Center for Operational Oceanographic Products and Services
NATIONAL OCEAN SERVICE

AI-Enabled Water Level Data Quality Control

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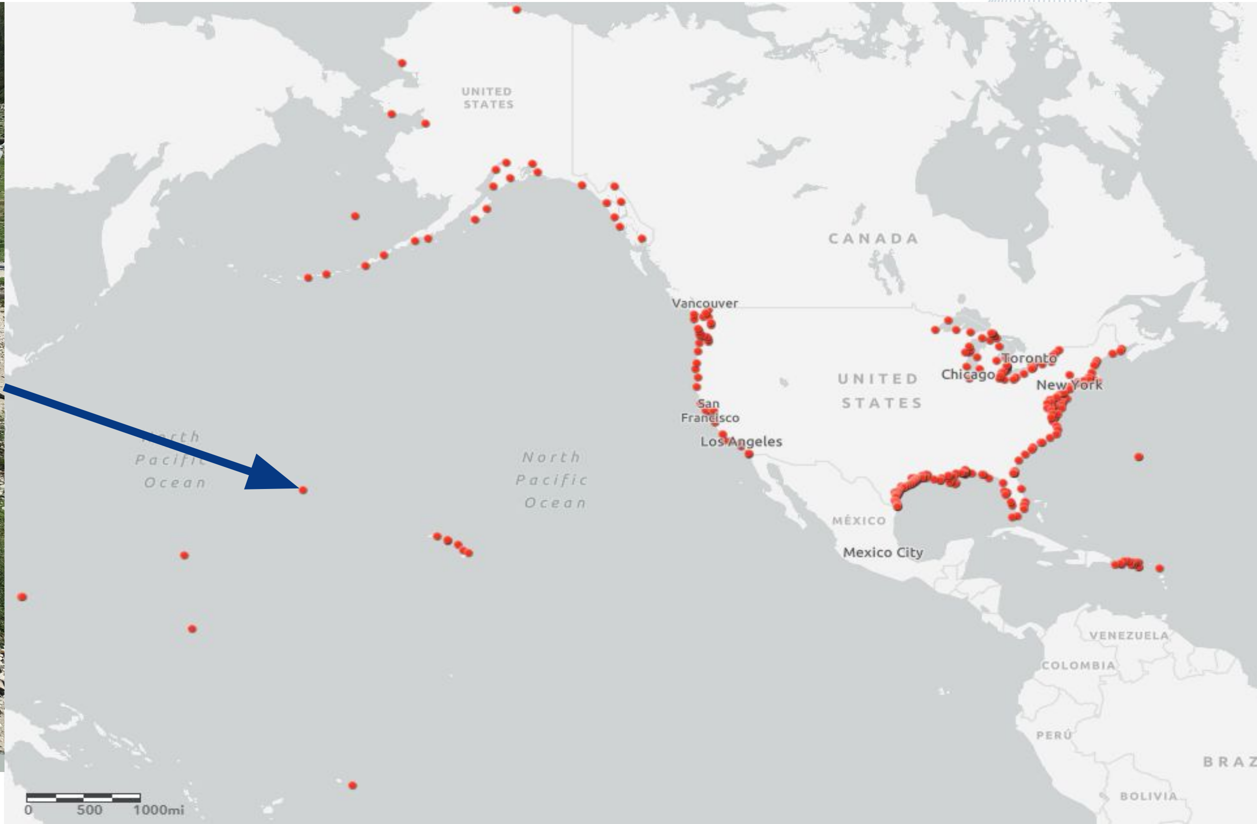
IOOS DMAC Annual Meeting
April 30th, 2025

Background

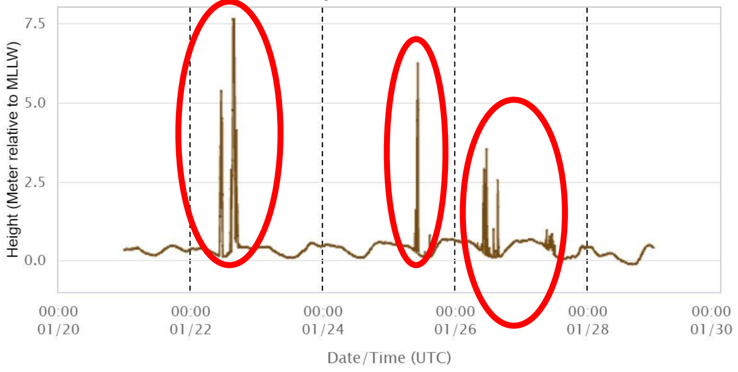
300+ Active NOAA NOS Water Level Stations

Sand Island, Midway Islands

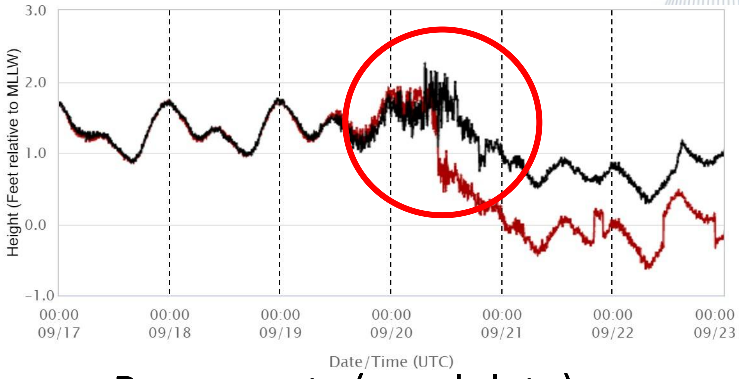


Common Data Quality Issues

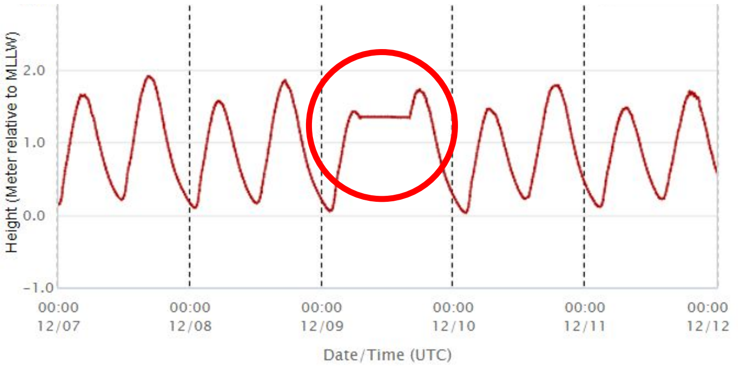
Spikes



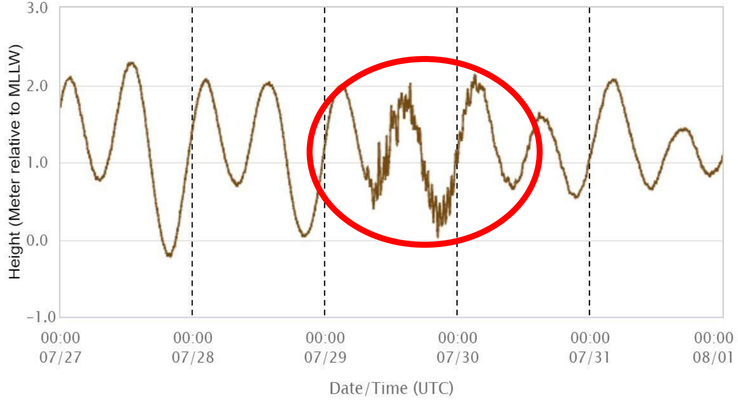
Data Shift



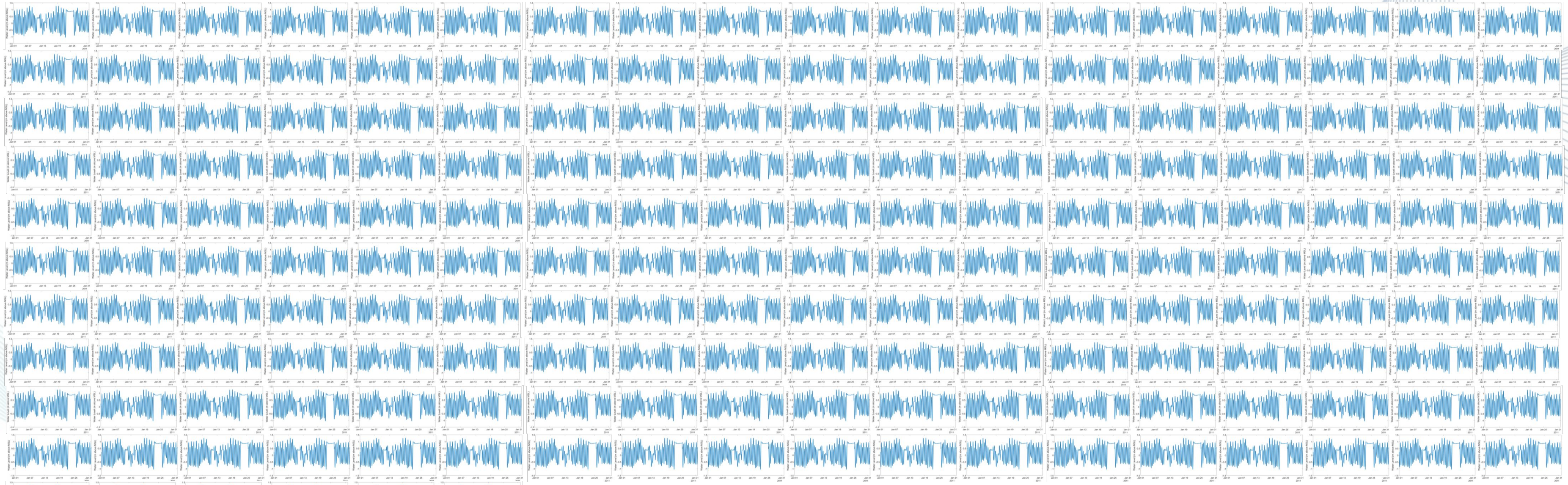
Flat-line

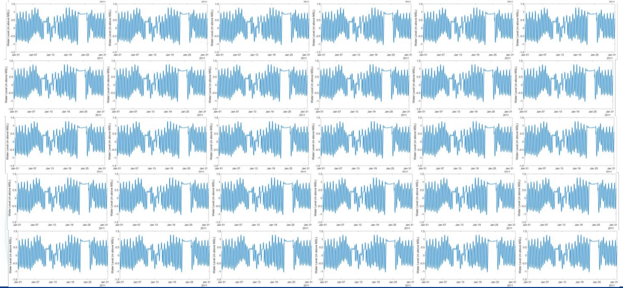


Rare events (good data)



Manual processing and verification each month





At least 2.1 million data points per month!

Goal: Develop and demonstrate an optimal AI approach to QC water level observations that:

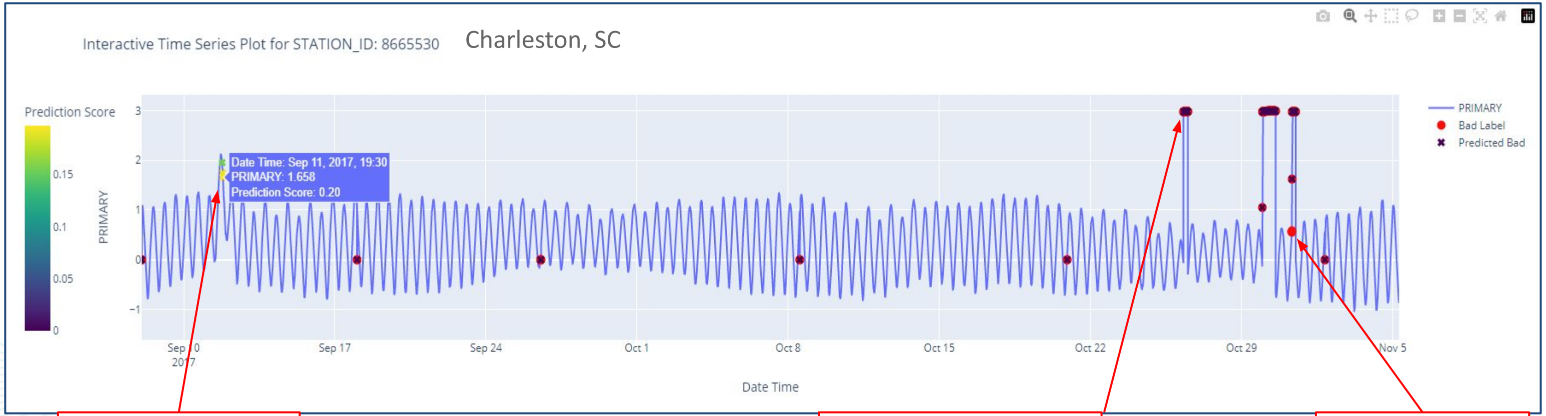
1. Classifies 6-minute water level data from the primary sensor as good or bad
2. Replaces bad data points and fills gaps with backup sensor data or other data and methods comparable to standard CO-OPS protocols
3. Has the potential to be adapted to partner-collected water level observations

Using: 18 years of data, 57 representative stations

Overall QC model skill assessment

		Actual Class	
Predicted Class		1	0
	1	True Positive	False Positive
	0	False Negative	True Negative

Validation Data Initial Results for All Stations (57)	
Accuracy Percentage For Bad Points: (True Negative / Total Negative)	**84.9%**
Count of False Negatives:	**2102**



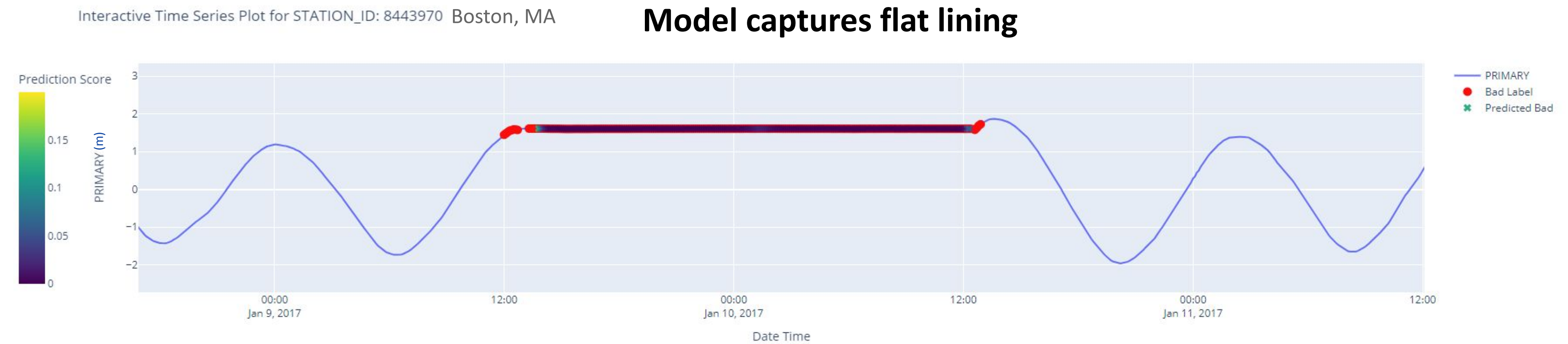
False Negative

True Negative (Hit)

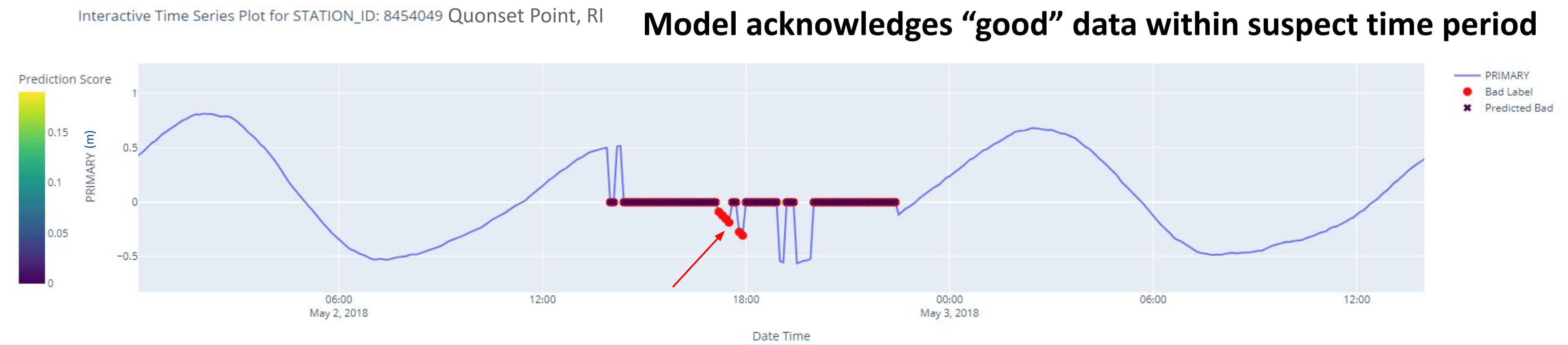
False Positive

Examples of model successes

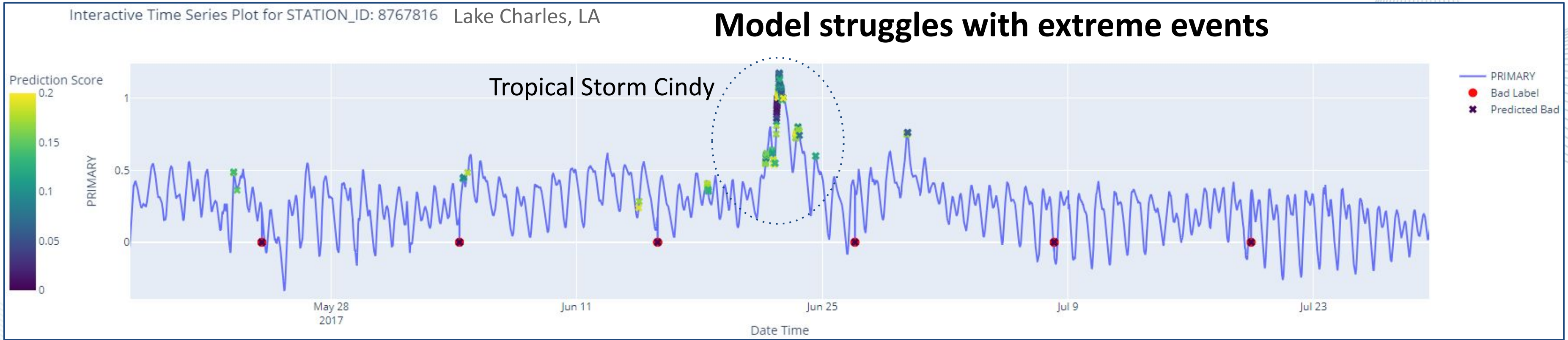
Model captures flat lining

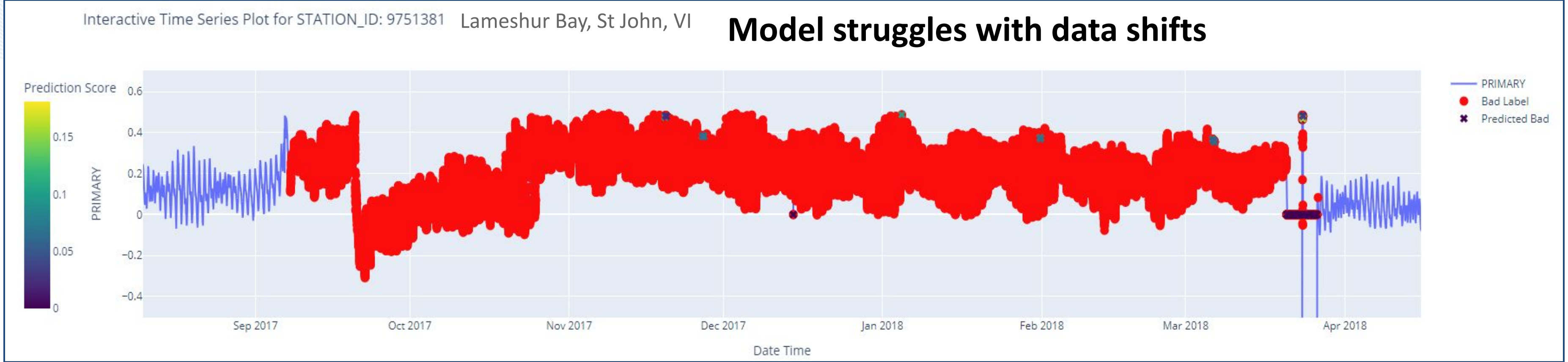


Model acknowledges "good" data within suspect time period



Examples of model issues





Development Timeline

Now	Fall 2025	Spring 2025/ Fall 2026	Fall 2027
Preparation	**AI Model Development**	**Test on partner data**	**Transition to Operations**
Data prep, HPC resources and AWS bucket, project planning	Project with GCOOS and Texas A&M Corpus Christi to complete peer-reviewed research demonstrating model approach	Test accuracy of AI model approach on external partner data	Implement the new AI model approach into CO-OPS' routine operations

Development of Automated QA/QC Methods for Texas Historical Water Level Data

- The Texas Coastal Ocean Observation Network (TCOON) has been operating since the late eighties - about 90 stations with data from several months to 30+ years

- **Overall Goal:** Restore a comprehensive 30+ year TCOON dataset consisting of historical and current data by reimagining the Lighthouse data platform

- Develop and assess automated methods, AI and non AI, to remove unphysical data and fill gaps with goal to approach CO-OPS verified water level data quality

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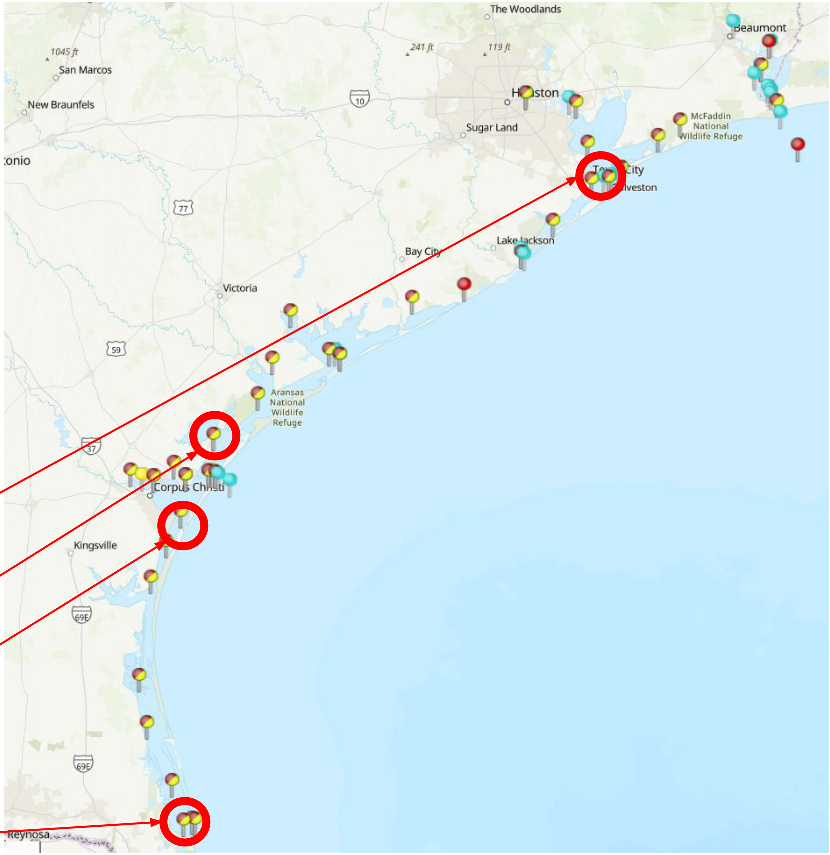
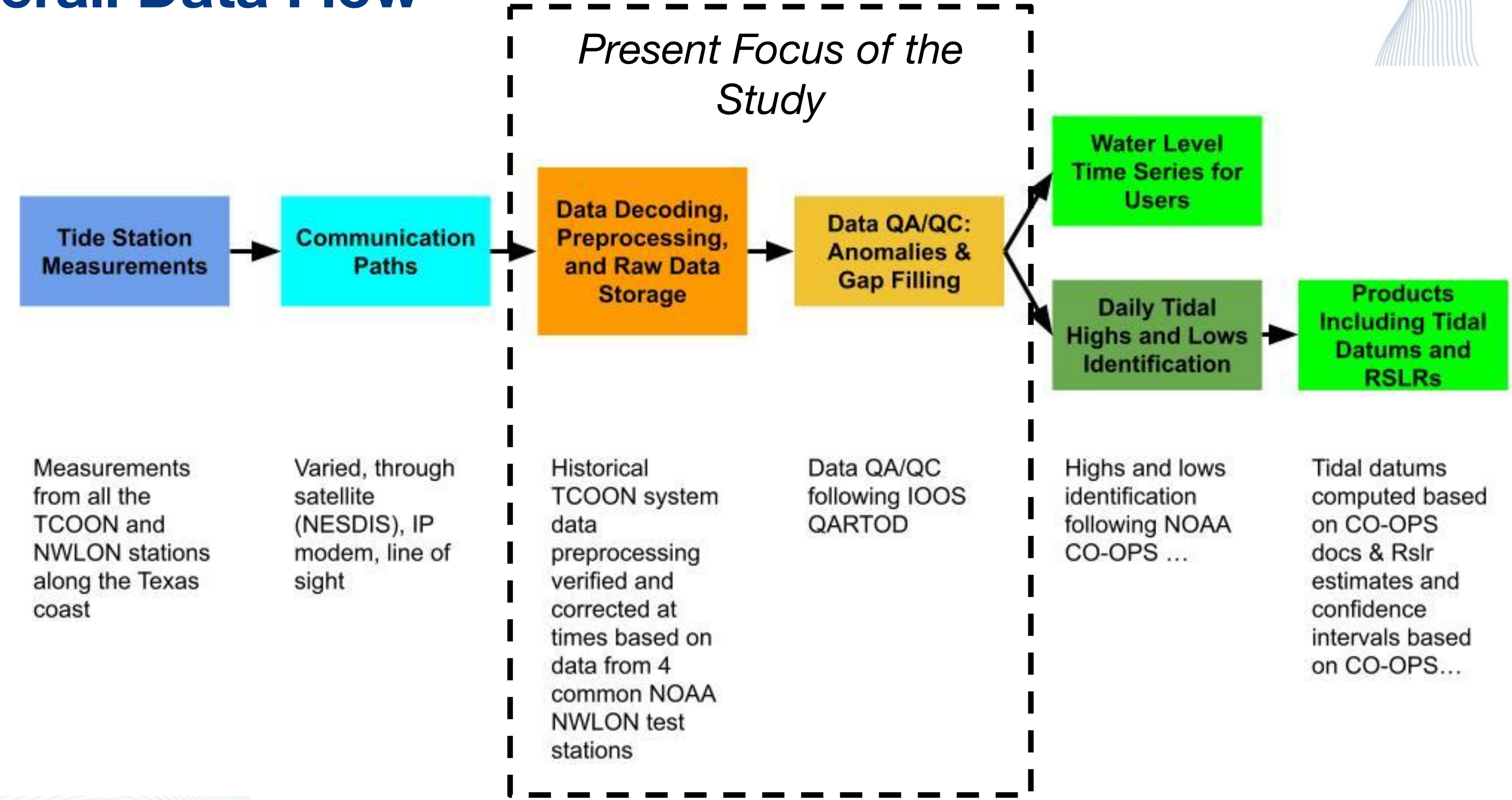
Strategy for Historical Data Quality Assessment

- Follow IOOS QARTOD for water levels
- Use CO-OPS methods as much as possible
- Compare data processed independently by the historical and new methods with NOAA Tides and Currents verified water levels for four NWLON tide stations
  - Pier 21 (back of barrier island, near ship channel, longest record in Gulf)
  - Rockport (shallow bay)
  - Bob Hall Pier (open coast)
  - Port Isabel (along ship channel)



https://tidesandcurrents.noaa.gov/map/index.html?region=Texas

Overall Data Flow



Historical Data Analysis

- Analyzed stations for respective data gap distributions and timing of presence of back up water levels
- Found 6-min lags for part of the data - corrected with updated LRGS messages processing code
- Vertical differences found, mainly due to timing of C1/C2 parameter update timing during inspection and instrumentation changes. No changes to the data as long as differences are < 2 cm

Developing Workflow

- Flat line flag: remove all flat lines 30 minutes or longer
- Compute median of analyzed time series
- Remove all data below or above 4m from median (Texas Spike Threshold)
- Remove points with high rate of change (1m/6 min at present)
- Initial neural net gap filling from nearby stations & comparison with measurements - removal if large difference
- Third difference algorithm test (forward and backward)
- Gap filling (gap length dependent):
  - If back up water levels exist use: https://doi.org/10.1109/OCEANS.2014.7003065
  - If no back water levels, use neural net nearby station gap filling method

Conclusions and Discussion

Water level data of high quality with minimal gaps is ideal for downstream products- AI enabled QC methods look promising

Questions:

- Provide user different levels of processing? (Ex: raw, qc flagged, gap filled, combination of all?)
- Indicate to the users if data has been processed with AI?
- Would you implement automated QC measures for your data type?
- Other suggestions and discussion topics?

Questions?

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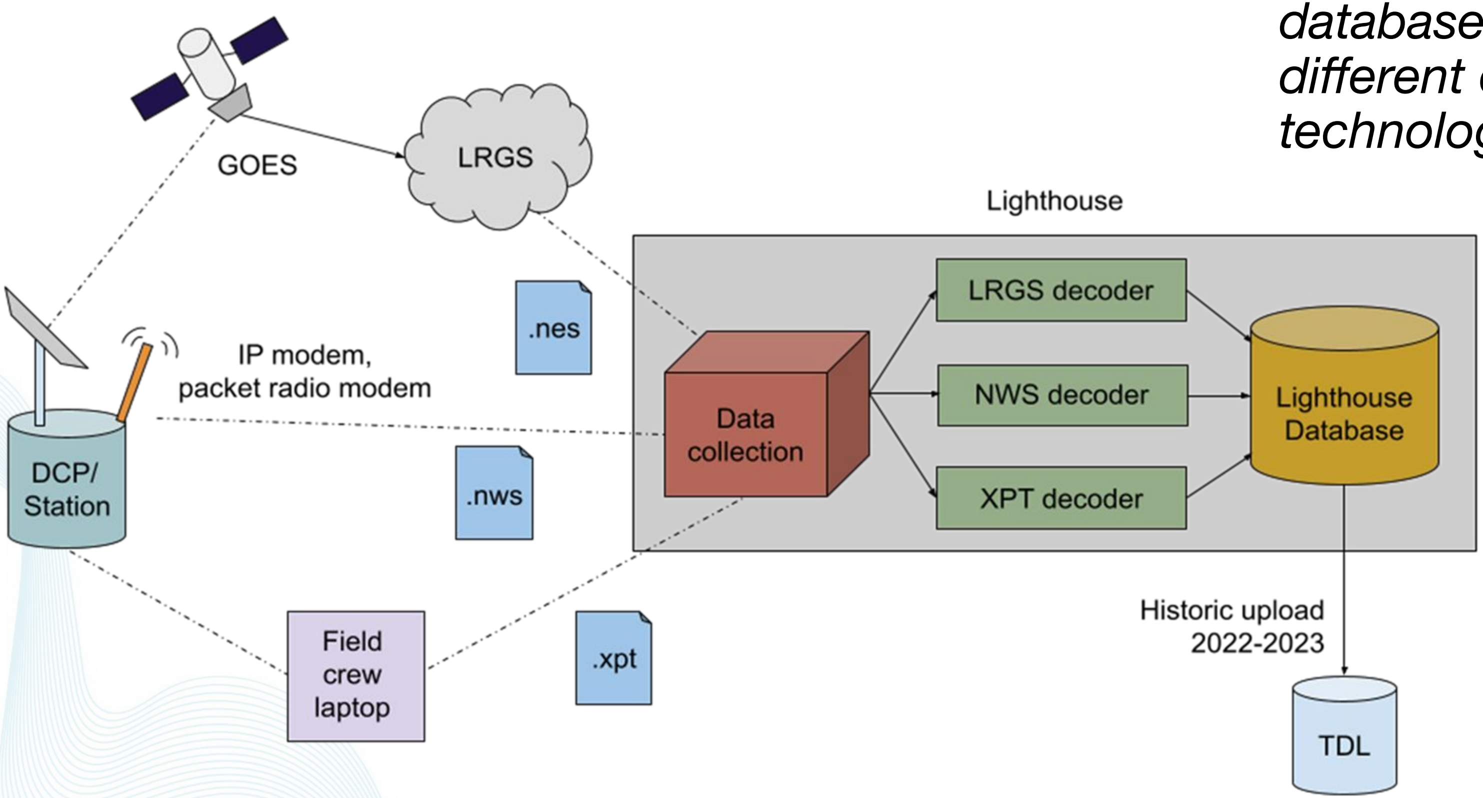
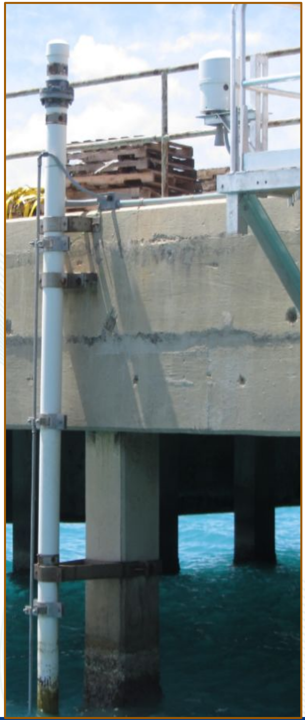
Data Messages Communication Paths

Illustration of data paths from measurements to database through different communications technologies



Existing Water Level QC Workflow

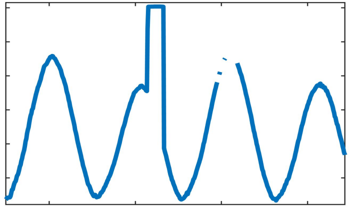
Primary + Backup
water level sensors



Onsite QC

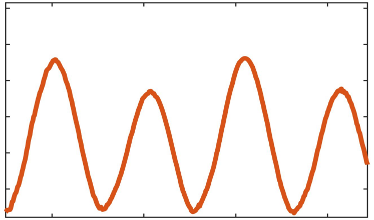
Outlier detection
6-minute averaging
Initial QC flags

Preliminary Data

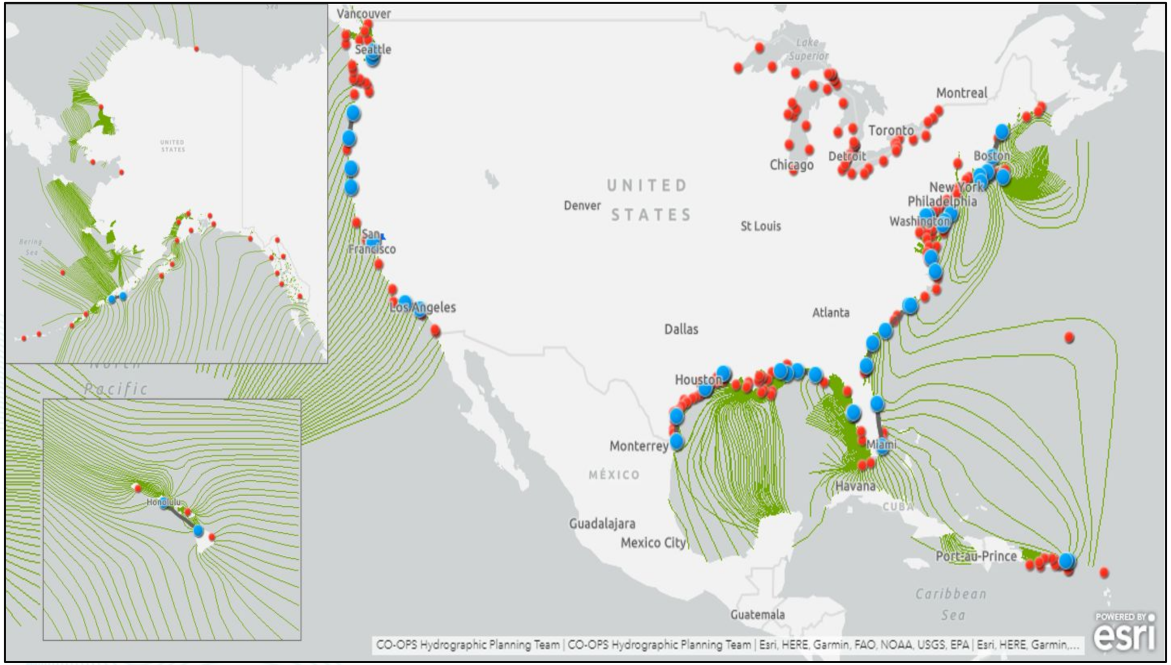


Manual processing
and verification

Verified data



Data and methods



Map of NOAA water level stations (red markers) and the stations that were included in the training dataset for the model (blue markers). Green lines are cotidal lines.

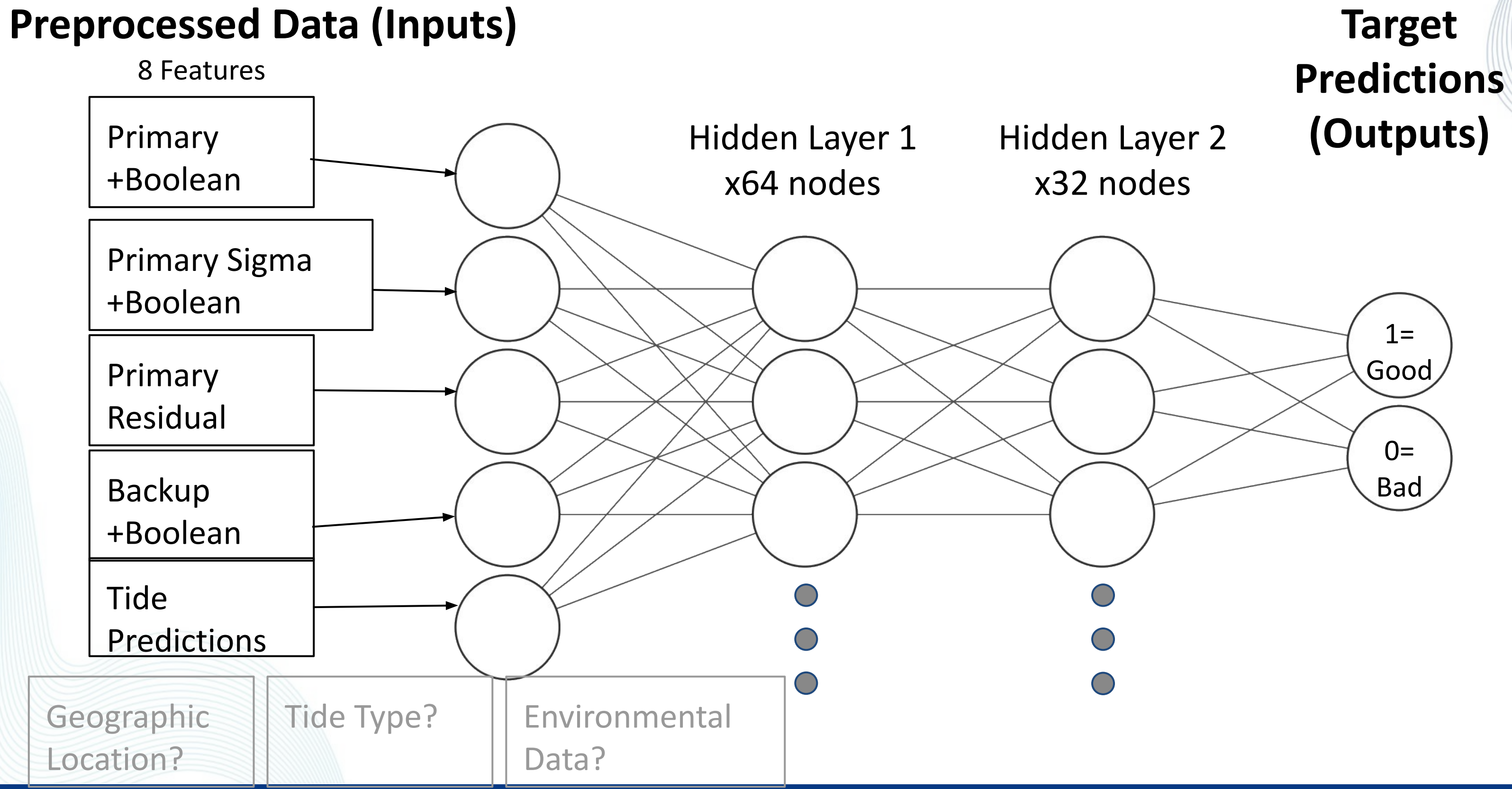
Data set

- 57 Representative Stations
- Training: 2007-16
- Validation: 2017-18
- Testing: 2019-20
- Data cleaned and scaled
- Resampling tested 90/10 split

Model Architecture

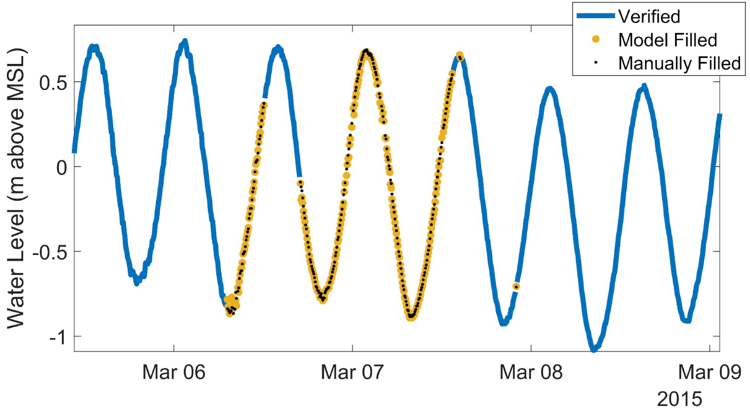
- MLP Neural Network
- 2 hidden layers (64,32)
- Activation: Sigmoid
- Optimizer: Adam
- Loss Function: Binary cross entropy

Model Architecture



Data fill model

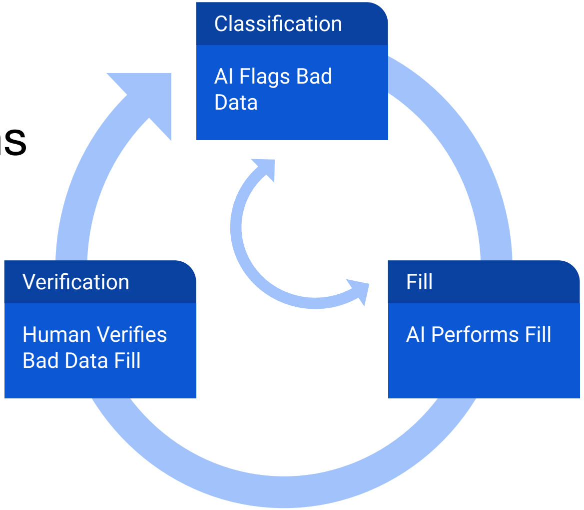
- Test AI/ML methods for filling missing data and replacing bad water level observation data
- Results using a similar MLP NN model and including water level points before and after showed promise:



- Further explored LSTM and GRU time series approaches, which showed further promise for an AI/ML approach to gap filling

Considerations for RTO

- Quality of data used for training is very important (**AI-ready data**)
- As authoritative data source, we need to be able to explain how data was inferred-plan to publish comparison of AI methods to CO-OPS' existing methods and explore **explainable AI** methods (XAI)
- **HPCs/GPUs** can be used to perform many model runs at once- essential for accelerating research and real-time operations
- Concerns of SME knowledge loss, **human-in-the-loop** methods must be considered:



Potential Outline

- The main challenges that we encountered when applying AI/ML models for Water Level Quality Control .

(e.g. Making Water Level Data AI-Ready, Harmonization strategies, Computing and Infrastructure Limitations, Integration into Operational Systems etc.)

- Overcoming these Challenges
- Key Takeaways and Recommendations