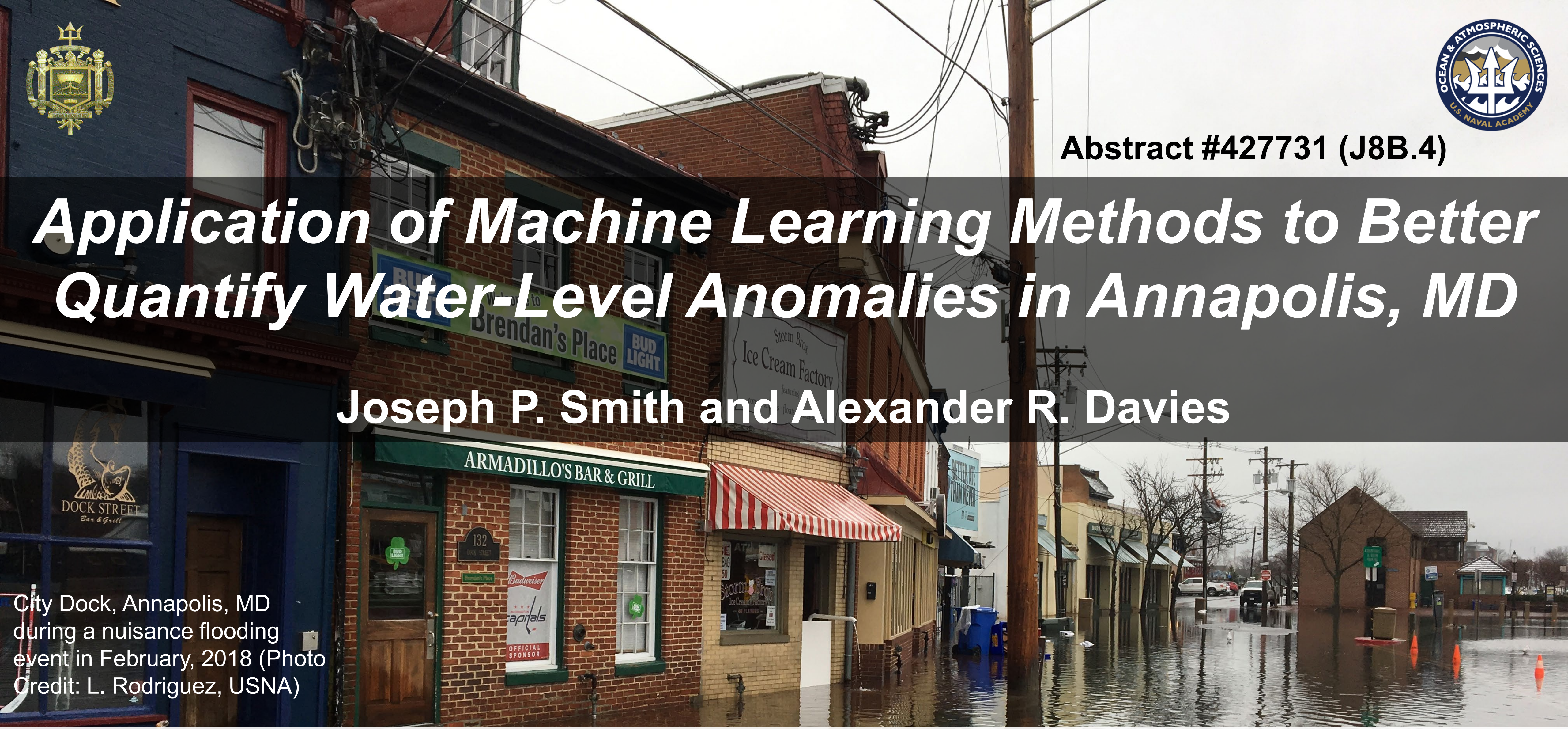
Abstract #427731 (J8B.4)

Application of Machine Learning Methods to Better Quantify Water-Level Anomalies in Annapolis, MD

Joseph P. Smith and Alexander R. Davies



City Dock, Annapolis, MD during a nuisance flooding event in February, 2018 (Photo Credit: L. Rodriguez, USNA)

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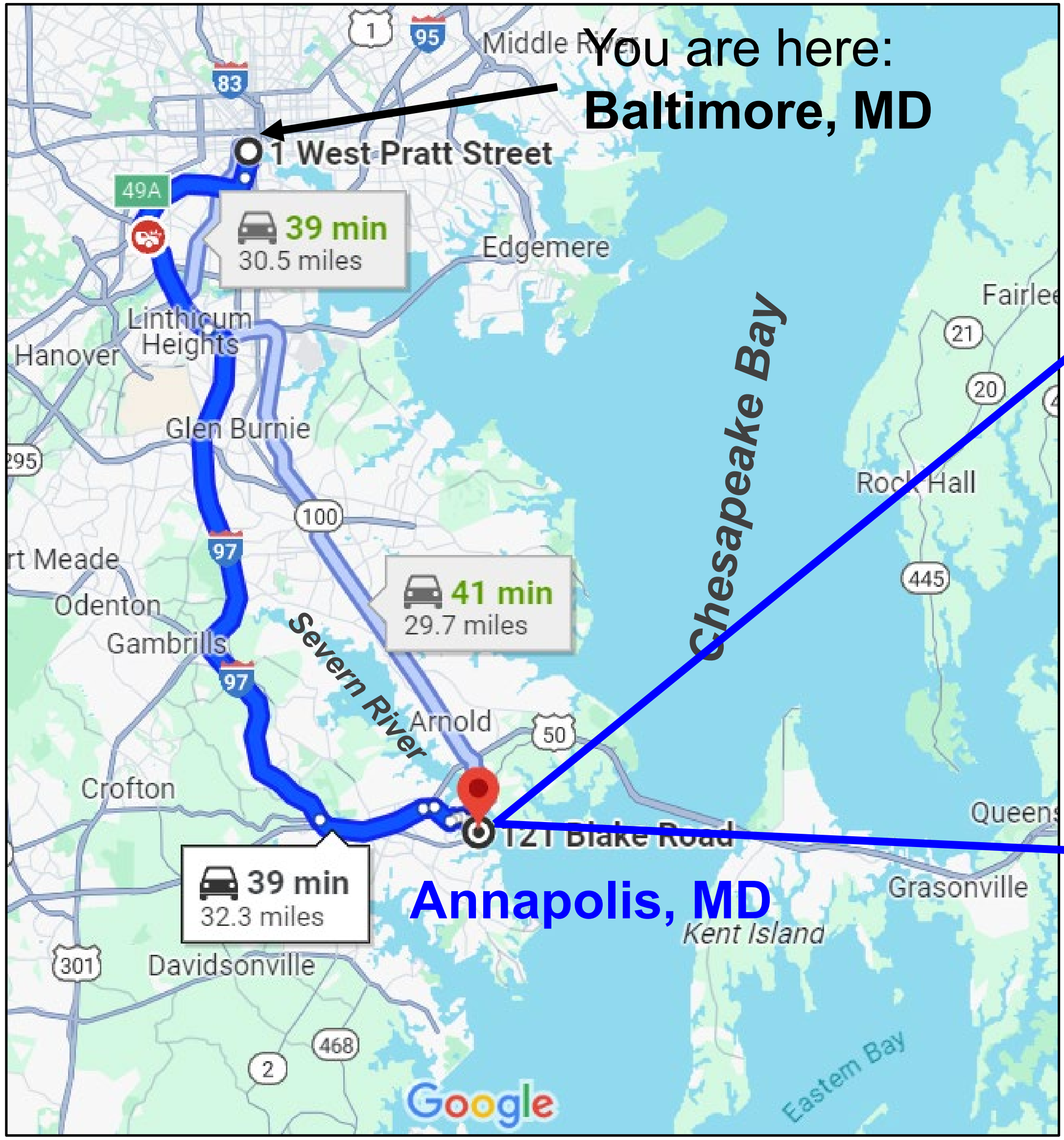
Joint Session J8B: 23rd Conference on Artificial Intelligence for Environmental Science and 22nd Symposium on the Coastal Environment - Applications of Artificial Intelligence to the Coastal Environment

AMS American Meteorological Society

AMS 2024
AMERICAN METEOROLOGICAL SOCIETY
104TH ANNUAL MEETING
28 JANUARY-1 FEBRUARY 2024
BALTIMORE, MD & ONLINE

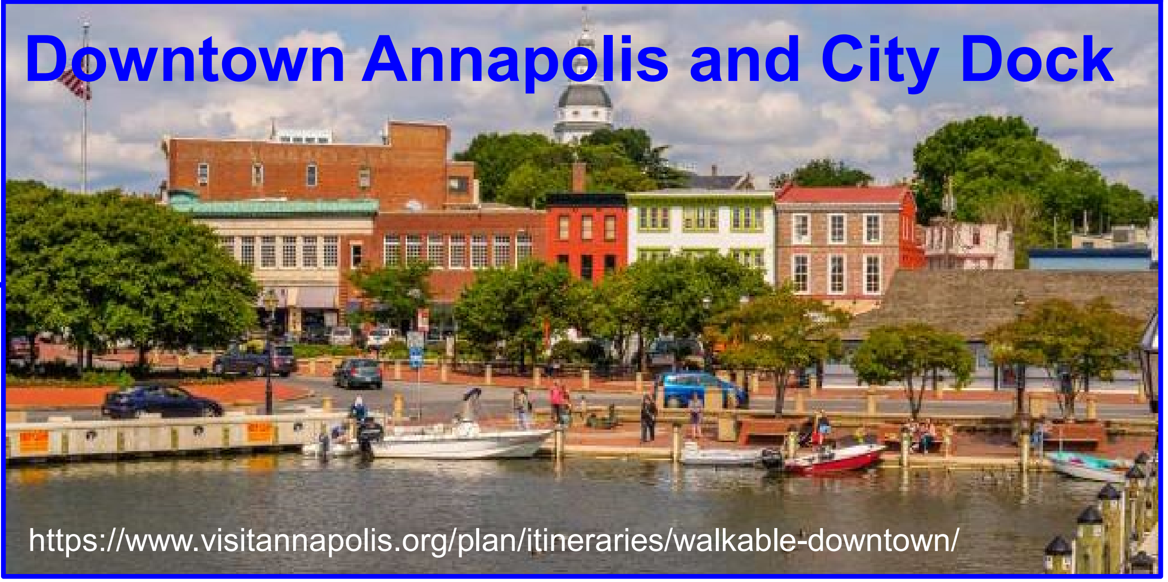
Welcome to Baltimore, MD and the Chesapeake Bay Region!



U.S. Naval Academy (USNA)

(https://www.military.com/base-guide/us-naval-academy; U.S. Navy photo by Mass Communication Specialist 1st Class Chad Runge)

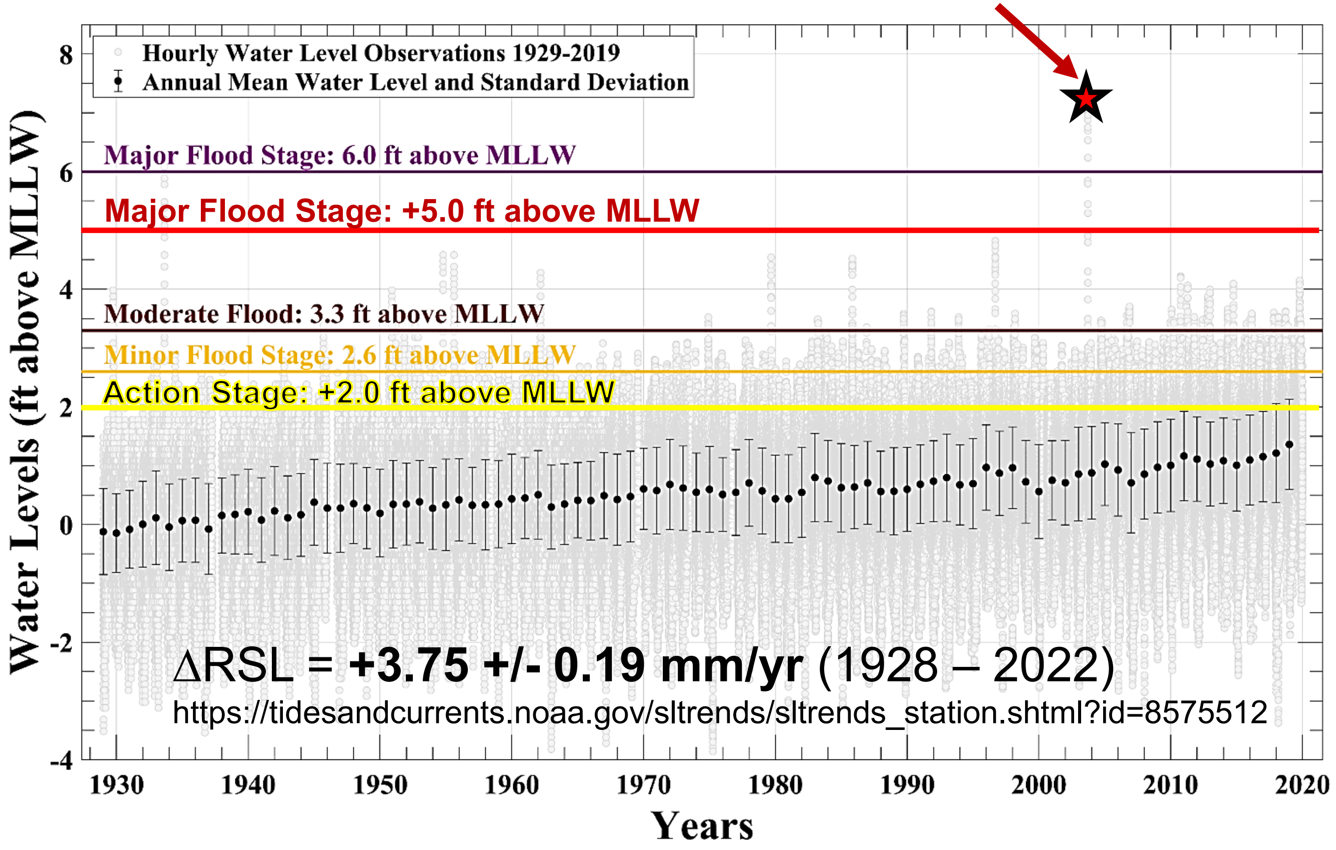
Downtown Annapolis and City Dock



https://www.visitannapolis.org/plan/itineraries/walkable-downtown/

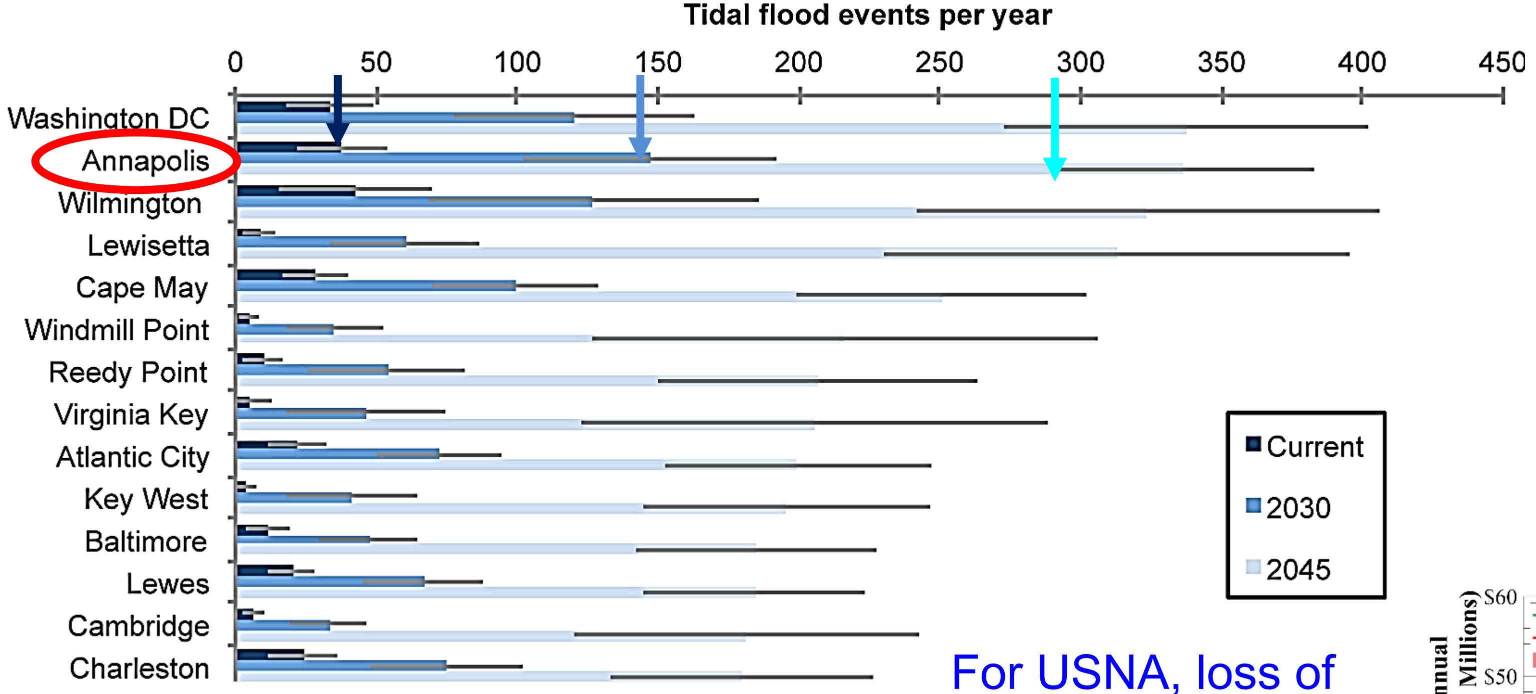
Coastal Flooding

Hurricane Isabel, SEP 2003; MLLW +7.16 ft



Annapolis hourly (light gray) and annual mean (black dots with standard deviation) water levels from 1929 to 2019 showing a near-linear rise in sea level. Minor (yellow; 0.79 m), moderate (red; 1.01 m), and major (purple; 1.83 m) flood stages, as defined by the NWS Baltimore/ Washington WFO, are plotted (from Fig. 1; *Davies et al., 2022*).

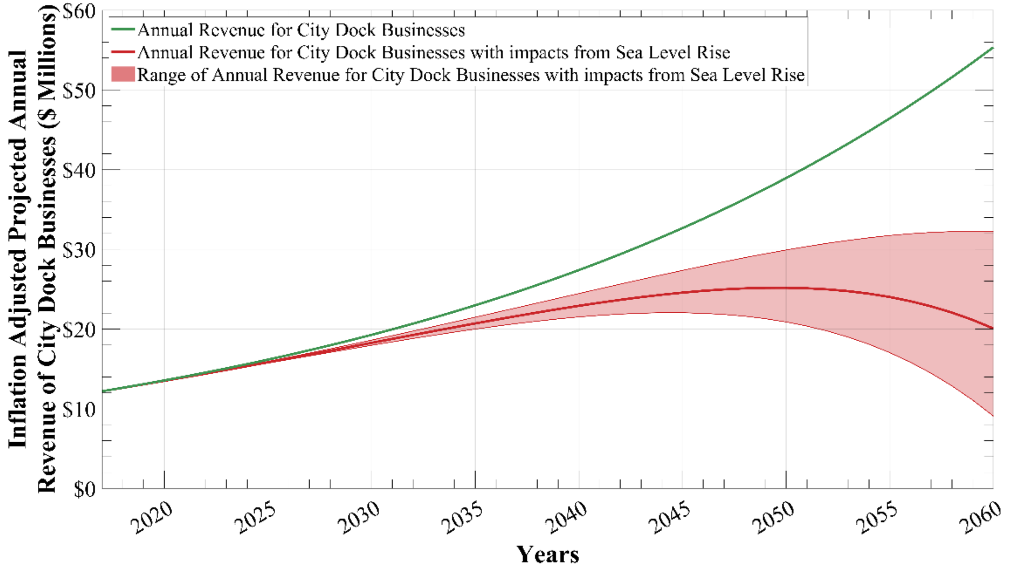
Frequency of Coastal (Tidal) Flooding and Potential Impacts



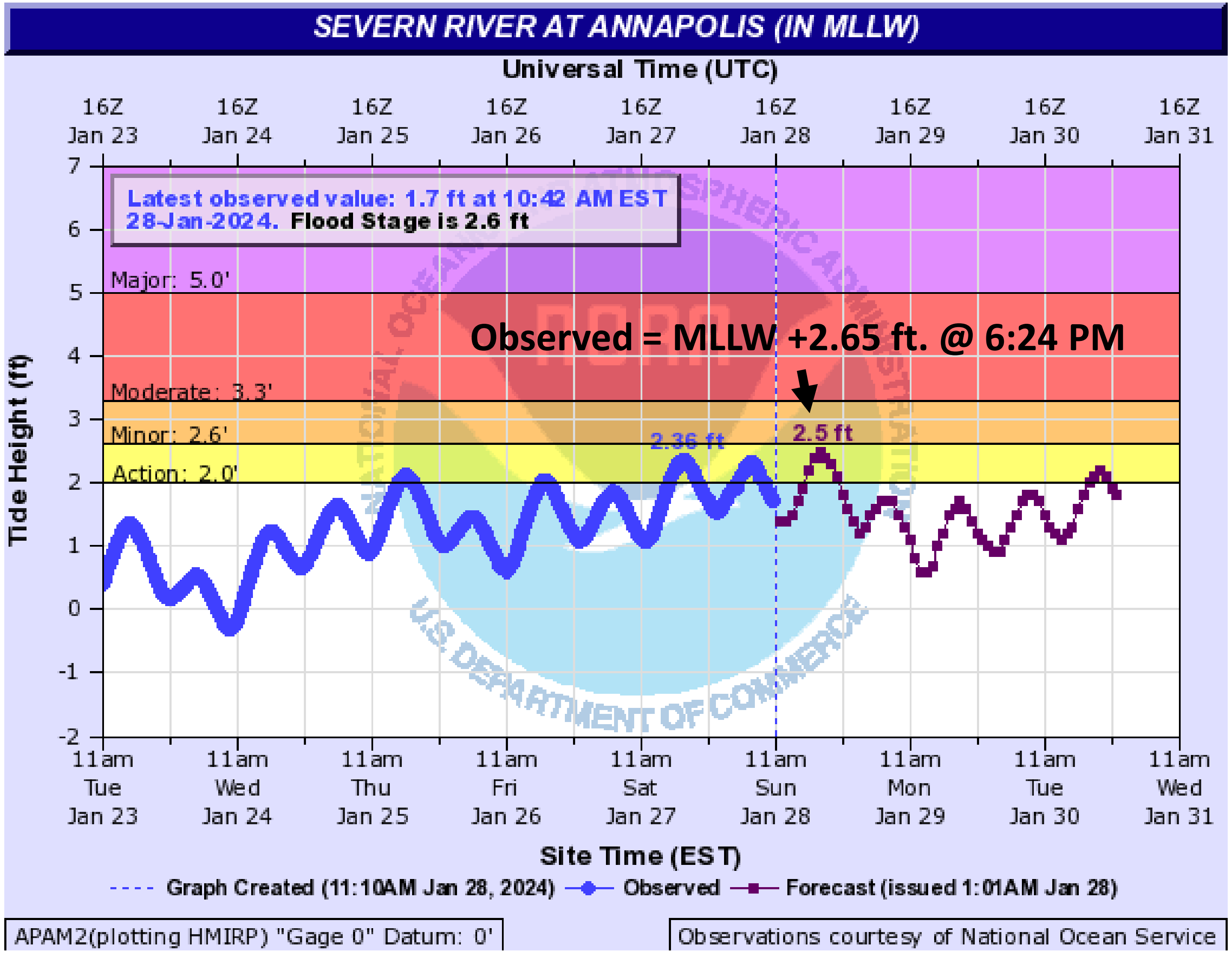
For USNA, loss of training days, damage to Infrastructure, etc.…

Tidal flooding events per year for all gauges observed today, and projected for 2030, and for 2045. Numbers shown represent annual averages and are based on localized sea level rise projections using the National Climate Assessment's Intermediate-High scenario (from Fig. 6, *Dahl et al., 2017*).

Inflation adjusted revenue for Annapolis City Dock businesses without impacts from relative SLR (green) and with the impacts of SLR (red). The ratio of 1% loss in visits corresponds to a 0.61% loss in revenue (0.4% to 0.8% range) from *Hino et al., 2019* (from Fig. 7, *Annapolis City 2023 FEMA HMGP*).



Coastal Water Level Predictions – To Act or Not to Act?



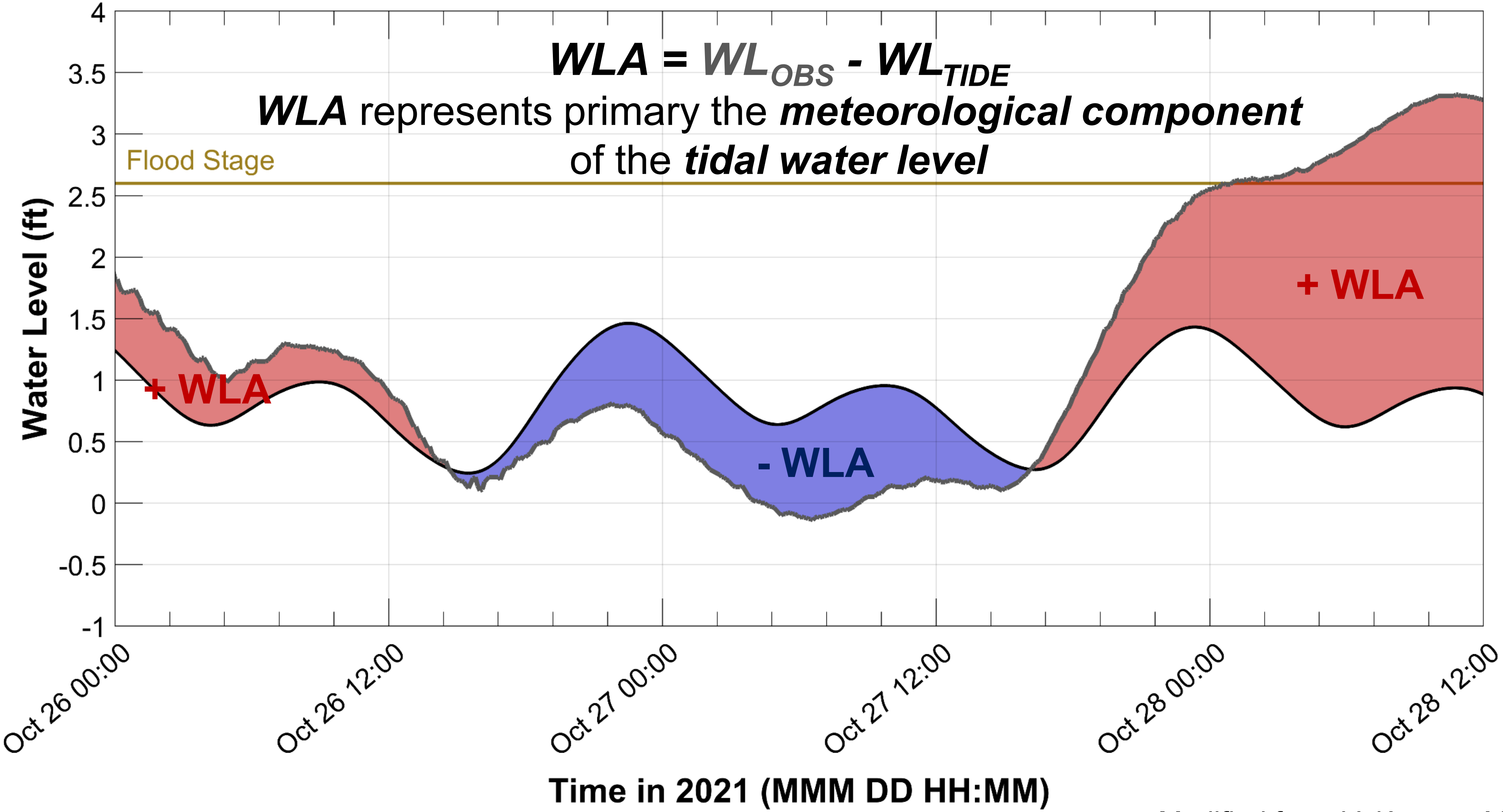
https://water.weather.gov/ahps2/hydrograph.php?gage=apam2&wfo=lwx

- U.S. Naval Academy and Naval Support Activity Annapolis and Annapolis City Office of Emergency Management (OEM) teams make decisions on actions (i.e. sandbagging) in response to potential coastal flooding events 6-24 hours in advance (semi-diurnal tide) based on best-available predicted/projected water levels
  - *Difference Between Minor Flooding and Action = + 0.6 ft.*
  - *Difference Between Moderate and Minor Flooding = + 0.7 ft.*
- Current NWS water level predictions are from deterministic models that do not capture uncertainties

⇒ Wrong decisions based on best available predictions can be costly…

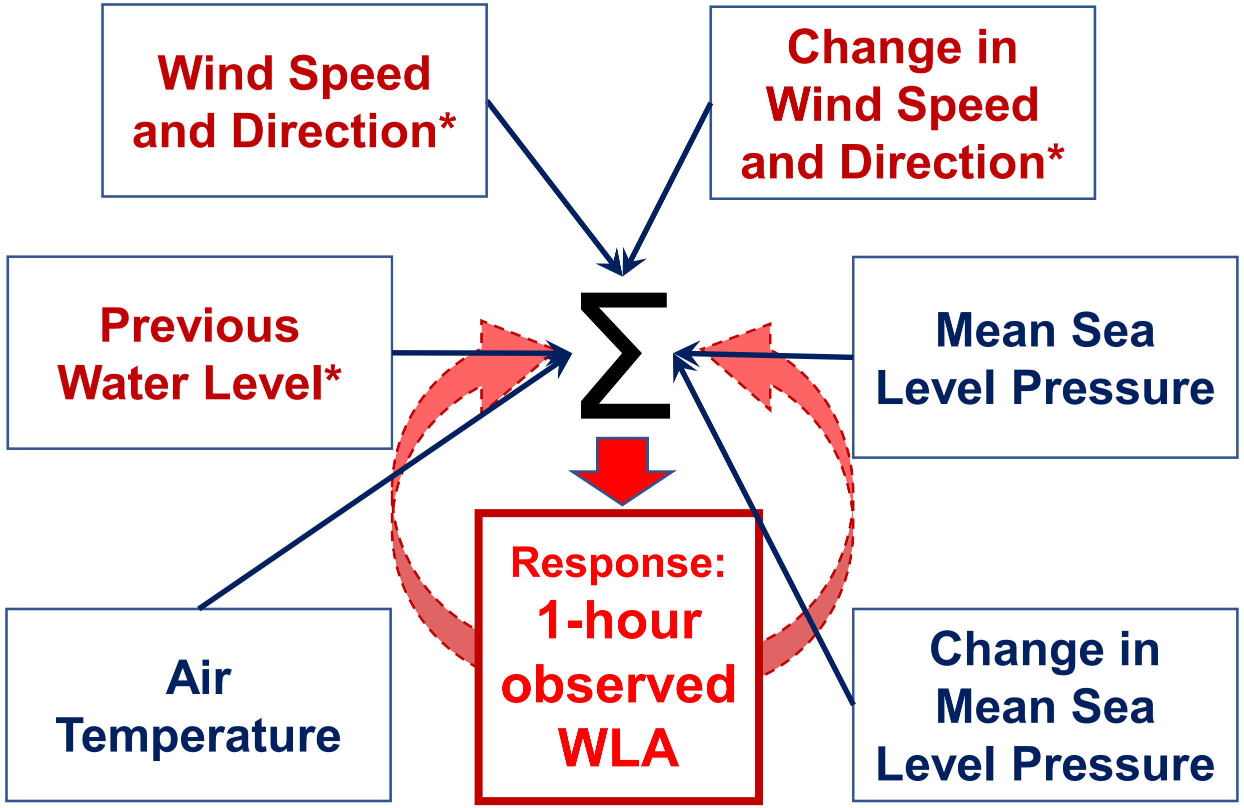
Water Level Anomalies (WLAs)

Can machine meaning methods based on readily-available environmental observations be used to better quantify WLAs?



Modified from *Velásquez-Montoya et al., 2022*

Machine Learning Modeling Approach



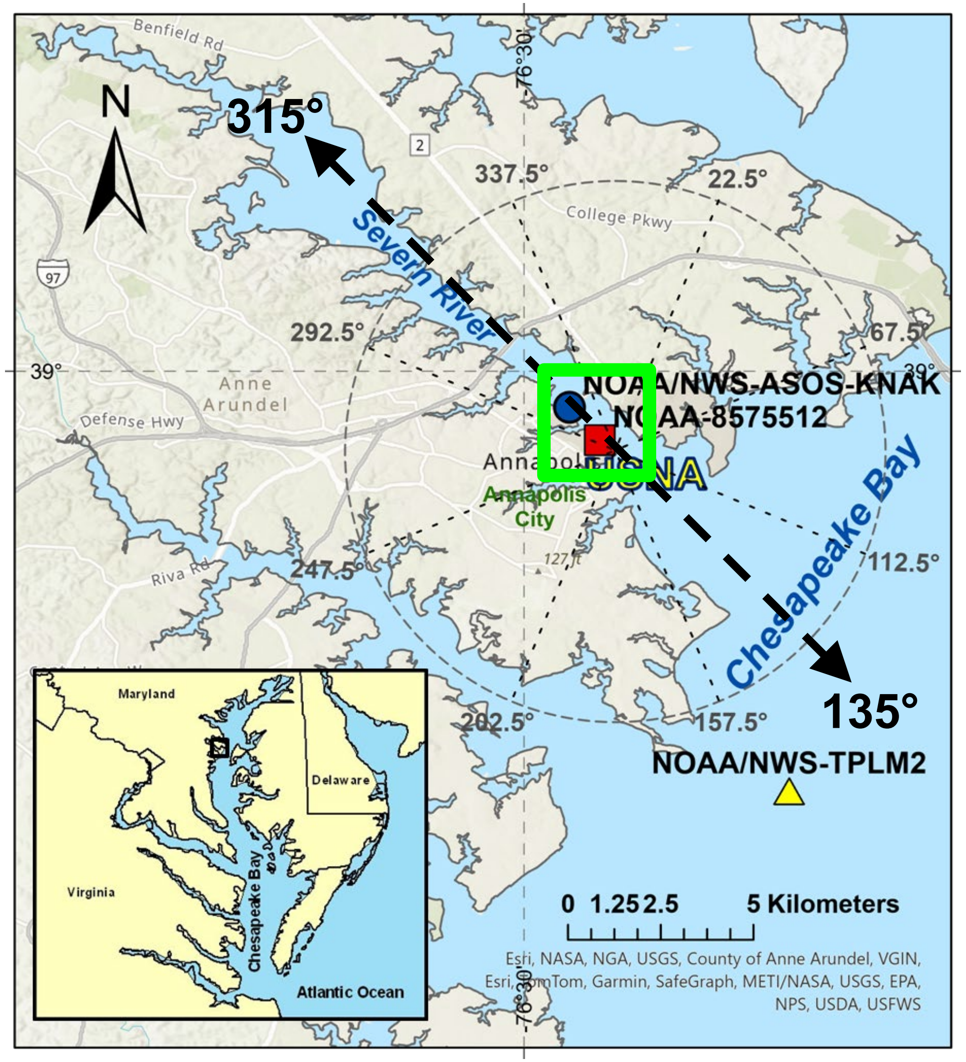
Hourly Water Levels – NOAA NOS COOPS Annapolis, Tides and Currents, Annapolis, MD - Station ID: 8575512 (https://tidesandcurrents.noaa.gov/stationhome.html?id=8575512)
Hourly Meteorological Data – NOAA NDBC Station TPLM2 - Thomas Point, MD (https://www.ndbc.noaa.gov/station_page.php?station=tplm2)

Assumptions:

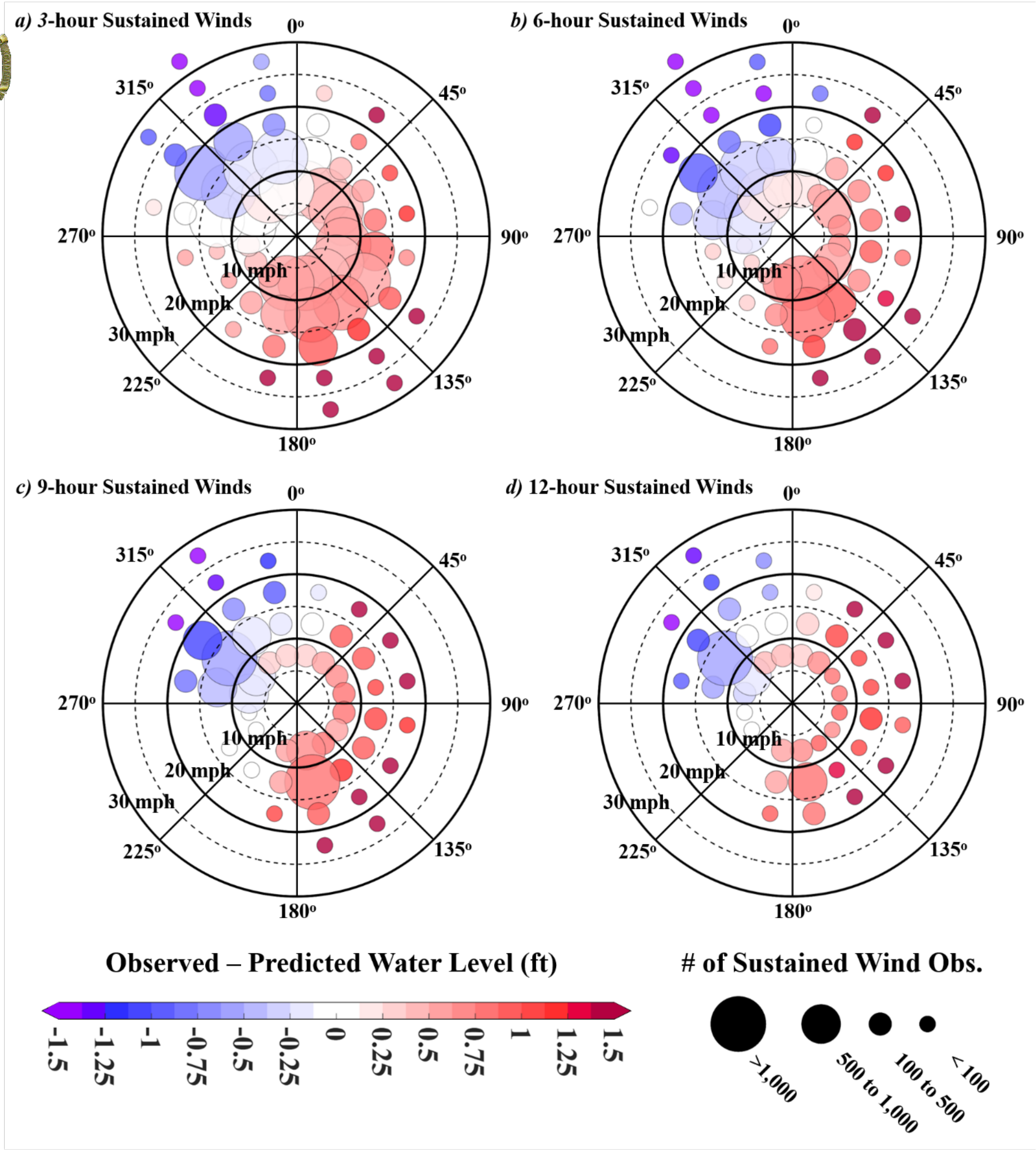
- Predictor variables should make sense from general principles (i.e. changes in mean sea level pressure can affect WL)
- Should expect a linear response in WLA to each predictor
- Data used for predictor variables should be from readily-available data sources
- Hourly data
- *Hourly data averaged over 3, 6, 9, 12 hours prior to observed WLA*
- Water level data used as a predictor should be from at least 6-12 hours prior to the water level
- ***Regression Model*** (MATLAB R2023a and Regression Learner App)

Predictor Variables – Wind Speed and Direction

From (*Davies et al., 2022*, Fig. 3)



WLAs in Annapolis are sensitive to short duration (< 24 hours) sustained wind speed and direction of winds relative to the orientation of the coast (*Davies et al., 2022*)

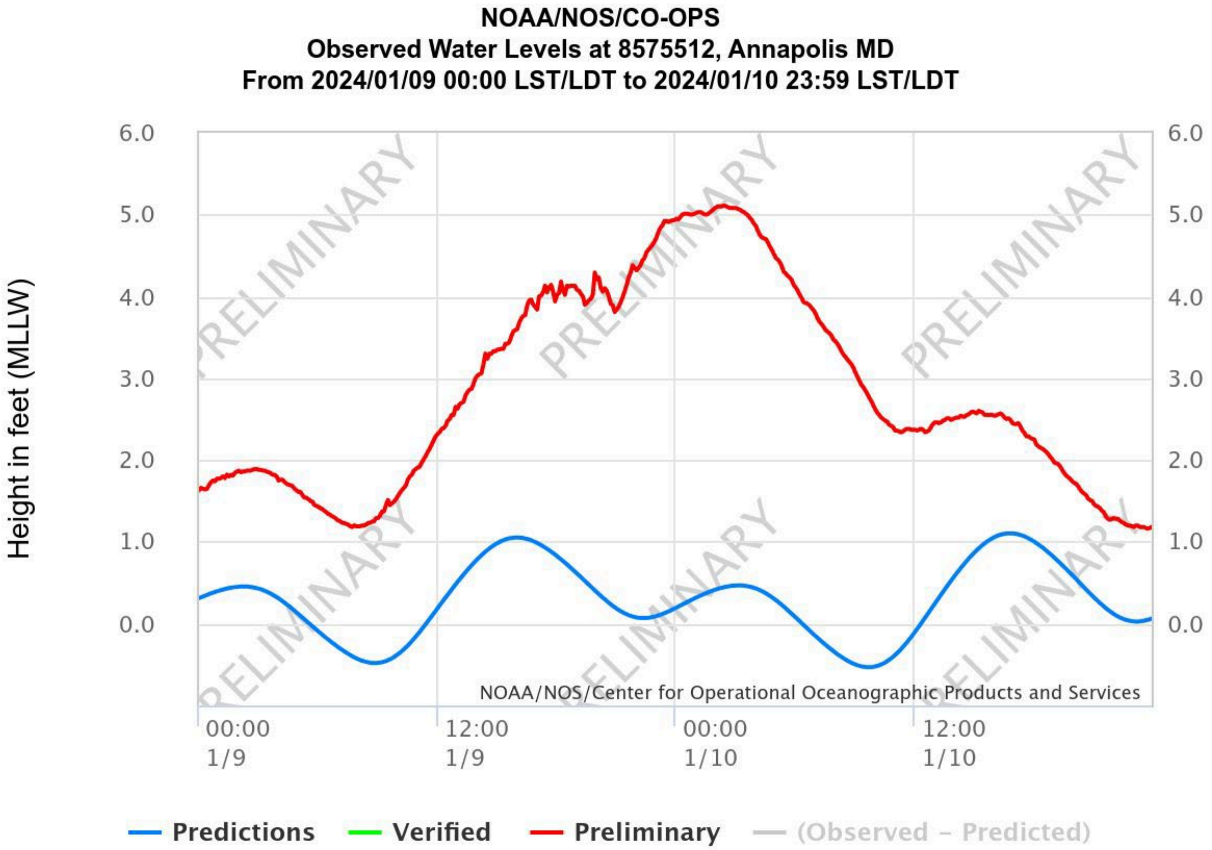


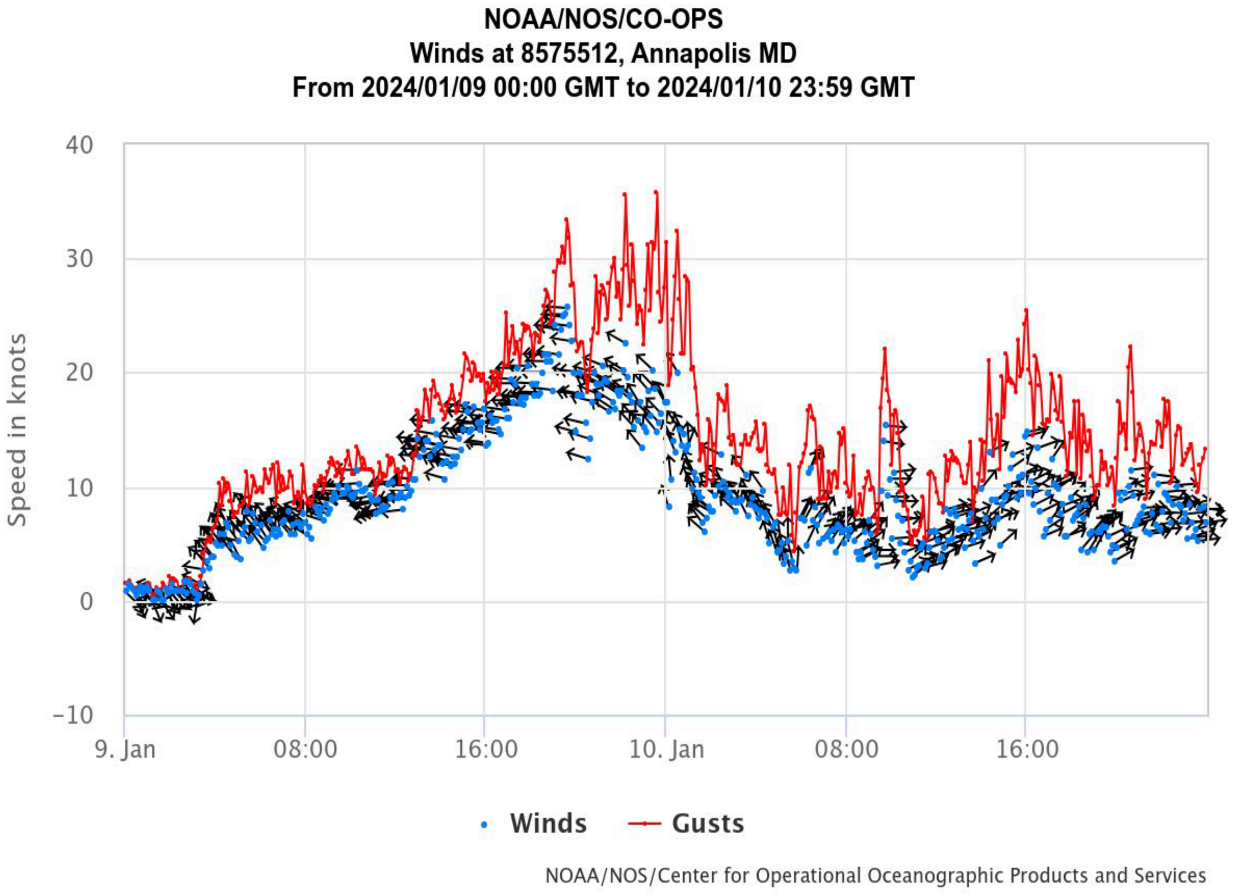
Axial Wind Speed

The impact of sustained wind forcing over (a) 3, (b) 6, (c) 9, and (d) 12 h on WLA in Annapolis plotted in wind speed and direction space (bin averaged). Dot color denotes the magnitude of the WLA, and dot size represents the number of observations in a given bin. Red or blue indicates instances in which the WLA is positive or negative, respectively. This figure bins WLAs by increments of 0.25 ft (0.08 m). The bins and their corresponding SI units (in parentheses) are 0.25 ft (0.08 m), 0.5 ft (0.15 m), 0.75 ft (0.23 m), 1.0 ft (0.31 m), 1.25 ft (0.38 m), 1.5 ft (0.46 m) (from *Davies et al., 2022*, Fig. 5).

Axial Wind Speed is the magnitude of the wind vector relative to the axis of the Severn River. The standard deviation of the Axial Wind Speed is a measure of sustained winds along the axis of the estuary

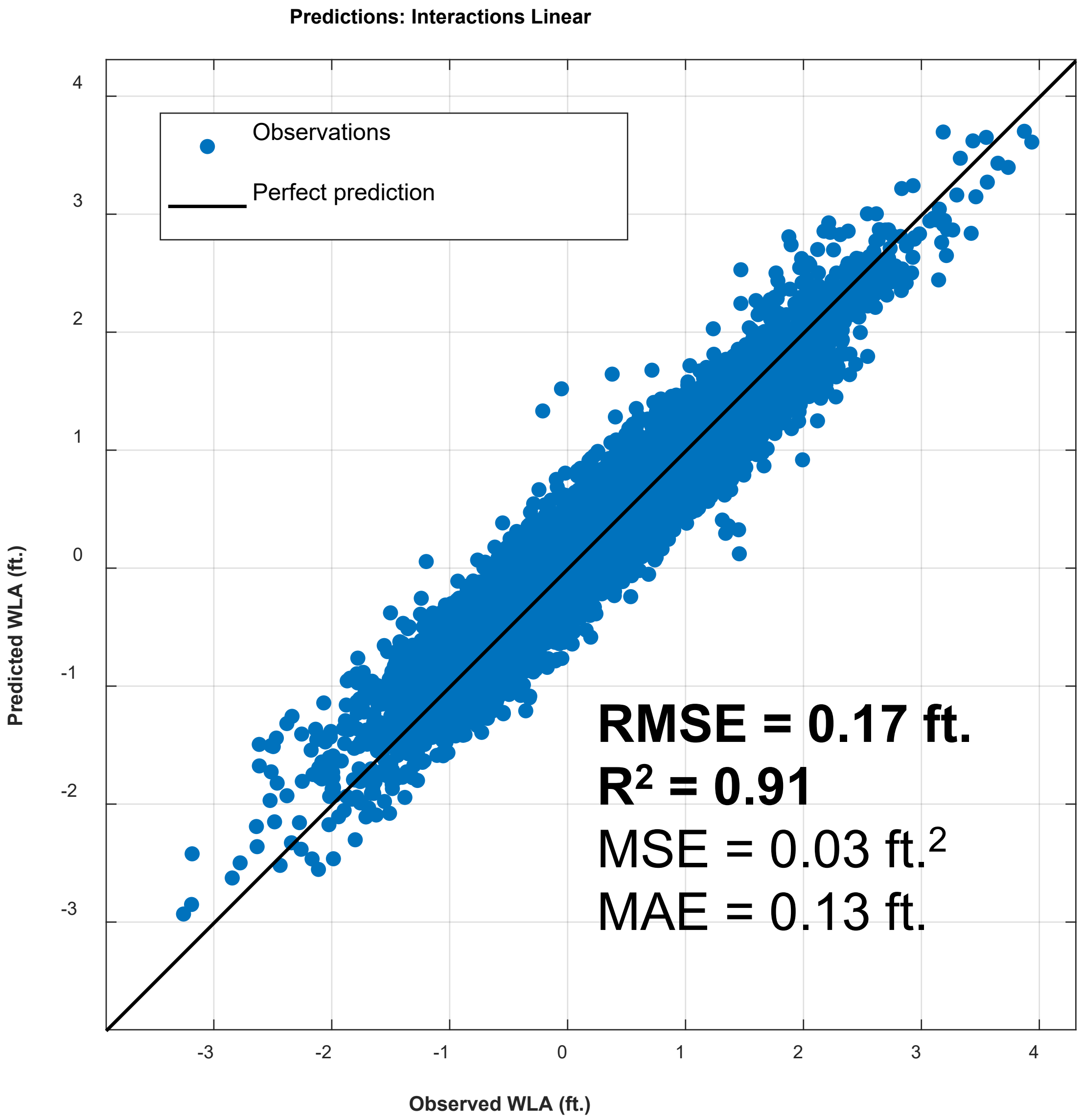
Predictor Variable – Previous WLA





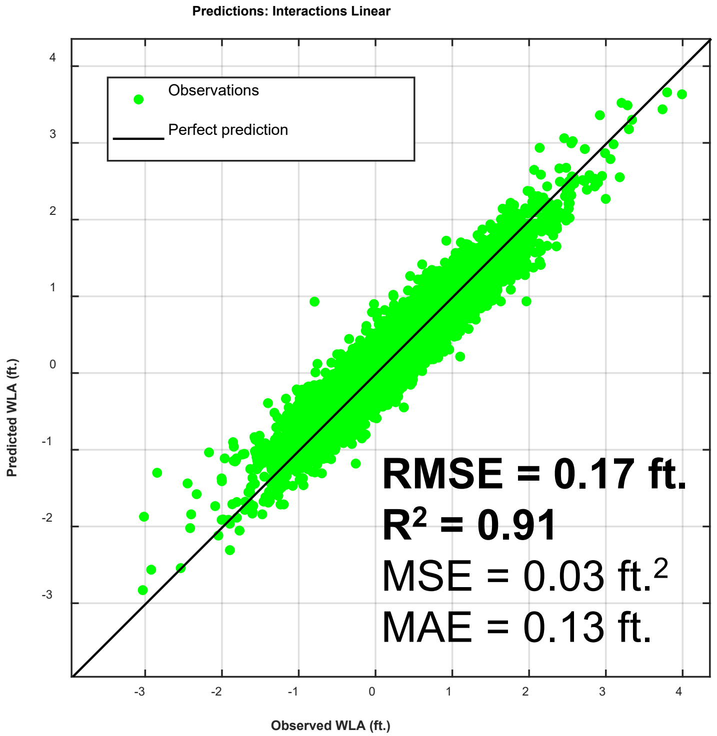
Water does not move instantaneously, must overcome inertia, current WLA is influenced by WLA during previous tidal phase (6, 9, 12 hours prior)

Linear Regression Model Results (w/ - 6 hr. WLA)

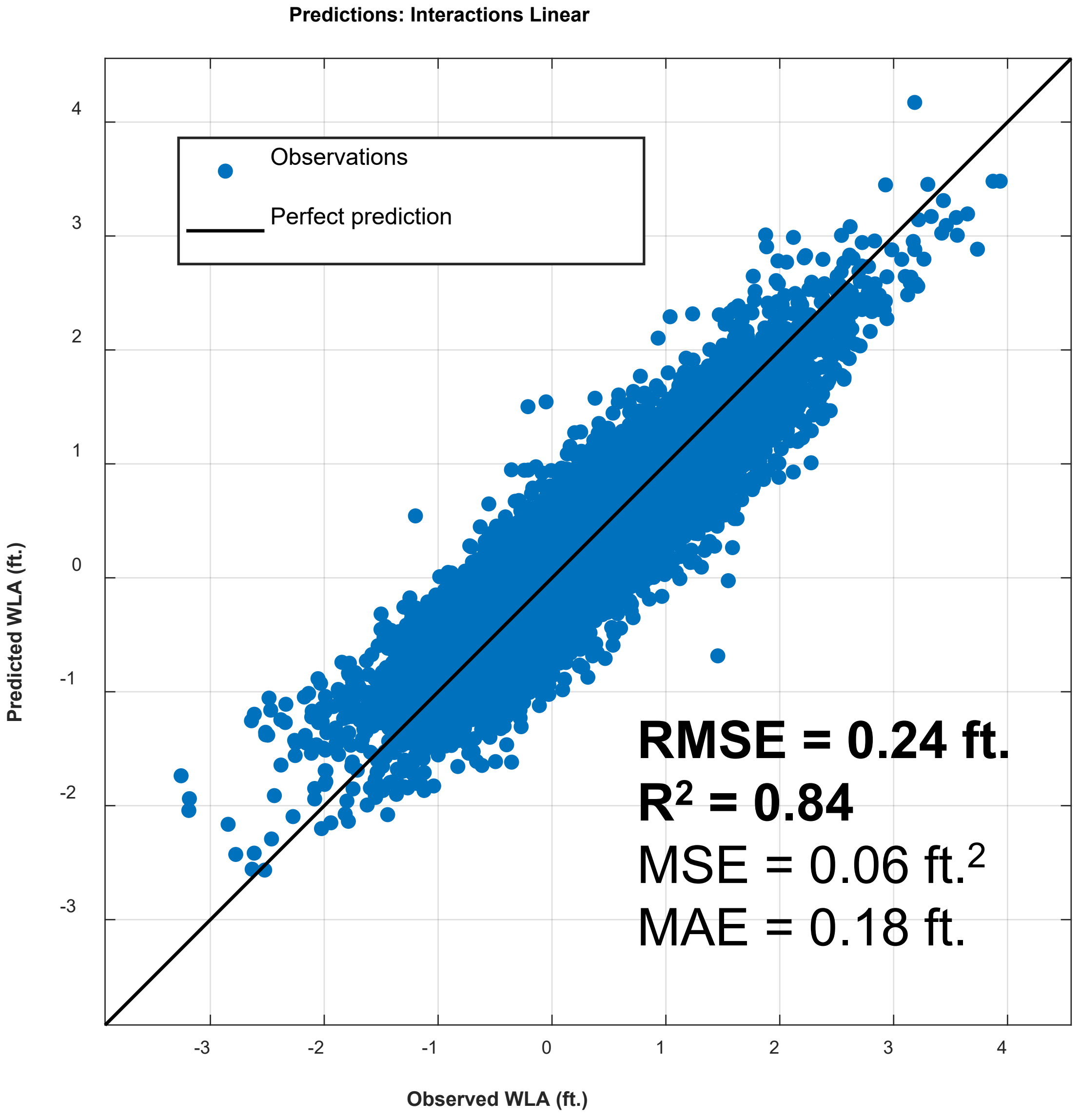


Linear Regression Model with Interactions (Robust):

- 23 Predictor Variables; 87631 Coincident hourly observations from January 2013 – December 2022
- Data set split randomly – **70% Training (61342 observations)**, **30% Test (26289 observations)**
- 5 Cross-validation folds



Linear Regression Model Results (w/ - 9 hr. WLA)



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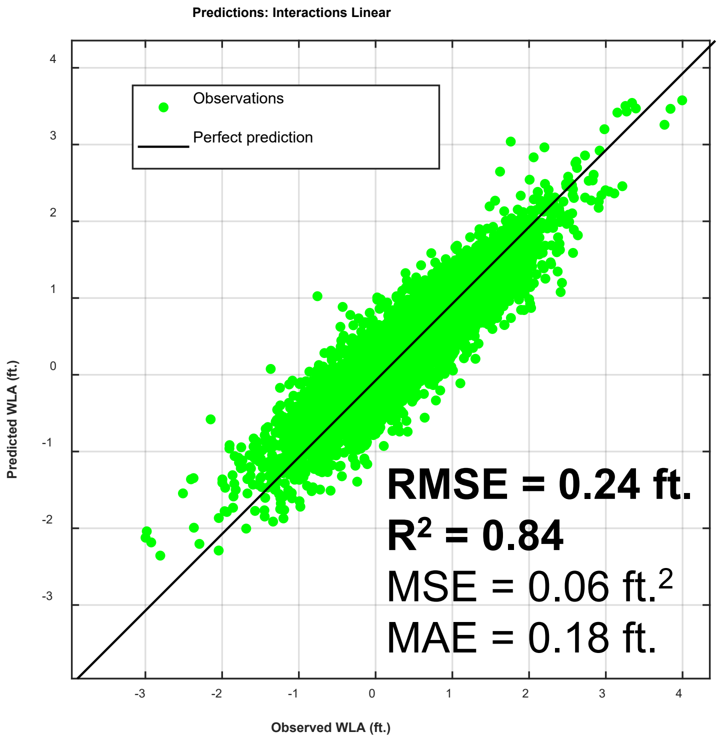
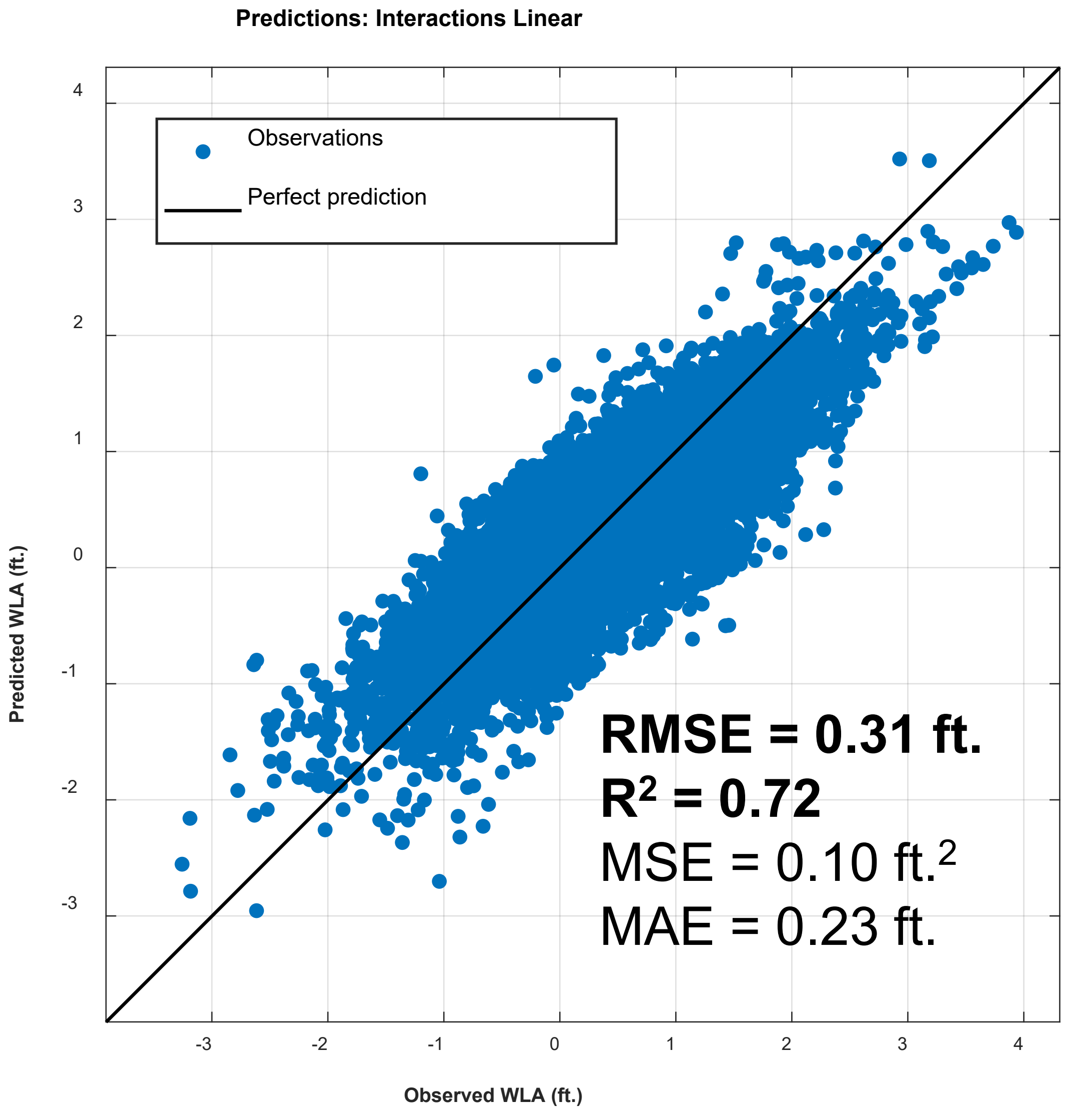


Linear Regression Model Results (w/ - 12 hr. WLA)



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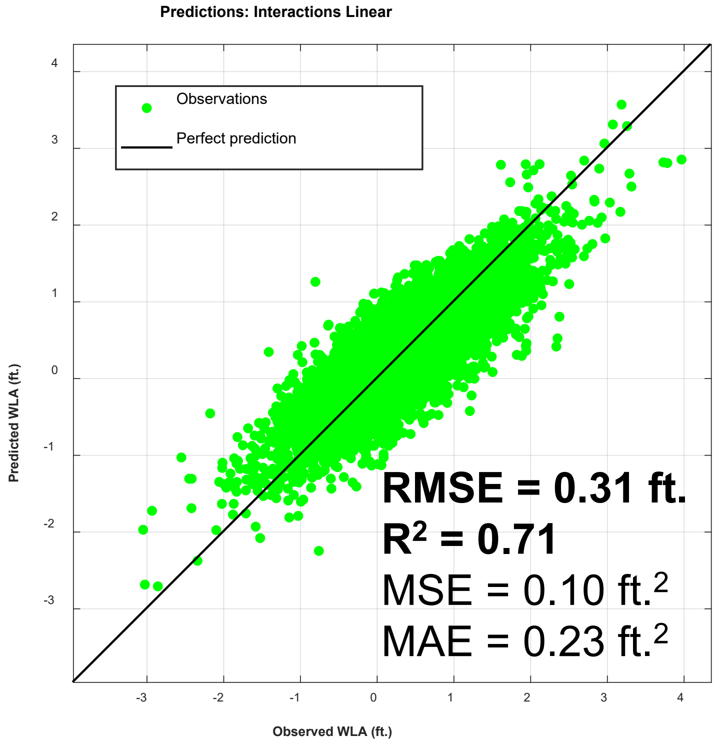

Conclusions and Future Work

A linear regression machine learning model based on readily-available data including observations of wind speed and direction relative to the coast, mean sea level pressure, atmospheric temperature, and WLAs during the previous tidal cycles can quantify WLAs in Annapolis, MD within a statistical margin of error less than the difference between local flooding thresholds

Results could be used to help develop better probabilistic predictions for WLAs in Annapolis, MD that would help local stakeholders mitigate against the economic and infrastructure losses resulting from coastal nuisance flooding

Future Work:

- *Test model sensitivity to current and additional predictor variables and continue to refine model based on results*
- *Train and test other regression models (i.e. Gaussian Processes Regression)*
- *Export model and test against future high or low WLA events using predicted future meteorological conditions (temperature, mean sea level pressure, wind speed and direction relative to the coast)*

Questions

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MLLW + 5.1 ft., January, 2024 (Photo Credit: Annapolis City OEM)

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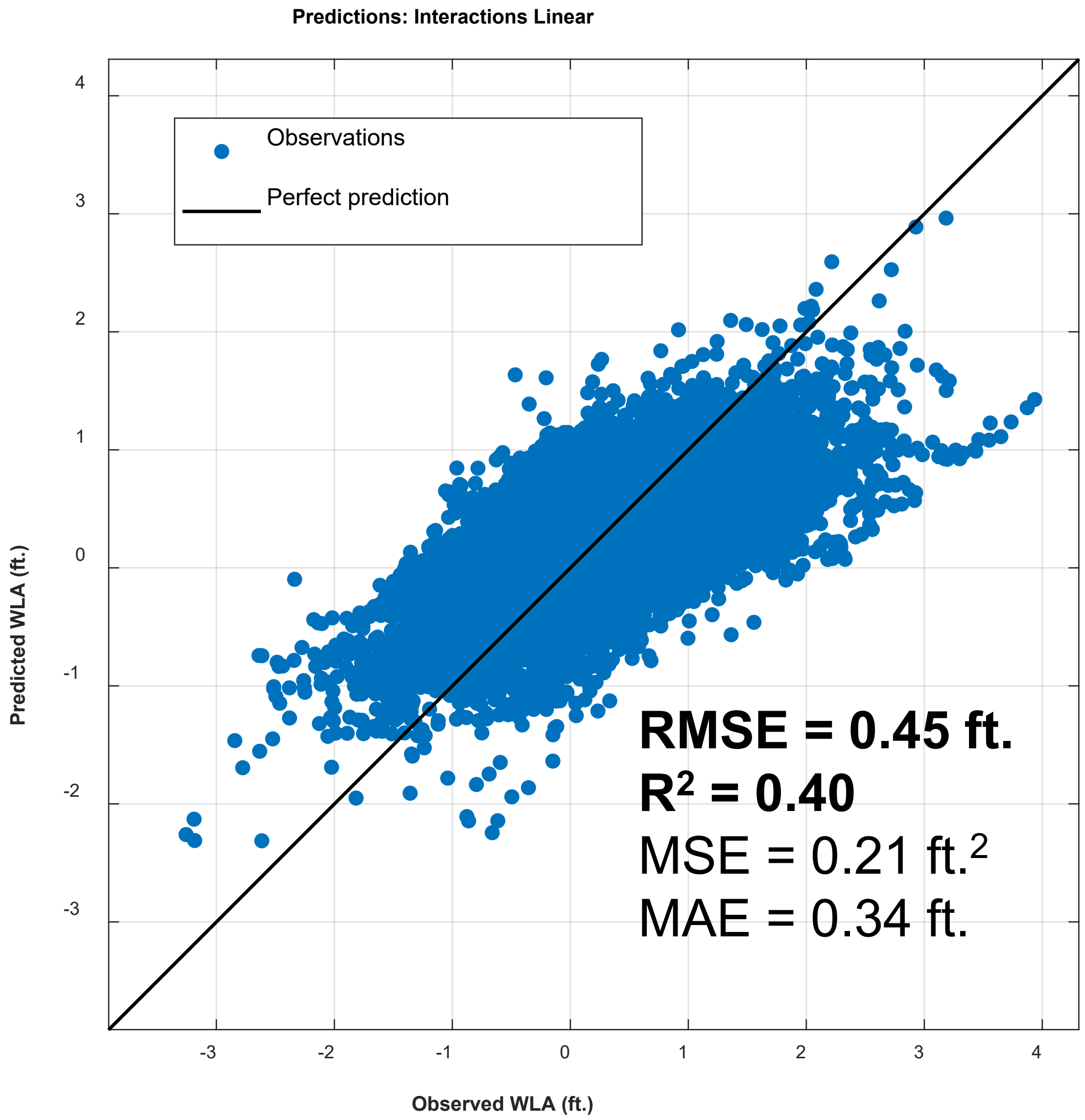
Hino, M., S. T. Belanger, C. B. Field, A. R. Davies, and K. J. Mach, 2019: High-tide flooding disrupts local economic activity. Sci. Adv., 5, eaau2736, https://www.science.org/doi/10.1126/sciadv.aau2736.

Velásquez-Montoya, L., A. R. Davies, P. Guth, T. Tomiczek, A. Laun, A. Wargula, G. Henderson, C. Steppe and L. Wallendorf, 2022: The Oktober Flut: An anomalous extreme high-water event in Annapolis, MD, USA, October 2021. Shore & Beach, 90(1), 27-38, http://doi.org/10.34237/1009013.

Linear Regression Model Results (w/ no previous WLA)



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