# Machine-Learning-Based Time-Series Forecasting for Rapid Correction of Global STOFS

Al Cerrone, Lee Westerink, Coleman Blakely, Damrongsak Wirasaet, Clint Dawson, Joannes Westerink

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#### **Global STOFS Overview**

- Global Surge and Tide Operational Forecast System (Global STOFS) runs at NOAA 4x daily.
- Driven by ADCIRC. Total water levels reported at hundreds of stations in USA, which we focus on here.



## Improving Global STOFS Rapidly?

- Sources of Model Discrepancy in Global STOFS
  - o lack of thermohaline circulation
  - o lack of hydrology
  - o poor bathymetry
  - o poor mesh resolution
  - o poor meteorological forcing
- Improvements are coming!



- However, we can improve Global STOFS "wholesale" without discriminating one error source from another...
- ... and we can do this while attending to both Global STOFS' input and output.

## **Rapid Improvement for Operations**



## **Rapid Improvement for Operations**



#### Global STOFS + ML Overview

- I. Global STOFS renders 7-day forecasts. We'll consider forecasts at NOAA stations.
- II. Source actual water levels and ADCIRC's previous predictions from prior 5 days.
- III.Source winds and tides for previous 5 days and 7-day forecast horizon.
- **IV.Exercise Transformer**



V. Post-Process

#### Training Temporal Fusion Transformer (TFT)

- I. Ran 3-year Global STOFS hindcast from 2016 2019.
- II. Sourced observed total water levels from NOAA from 2016 2019.
- III.Sourced winds from CFSV2 from 2016 2019.
- IV.Ran tidal re-synthesis from 2016 2019.
- V. Merged data. 1-hour temporal resolution. Excluded time stamps with missing data.
- VI.Separated data into 12-day contiguous chunks. Each contained target (ADCIRC hindcasted error), 5 days of past covariates, and 7 days of future covariates. 70% of each station's chunks allocated for training.
- VII.A single TFT was trained on all stations chunk by chunk. The TFT was trained to forecast ADCIRC error 7 days into the future.

## Model Tuning

- We used a tree-structured Parzen estimator to optimize the hyperparameters of the transformer model.
- The performance of the transformer was largely batch-size invariant.
- 10% dropout helped circumvent overfitting.
- Transformer trained with quantile loss.
- In general, a transformer trained on all NOAA stations was more performant than a region-centric transformer.

#### **Example Global STOFS Output**



#### **Example Global STOFS Output**



#### Adding ML Expected Forecast



#### Adding ML Confidence Bounds



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#### **Error Across Horizon**



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#### **Assessing Performance**

- To help quantify performance, we consider normalized root mean square error (NRMSE).
- NRMSE calculated for each 7-day validation period (hundreds per station).



#### Importance of Winds in Chesapeake & Delaware



#### Importance of Winds in Chesapeake & Delaware

Annapolis



## Live and Die by Winds



Large ADCIRC errors strongly correlated to winds!

#### TFT in Delaware River: Bridesburg, PA



#### ML Performance Across USA

- The TFT performs well for tidally-dominant stations.
- It does not perform as well in the Gulf of Mexico where stations are wind-driven and surrounded by relatively shallow water.



#### ML Performance Across USA

(NRMSE ADCIRC) / (NRMSE ADCIRC+ML)



#### Aggressive Correction at Tidally-Dominant Station



#### Very Weak Correction at Wind-Driven Station



#### **Aggressive Correction Addressing Bias**



#### Conclusions

- The transformer is a rapid way to correct ADCIRC.
  - o Highly performant for tidally-dominant stations.
  - o Not as attentive to wind-driven stations, but renders corrections nevertheless.
- In the future...
  - o Expose transformer to longer training period.
  - o Generalize this approach to extrapolate corrections between stations.
  - o Make the transformer attentive to tropical cyclones.

