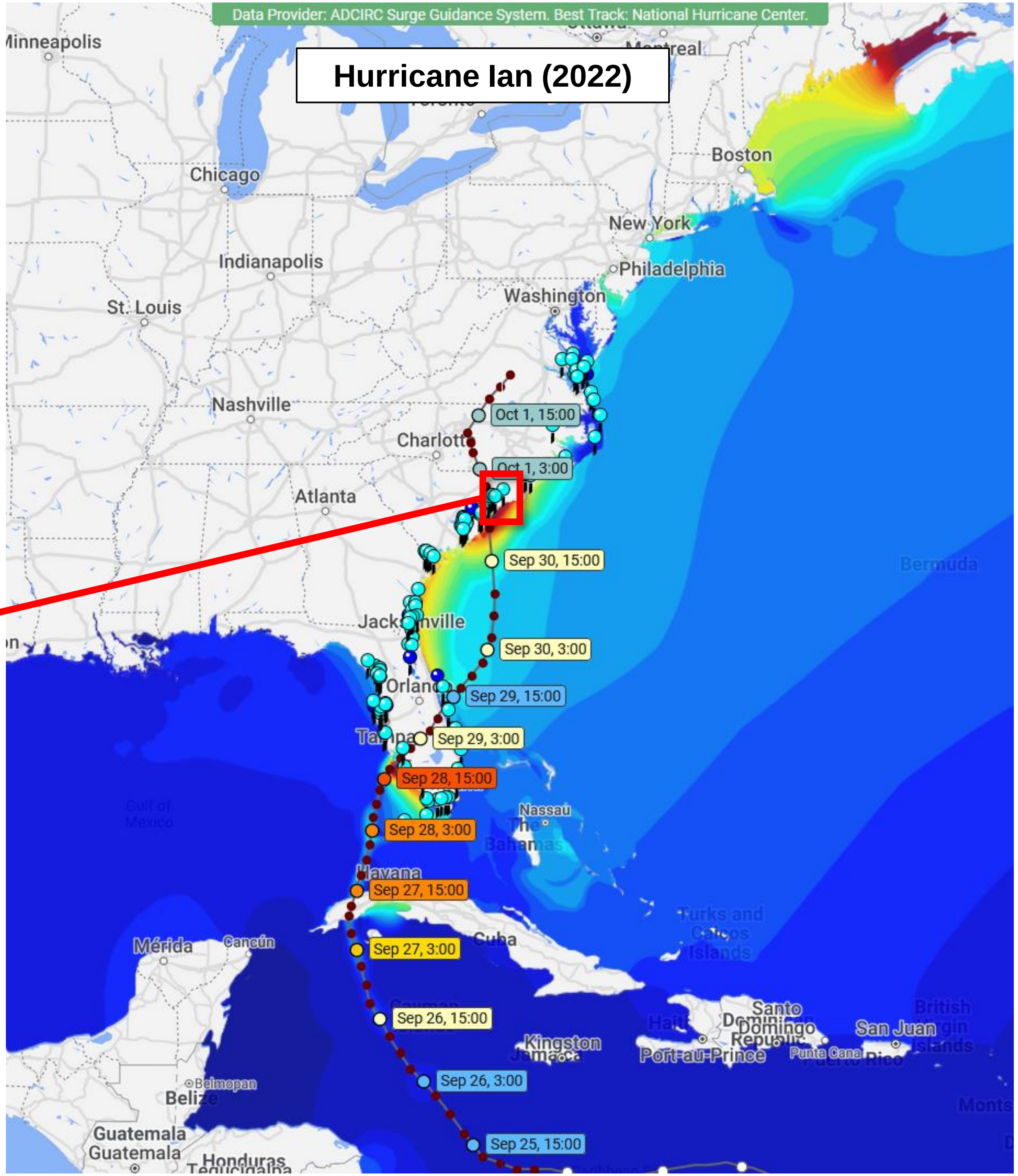




Background

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





Data

Historical Storm Archive

historicalstorms.coastalrisk.live

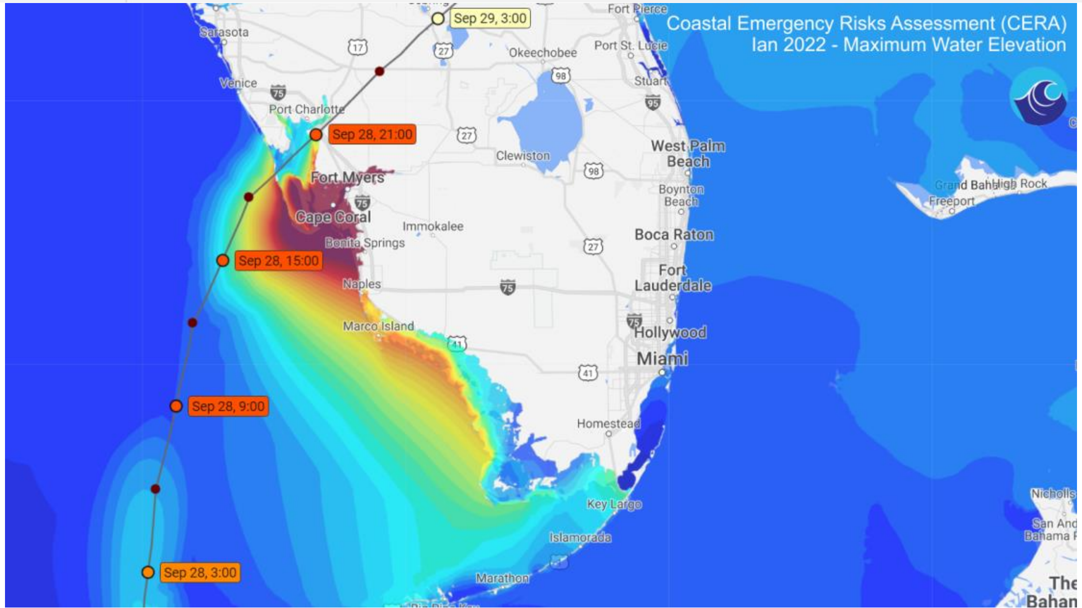
- User-friendly archive with water levels from 60+ **U.S. tropical storms** from the past 20 years, interfaced to the CERA website

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



Case Studies

Scenario	Training	Test	
1	**Ian (2022)**	**Ian (2022)**	Same storm
2	**Charley (2008)**	**Ian (2022)**	Similar storms
3	**Harvey (2017)**	**Ian (2022)**	Different storms
4	**Charley (2008), Wilma (2005), Matthew (2016), Irma (2017), Eta (2020), Elsa (2021)**	**Ian (2022)**	Multiple similar storms

Data Info

Hurricane	No. of available gauge stations	Total no. of hourly data for all stations
Ian (2022)	263	41764
Charley (2008)	103	14581
Harvey (2017)	89	18334
Wilma (2005)	8	1382
Matthew (2016)	66	10343
Irma (2017)	52	6944
Eta (2020)	252	42327
Elsa (2021)	40	6792
Total		82369

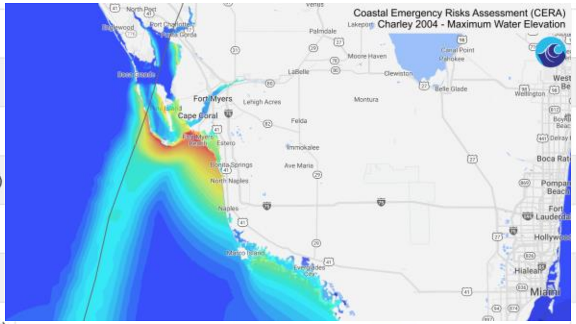
Example of ADCIRC Storm Data from CERA

Charley (2008)
Harvey (2017)
Wilma (2005)
Matthew (2016)
Irma (2017)
Eta (2020)
Elsa (2021)

Hurricane CHARLEY 2004

Aug 9 2004 - Aug 15 2004

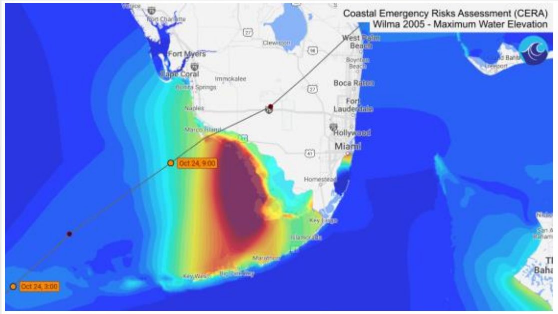
NHC Storm Number	03L
Number of Advisories:	26
Category:	H4
Highest Sustained Winds:	150 mph (242.0 km/h)
Lowest Pressure:	941 mbar (hPa)
Fatalities:	35
Damage:	16.9 billion (2004 USD)
Areas affected:	Jamaica • Cayman Islands • Cuba • U.S. West Florida, East Florida, South Carolina, North Carolina



Hurricane WILMA 2005

Oct 15 2005 - Oct 26 2005

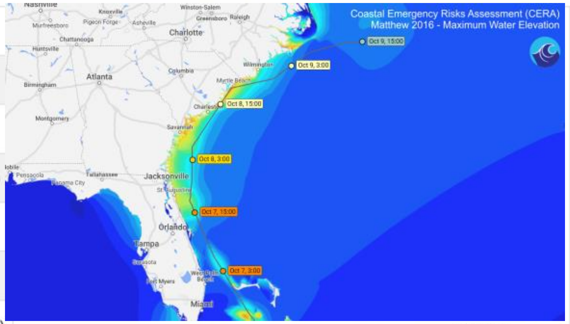
NHC Storm Number	24L
Number of Advisories:	43
Category:	H5
Highest Sustained Winds:	184 mph (297.0 km/h)
Lowest Pressure:	882 mbar (hPa)
Fatalities:	52
Damage:	22.4 billion (2005 USD)
Areas affected:	Mexico • Cuba • U.S. West Florida, East Florida • Bahamas



Hurricane MATTHEW 2016

Sep 25 2016 - Oct 9 2016

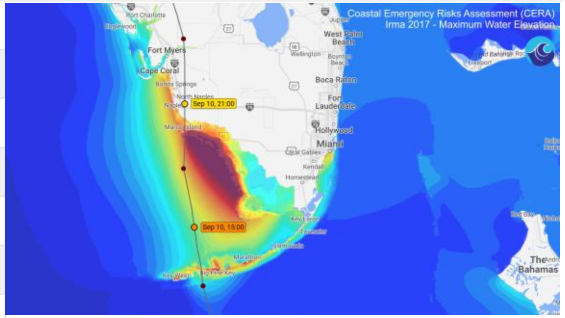
NHC Storm Number	14L
Number of Advisories:	47
Category:	H4
Highest Sustained Winds:	161 mph (260.0 km/h)
Lowest Pressure:	934 mbar (hPa)
Fatalities:	603
Damage:	16.5 billion (2016 USD)
Areas affected:	Hispaniola • Jamaica • Cuba • Turks & Caicos • Bahamas • U.S. East Florida, Georgia, South Carolina,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



Hurricane IRMA 2017

Aug 28 2017 - Sep 12 2017

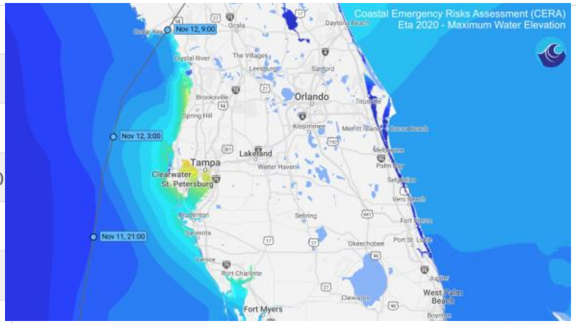
NHC Storm Number	11L
Number of Advisories:	52
Category:	H5
Highest Sustained Winds:	184 mph (297.0 km/h)
Lowest Pressure:	914 mbar (hPa)
Fatalities:	134
Damage:	77.2 billion (2017 USD)
Areas affected:	Hispaniola • Turks & Caicos • Bahamas • U.S. Virgin Islands, Puerto Rico, West Florida, East Florida, Georgia, South Carolina



Hurricane ETA 2020

Oct 29 2020 - Nov 13 2020

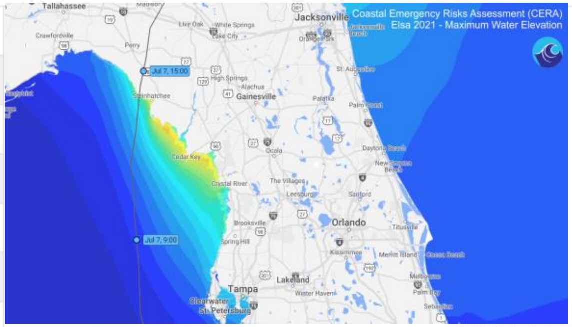
NHC Storm Number	29L
Number of Advisories:	52
Category:	H4
Highest Sustained Winds:	150 mph (242.0 km/h)
Lowest Pressure:	922 mbar (hPa)
Fatalities:	175
Damage:	8.3 billion (2020 USD)
Areas affected:	Central America • Cayman Islands • Cuba • Bahamas • U.S. West Florida, East Florida, Georgia, South Carolina



Hurricane ELSA 2021

Jun 30 2021 - Jul 10 2021

NHC Storm Number	05L
Number of Advisories:	39
Category:	H1
Highest Sustained Winds:	86 mph (139.0 km/h)
Lowest Pressure:	991 mbar (hPa)
Fatalities:	13
Damage:	1.2 billion (2021 USD)
Areas affected:	Hispaniola • Jamaica • Cuba • U.S. West Florida, New Jersey, New England



Historical Storm Archive

historicalstorms.coastalrisk.live

Workflow Pipeline

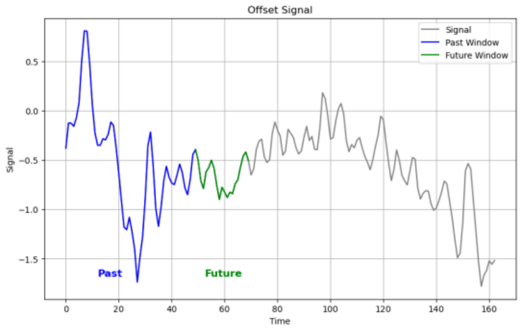
- Timeseries prediction in gauge stations **offset data**

Offset Data

Data Cleaning

Normalization

Stations:
Sliding window



LSTM Model Comparison

Hypertuning parameters

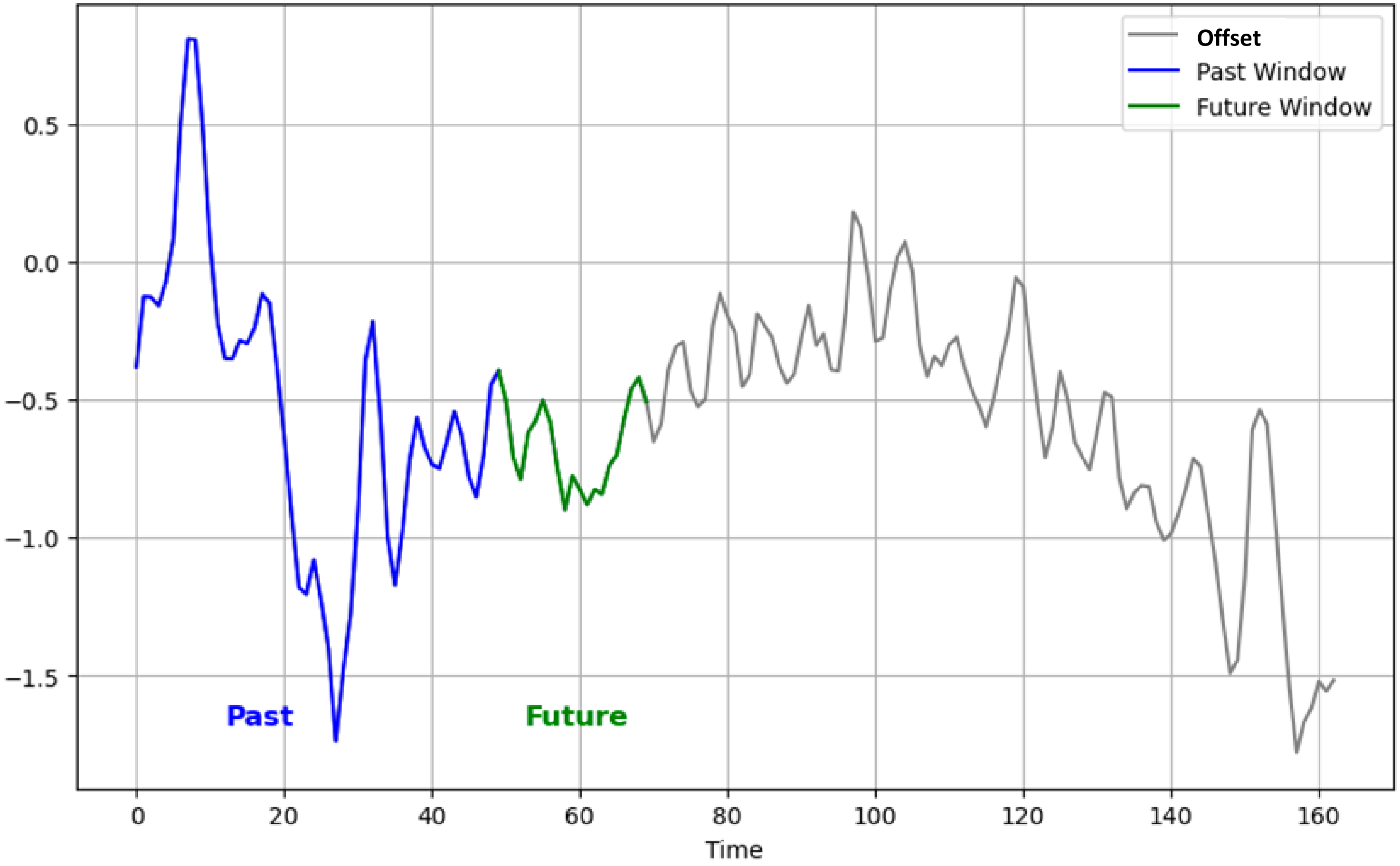
Performance evaluation

Data Preprocessing

Modelling

Sliding Window Approach

- **Past:** Past hourly data
- **Future:** Predicted hourly data



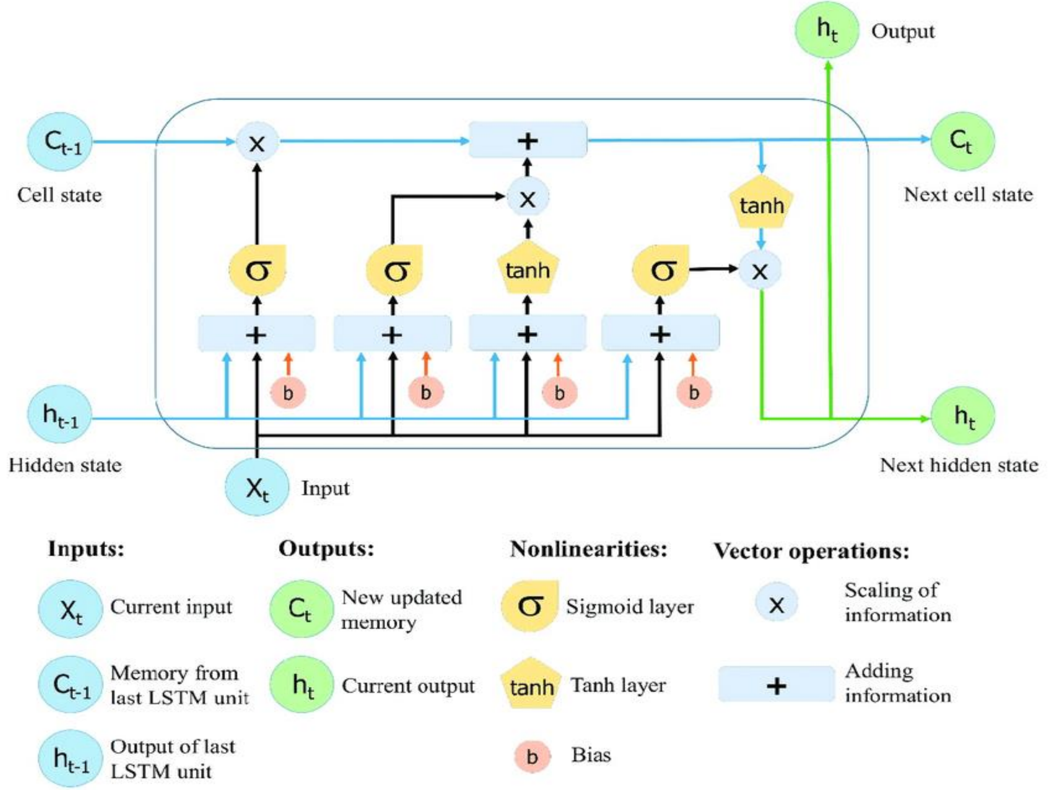
LSTM Based Networks

Type of Recurrent Neural Network (RNN) capable of **“understanding” patterns in sequences**

Literature: LSTM used extensively in meteorological studies, i.e. for prediction of timeseries of data such as:

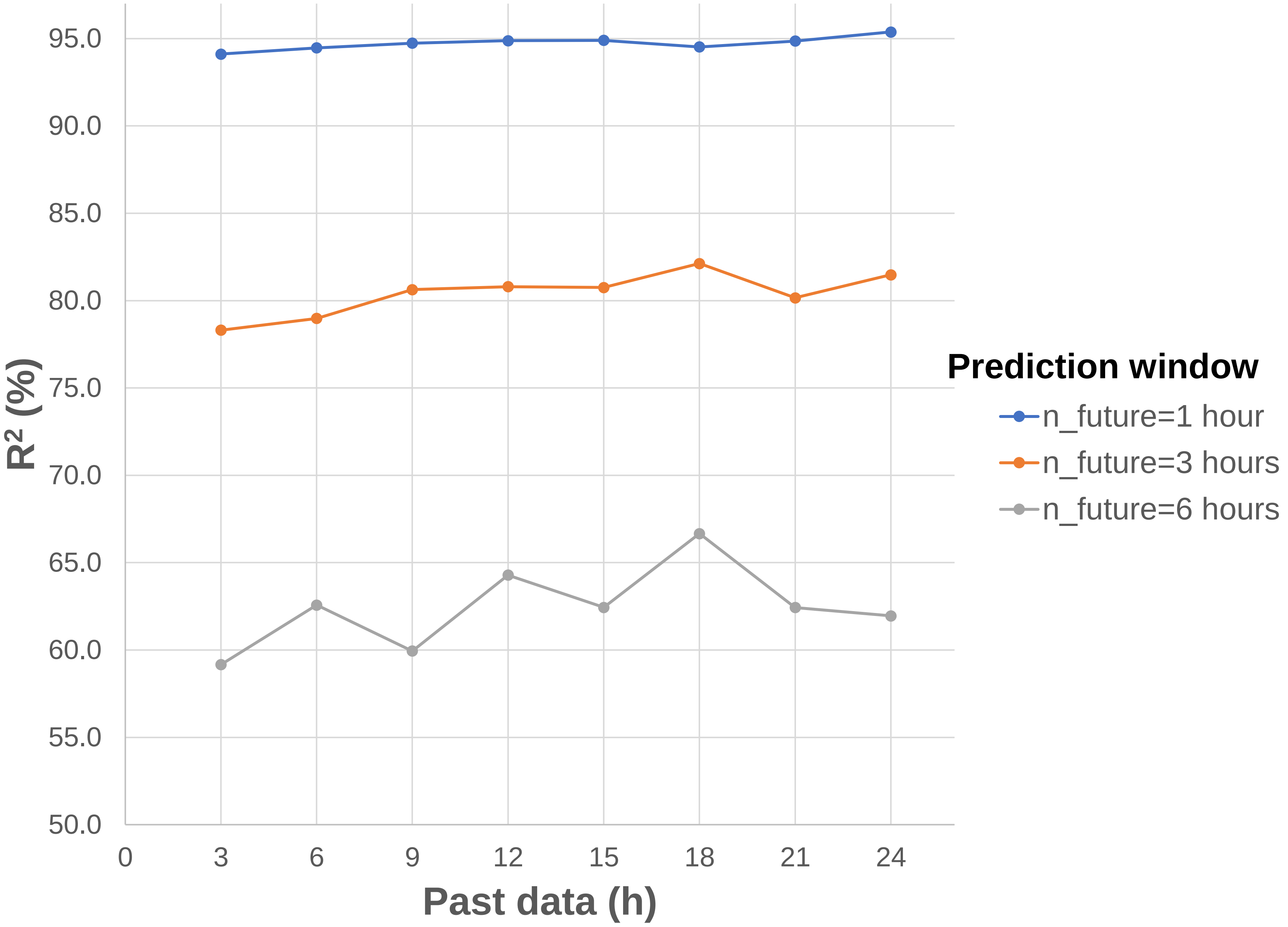
- Flood
- Rainfall
- Wind/wind power
- $PM_{2.5}$ concentration

etc.



Results

- **Scenario 1:**
  - Training set: first 75% of timesteps (Ian)
  - Test set: last 25% of timesteps (Ian)



Results

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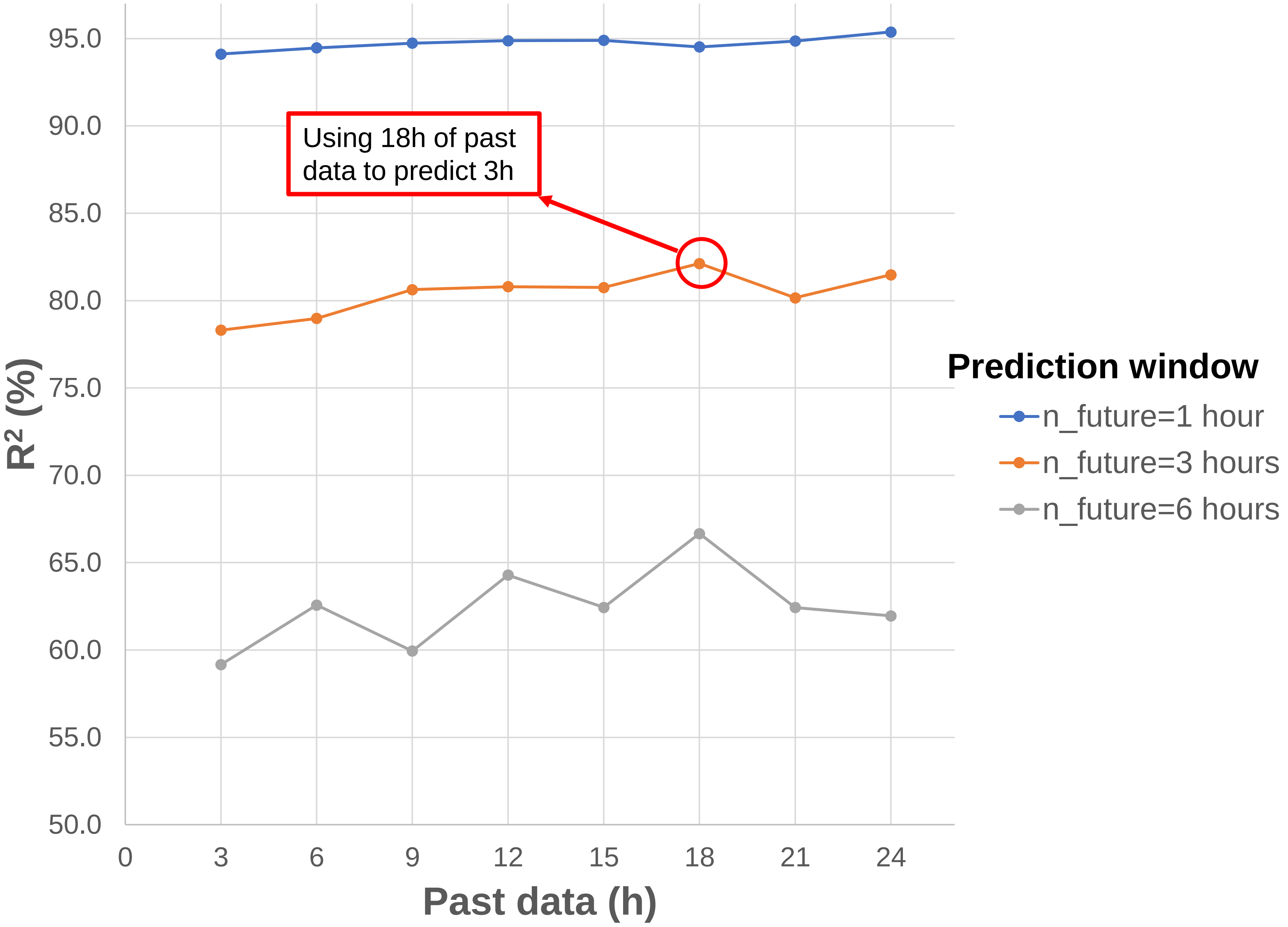
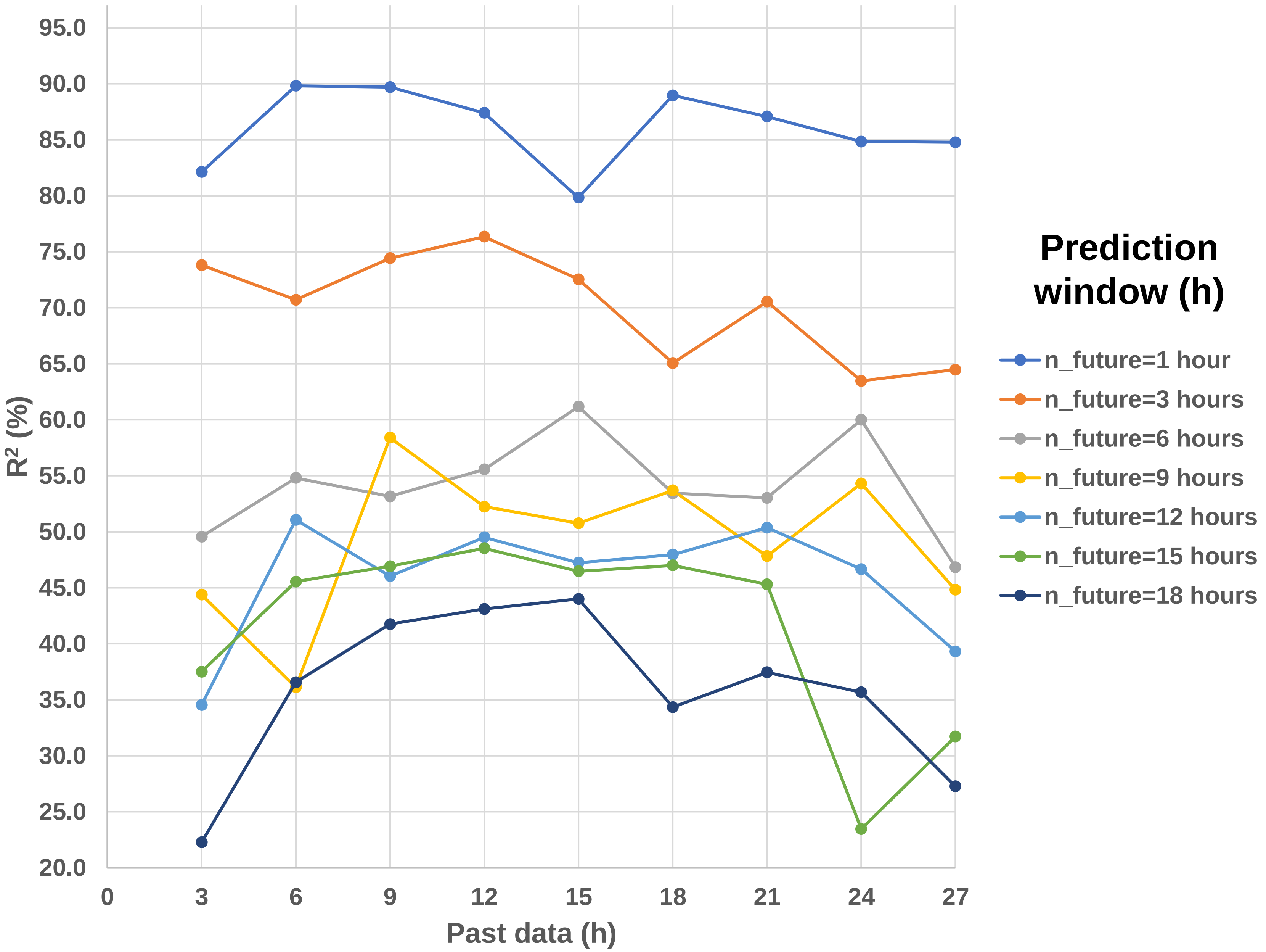


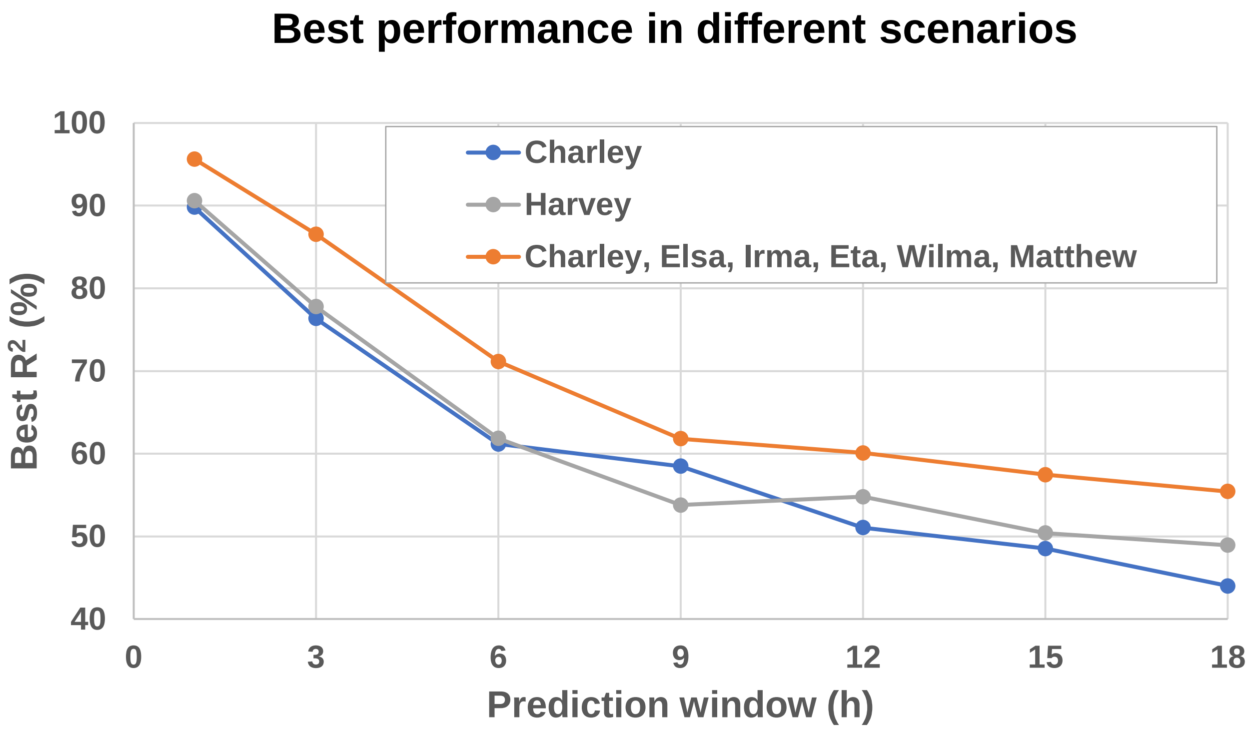
Results

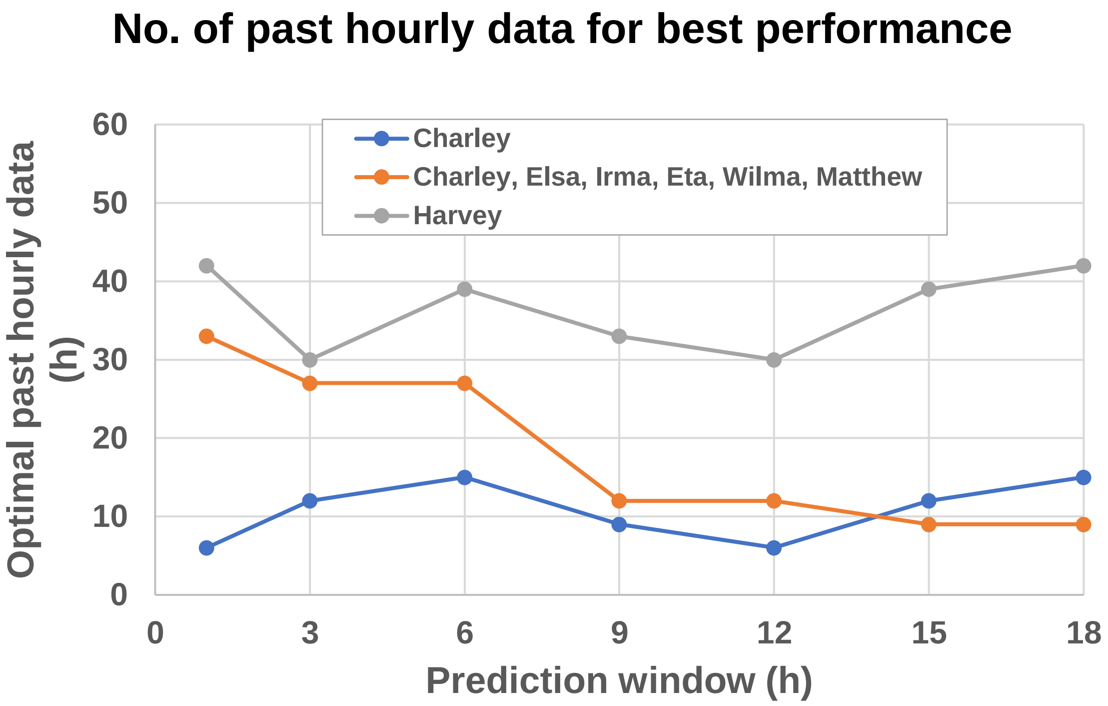
- **Scenario 2**
  - Training set: Charley dataset (2008)
  - Test set: Ian dataset (2022)

Result: Expected limitations the further we predict into the future



Results



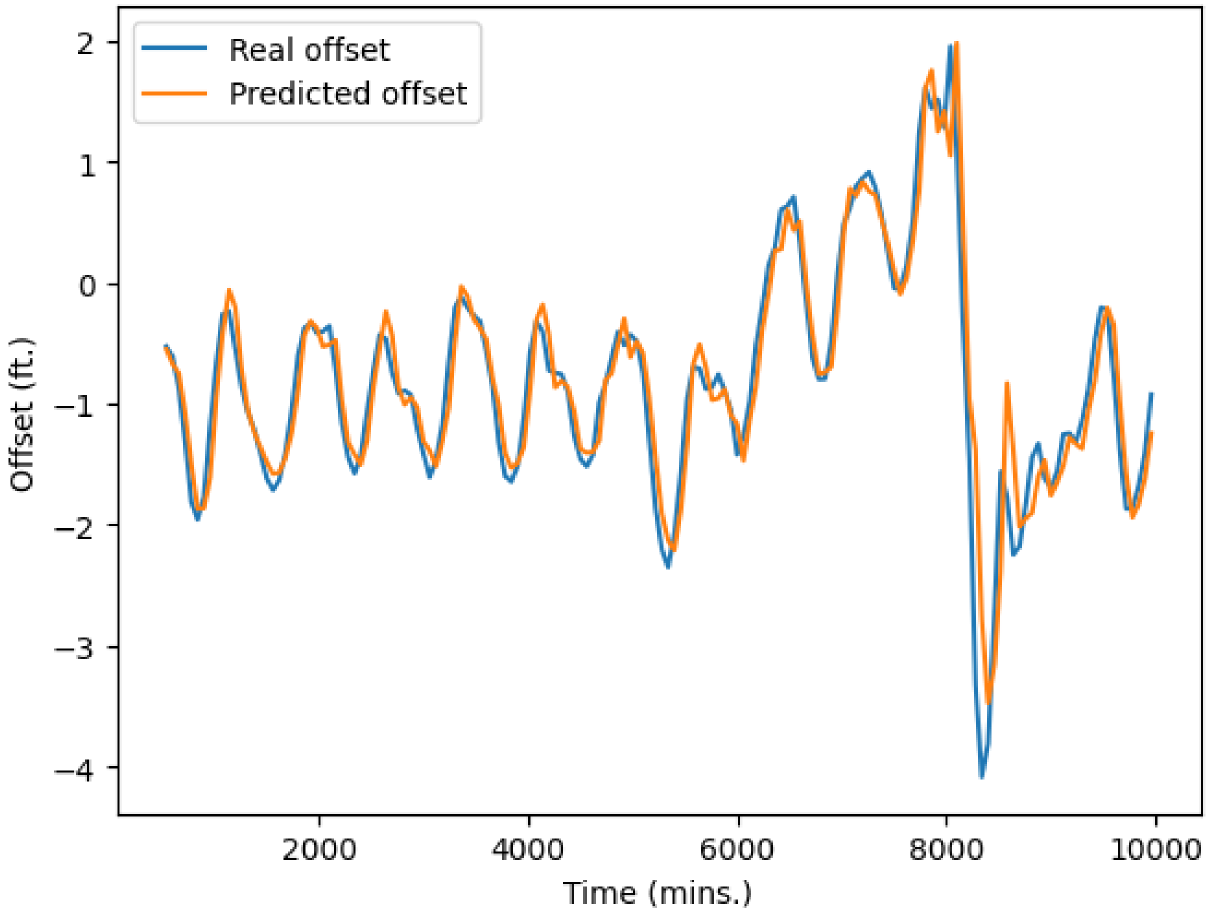


Results:
- Similar performance when using only one hurricane with either similar (Charley) or different (Harvey) characteristics (compared to Ian)
- Improvement when using more similar hurricanes

Results:
- More past hourly data needed to achieve optimal performance for a hurricane with different characteristics (Harvey)
- Optimal hourly data decreases with increasing prediction window when using 6 hurricanes

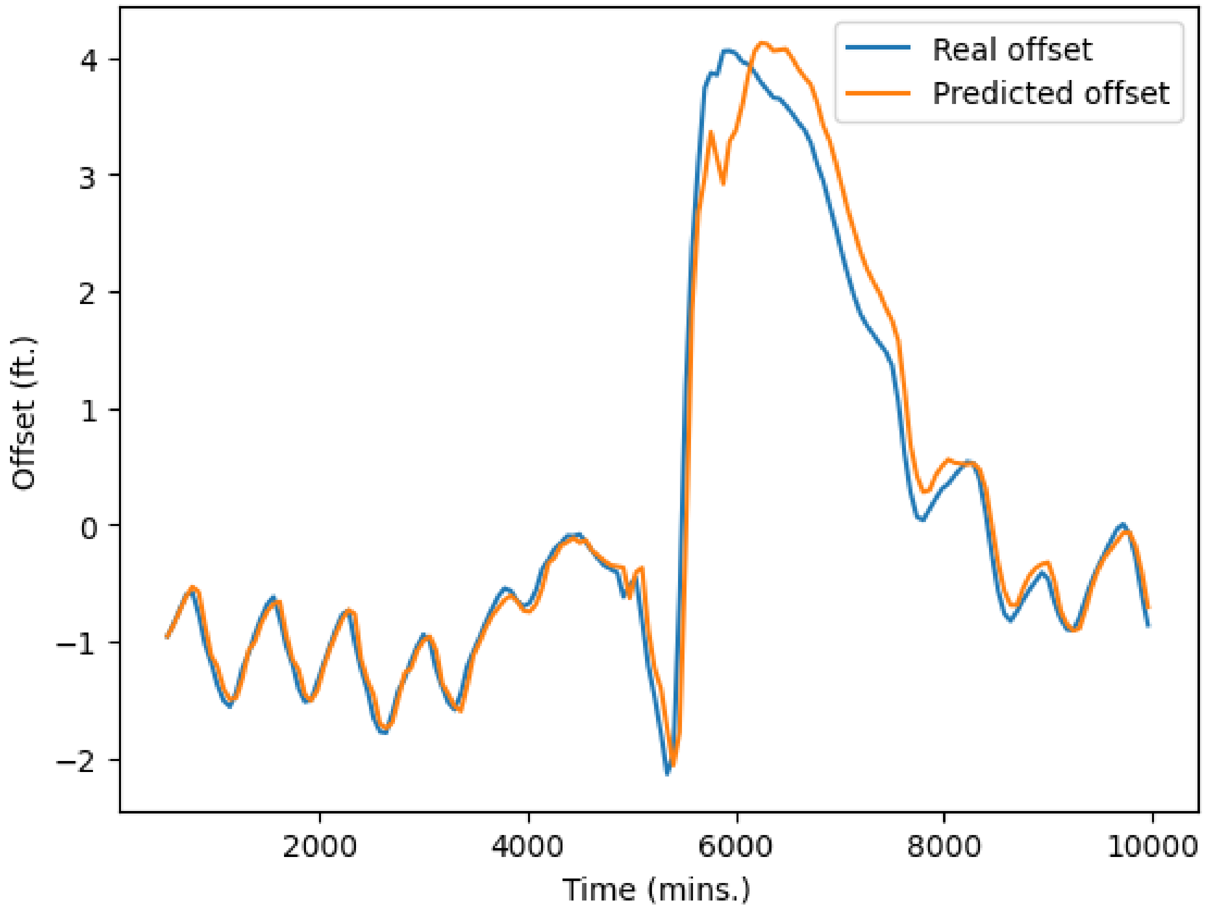
ML Correction on Gauge Stations

Charleston Cooper River Entrance, SC, ID: 8665530, NOAA-NOS



R^2 score: 87.73%

Fort Myers, FL, ID: 8725520, NOAA-NOS



R^2 score: 93.15%

Conclusions and Next Steps

Conclusions:

- Predicting offsets at gauge stations shows promising results
- LSTM based ML models are good candidates for this approach
- Noticeable impact of the choice of storms used for training the ML model
- Performance limitations when increasing prediction length
- Can we get ML corrections outside gauge stations?

Next steps:

- Further investigate different ML architectures
- More case studies (different input parameters, more storms to add etc.)
- Extending prediction window for practical use
- Explore appropriate ML models for geospatial extrapolation outside gauge stations

Assessing the systemic error of storm surge model predictions by using LSTM neural networks

Publication (under preparation)**:**
LSTM based machine learning for bias correction of storm surge modelling
S. Giaremis, N. Nader, H. Kaiser, C. Kaiser, S. Nikidis

Our team:

Hartmut Kaiser Head of STE||AR GROUP, Research Professor, LSU-CCT

Carola Kaiser Team Lead of the CERA Storm Surge and Flood Web Mapping Visualization Tool-LSU

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