Forecasting the Effectiveness of Beach and Dune Nourishments in a Changing Climate

NC STATE UNIVERSITY

USCRP

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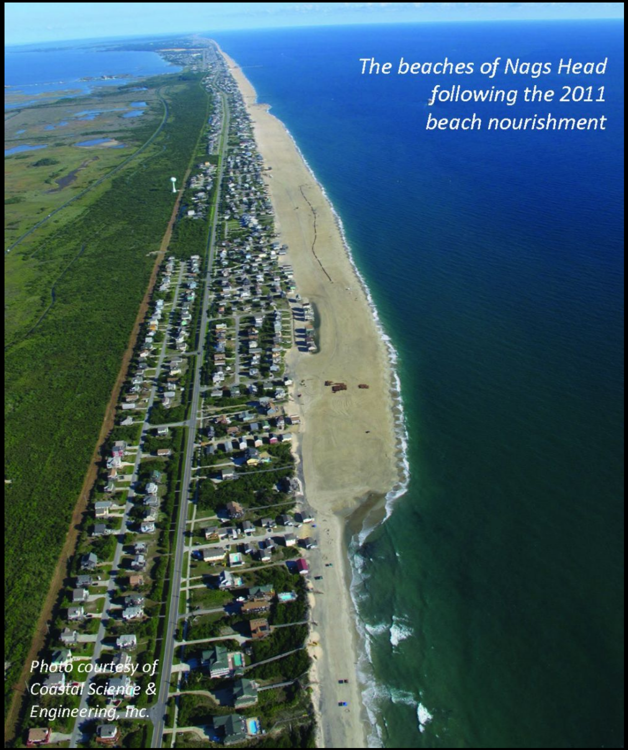
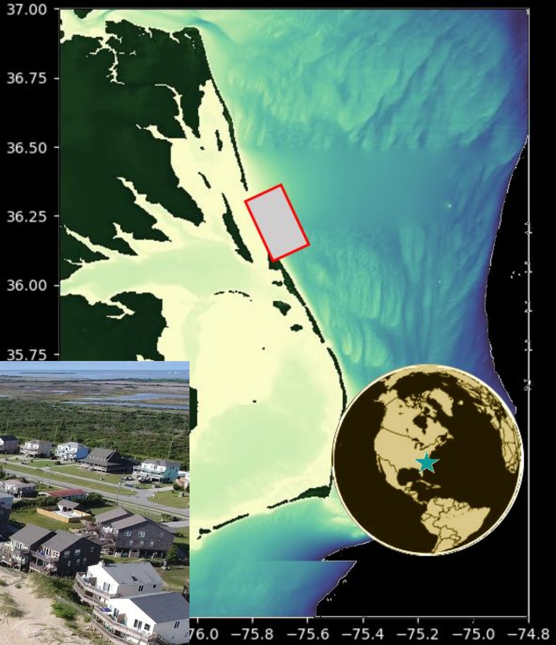
Two recent beach nourishments in Nags Head, NC, USA

<u>2011 Nourishment</u> ($32m)
Hit by Hurricane Matthew in 2016.

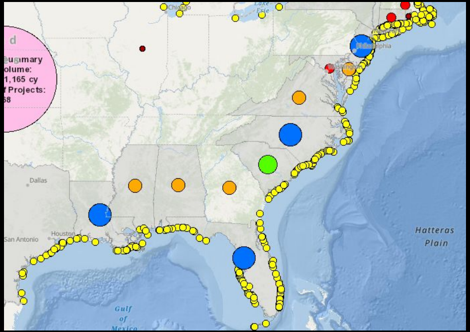


<u>2019 nourishment</u> ($32m)
Hit by Hurricane Dorian in 2019
Requiring 2022 repairs ($14m)



Increased use of soft coastal defenses

New investments and maintenance of old nourishments found throughout Atlantic and Gulf coasts



ASBPA (2022)

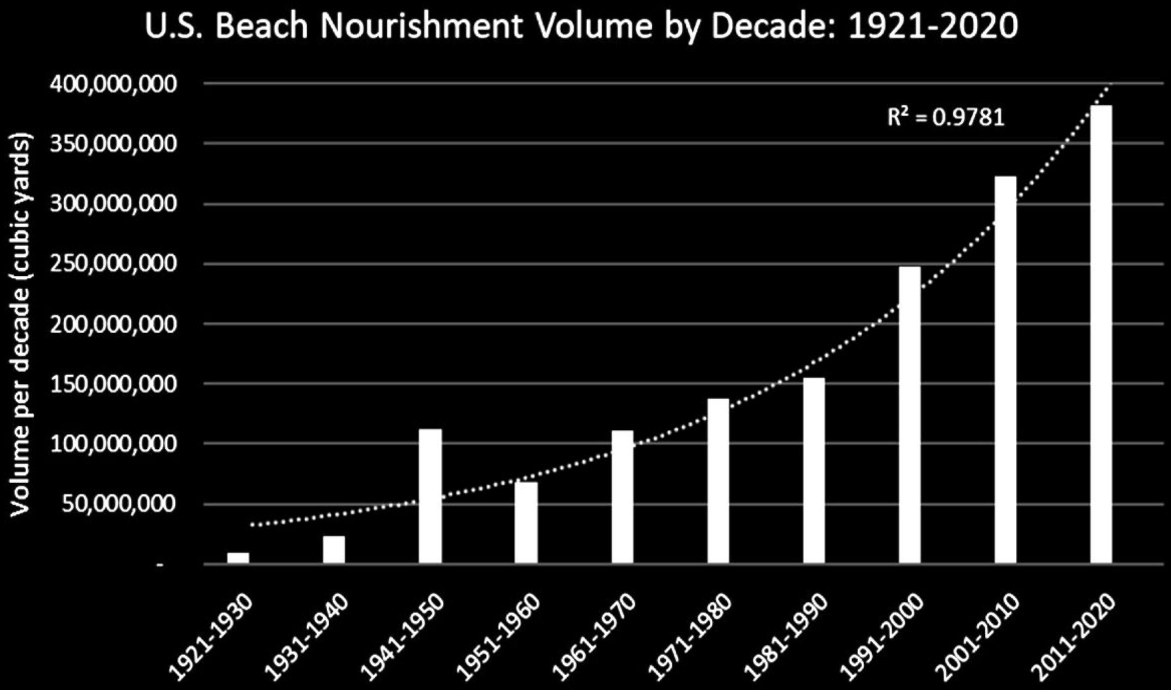
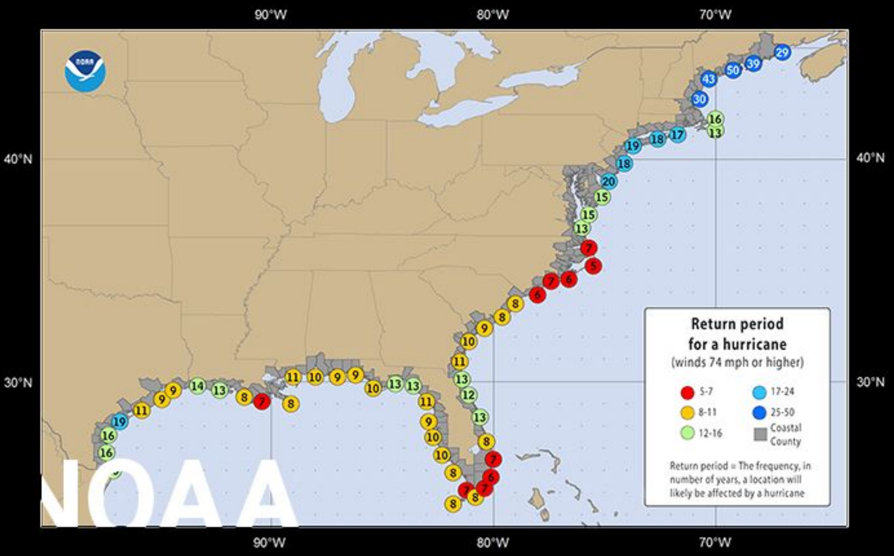


Fig. 6. U.S. beach nourishment volume by decade, fit to an exponential trend line with an R-squared value of 0.98.

Elko et al. (2021)

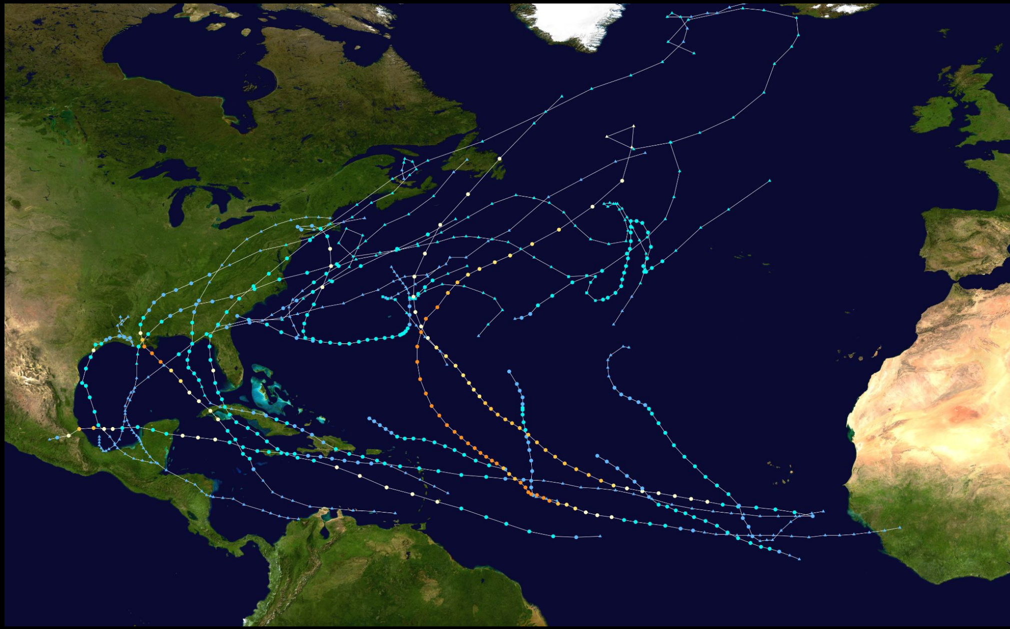
Hurricanes paths/characteristics are a stochastic process

Hurricane Climatology



NOAA (2022)

2021 Hurricane Season



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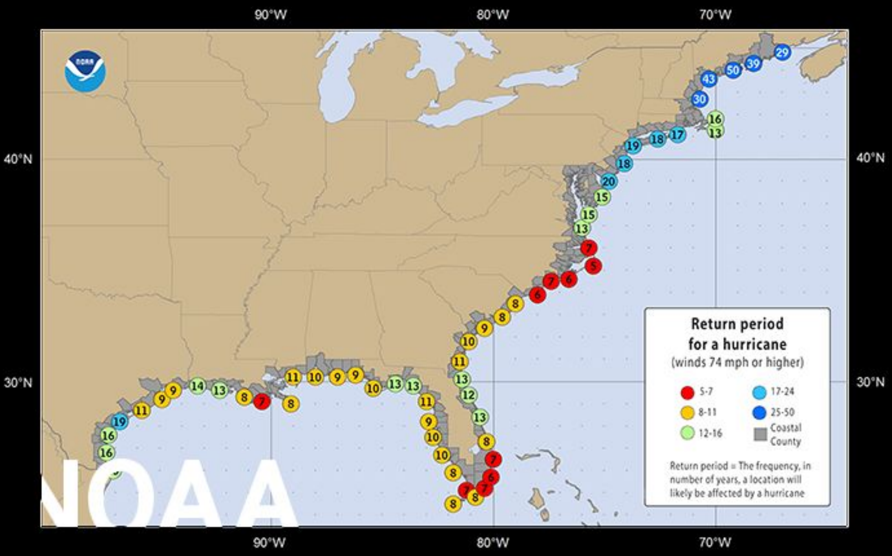
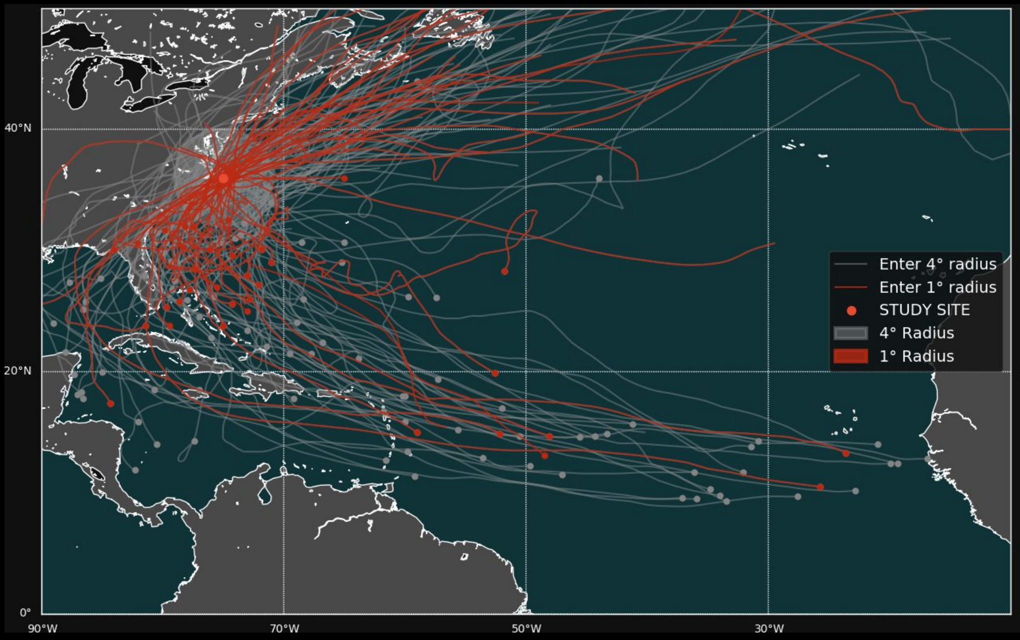


NOAA (2022)

~50 years of hurricane tracks

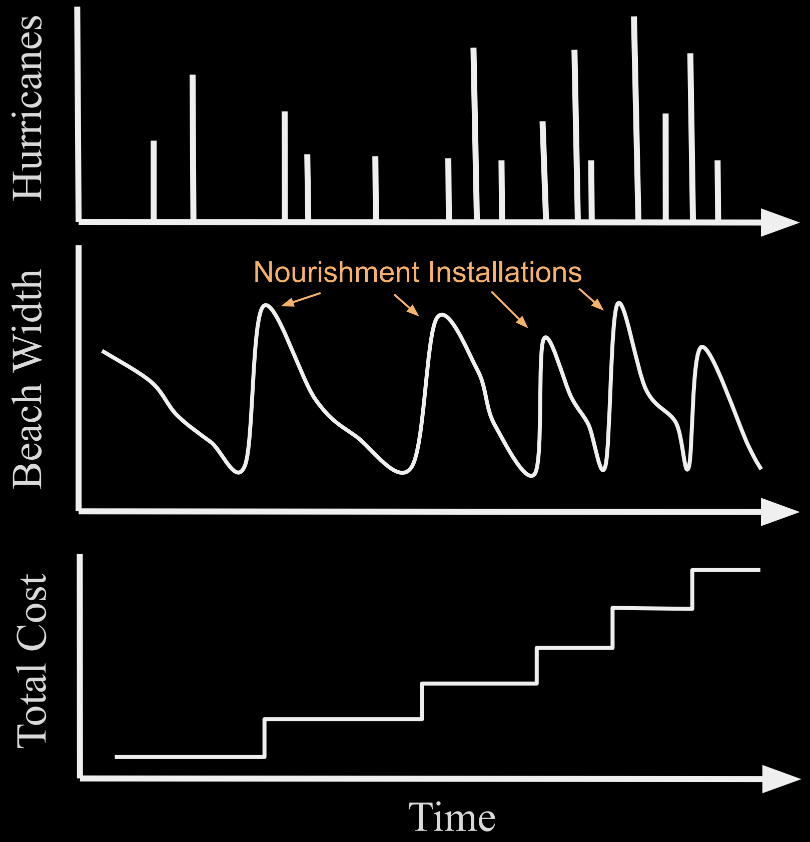


IBTrACS (2021)

Our predominant form of coastal protection is dependent on the randomness of storm events…

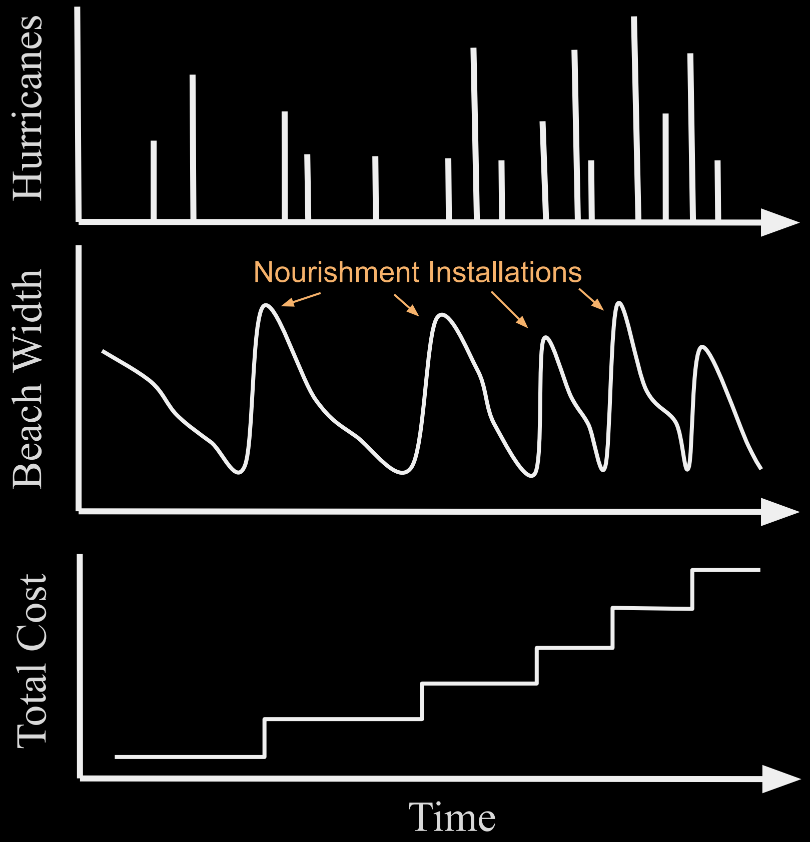
But we have only seen one roll of the weather dice…

- What is the range of likely storm chronologies?
- How does that variability translate to nourishment lifespans?
- Is it relevant to management decisions?
- Will future sea levels and storminess affect those lifespans?



Goal: Build an efficient framework to assess nourishment lifespan variability.

- Need to be able to generate synthetic chronologies of storm events.
- Need to be able to erode an engineered nourishment profile with fidelity.
- Need to be able to generate many realizations to quantify variability.



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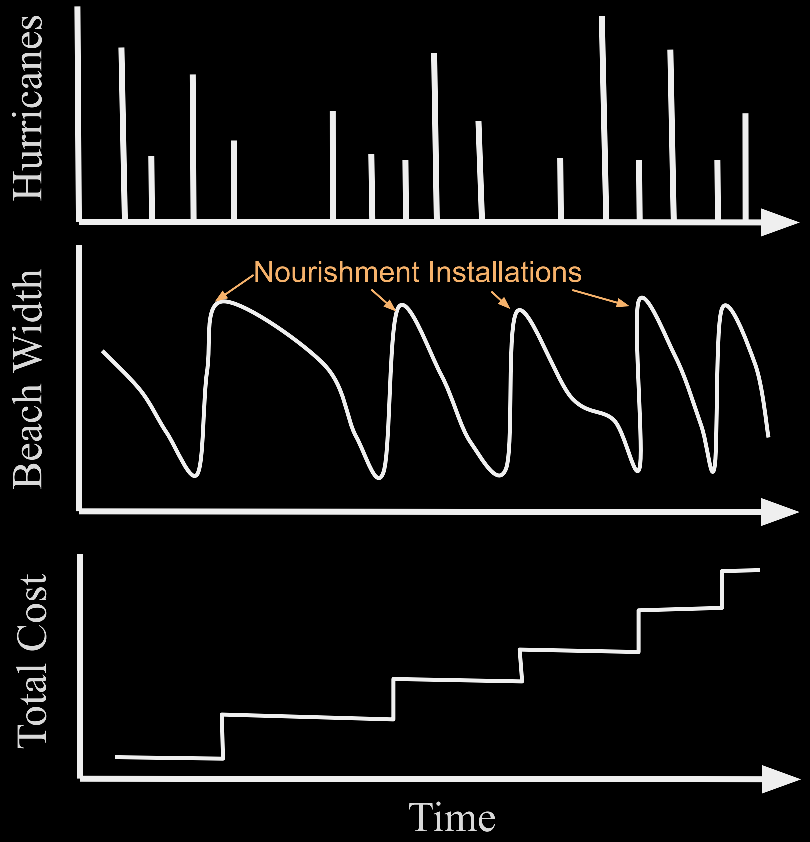
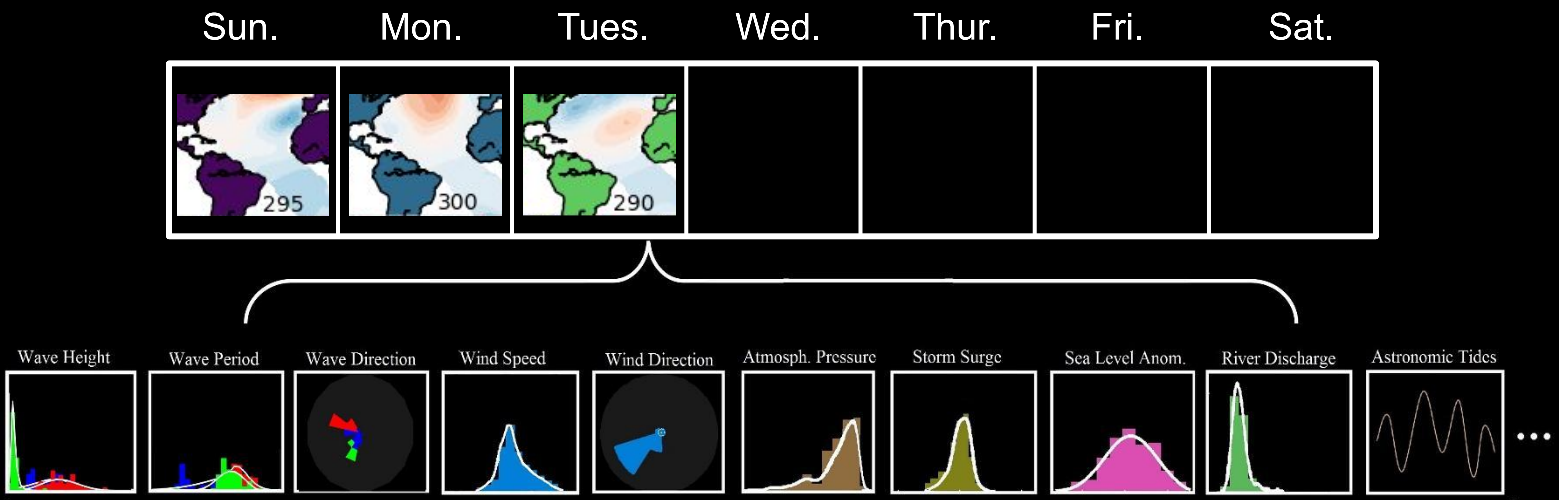


1. Generating synthetic chronologies of storm events.

Using a stochastic weather generator known as TESLA-flood:

Anderson et al. (2019) ***T**ime-varying **E**mulator for **S**hort and **L**ong-term **A**nalysis of coastal flood hazard potential.* JGR:Oceans, 124(12), 10.1029/2019JC015312

Assumption: similar weather patterns will generate similar environmental conditions



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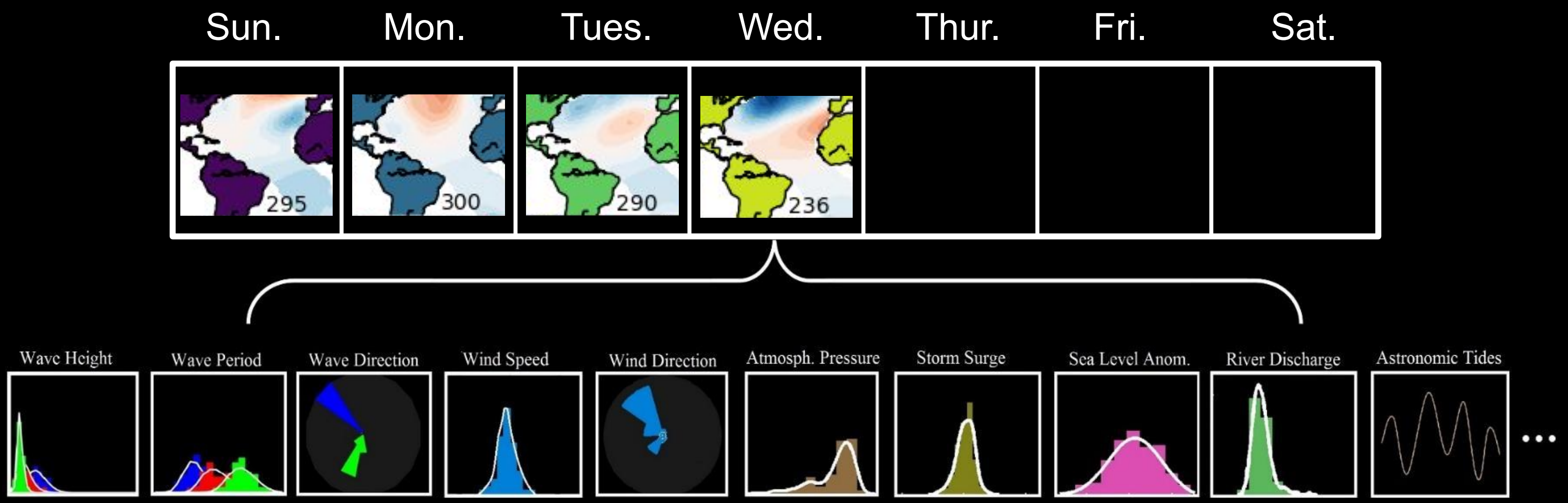
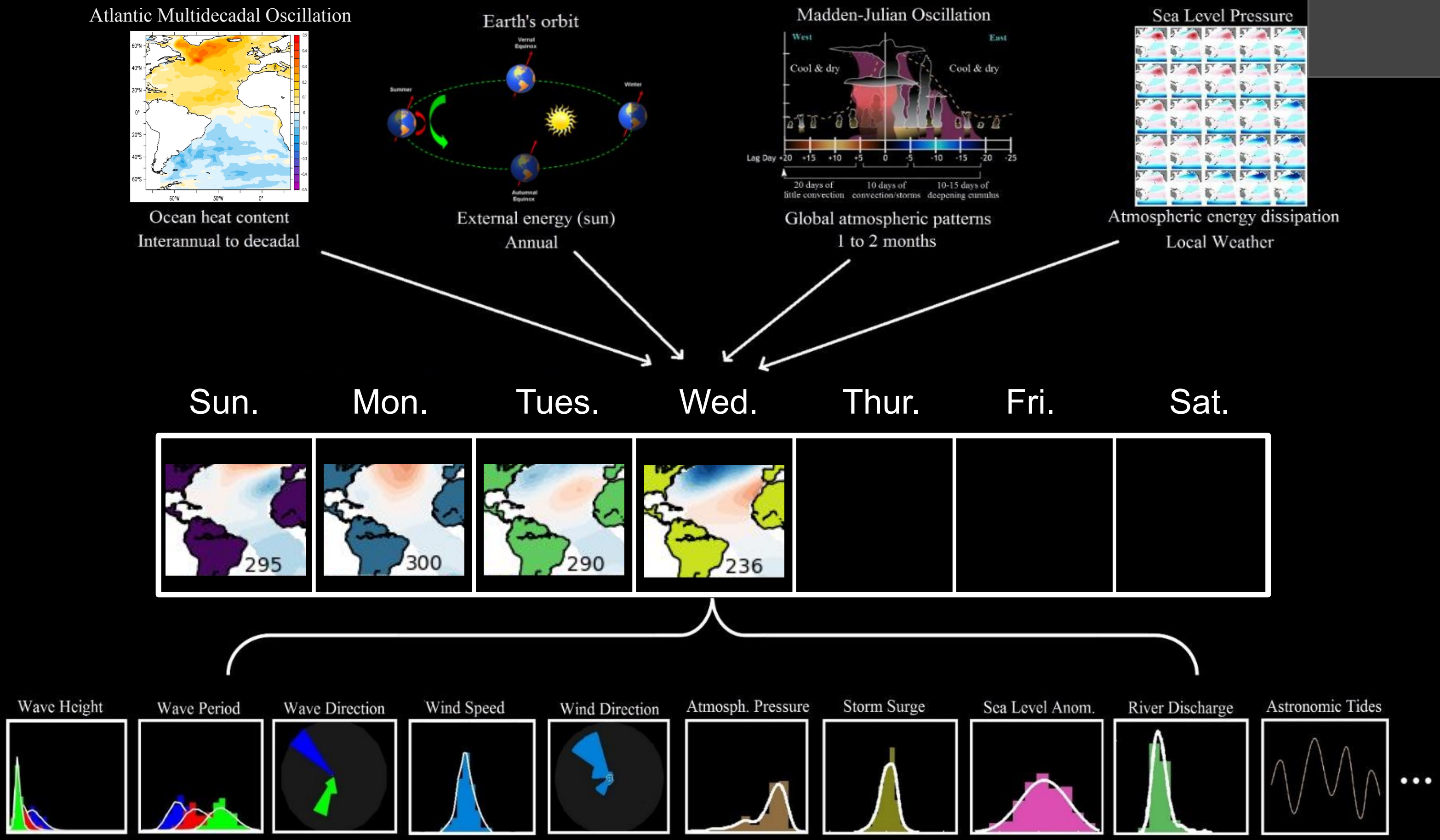


Idea: connect climate drivers to chronological behavior

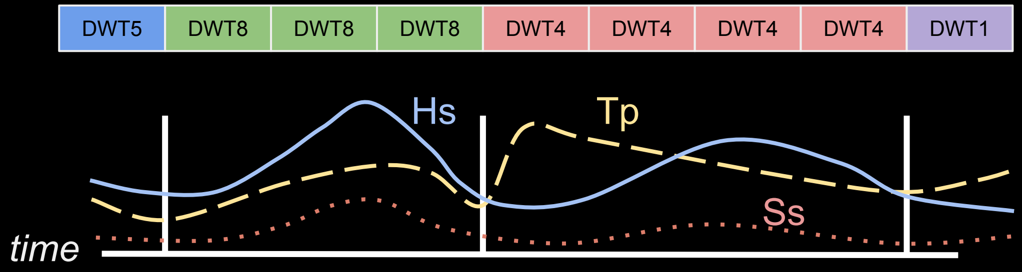


NOAA Extended Reconstructed SST V5 (2021), NOAA NCEP MJO Index (2021), Climate Forecast System Reanalysis (2021)

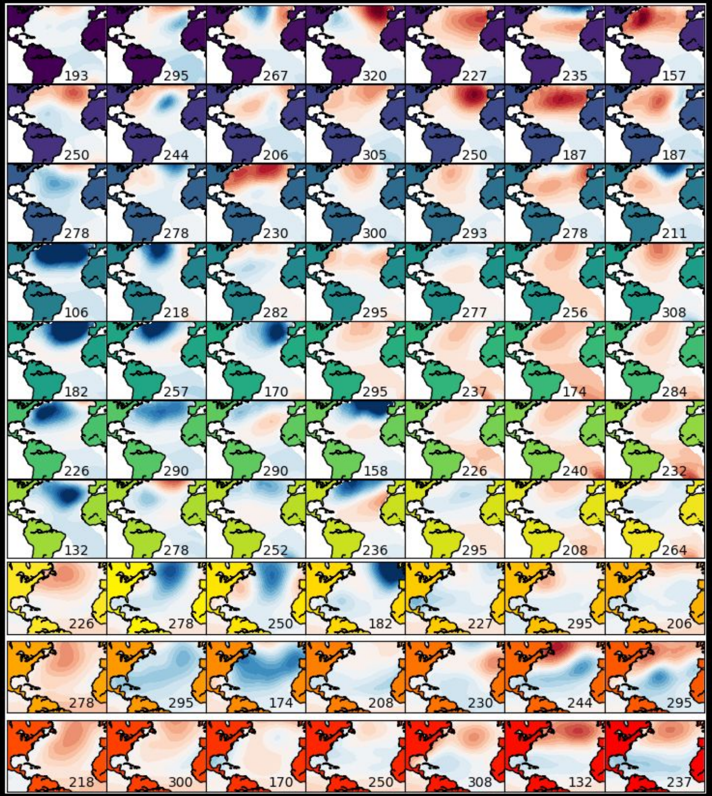
Methods: Weather Typing - identifies common spatial patterns

1. K-means Clustering of all daily Sea Level Pressure patterns between 1979-2021.
   a. Tropical Weather vs. Extra-Tropical Weather

2. Isolate wave hydrographs to create unique distributions for each DWT.



70 DWTs



Camus et al. (2011, 2014), Cagigal et al. (2021)

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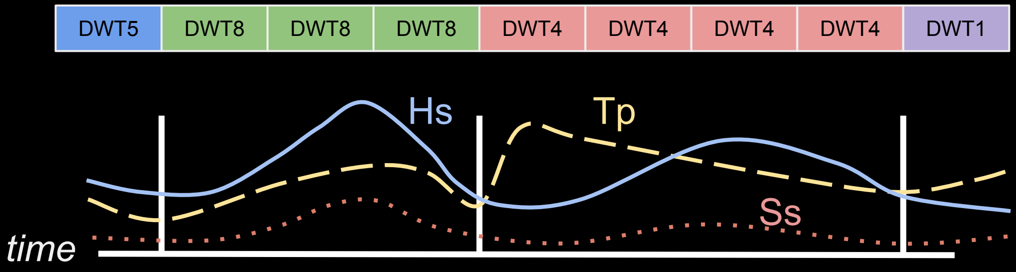

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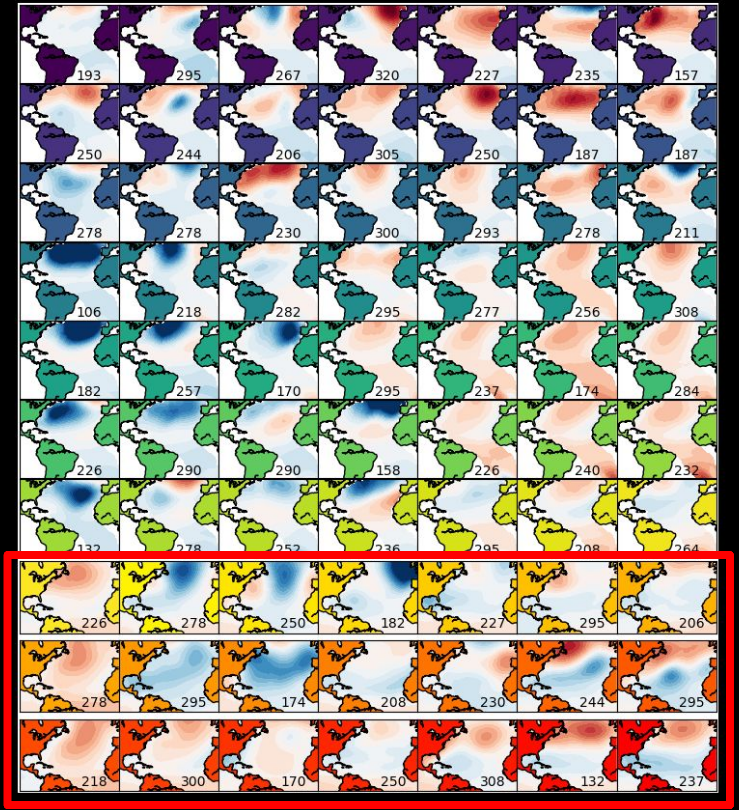

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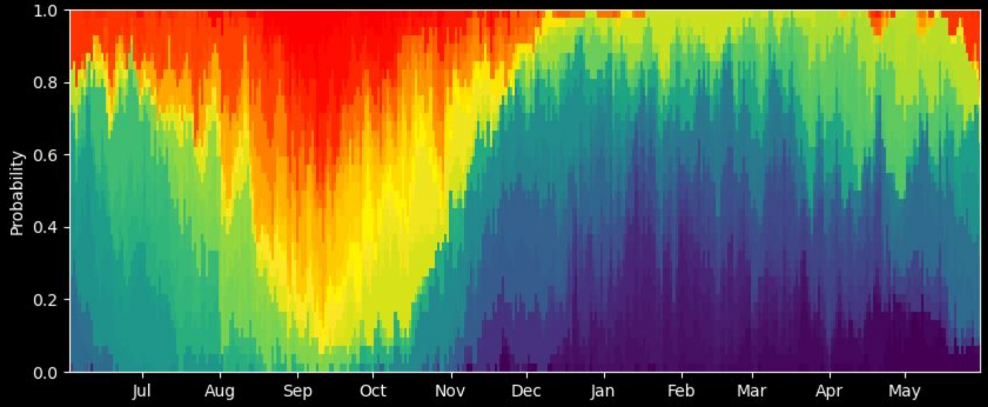
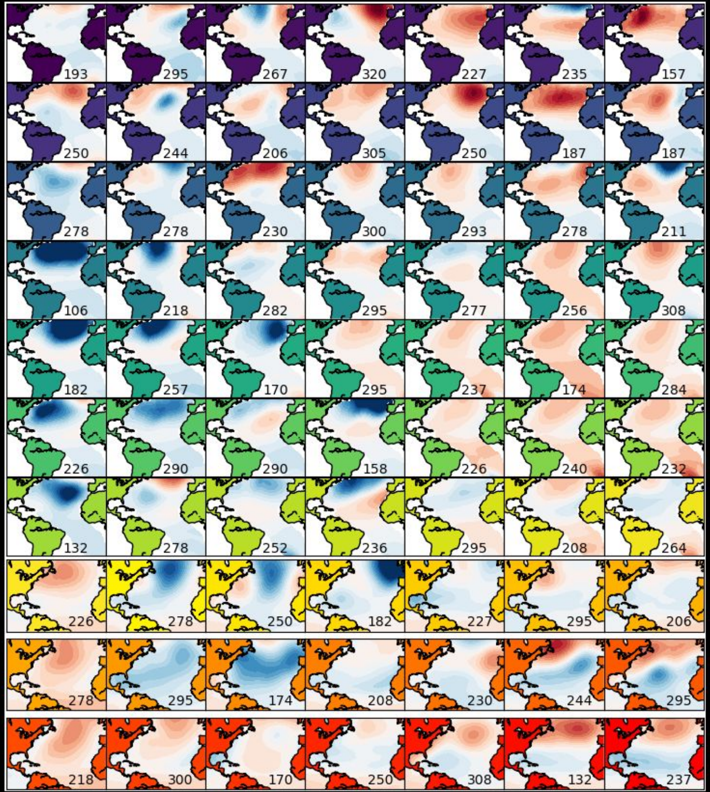
Camus et al. (2011, 2014), Cagigal et al. (2021)

Methods: Seasonality captures intra-annual variability

Stacked probability of occurrence on each calendar day

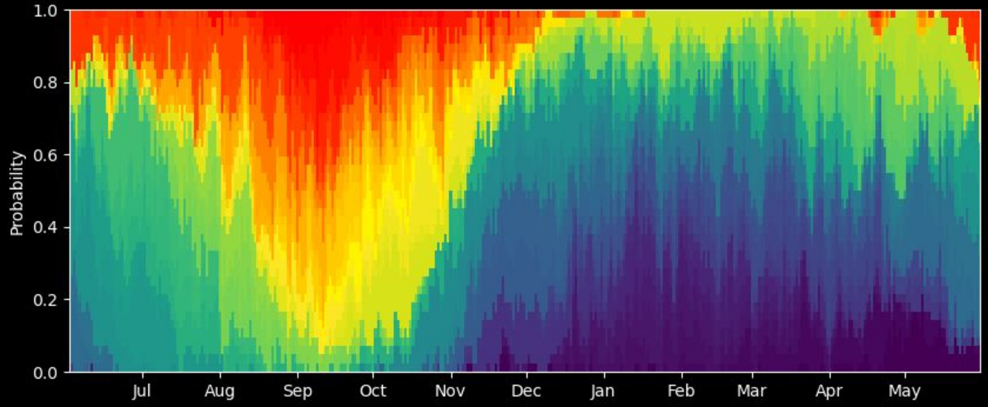


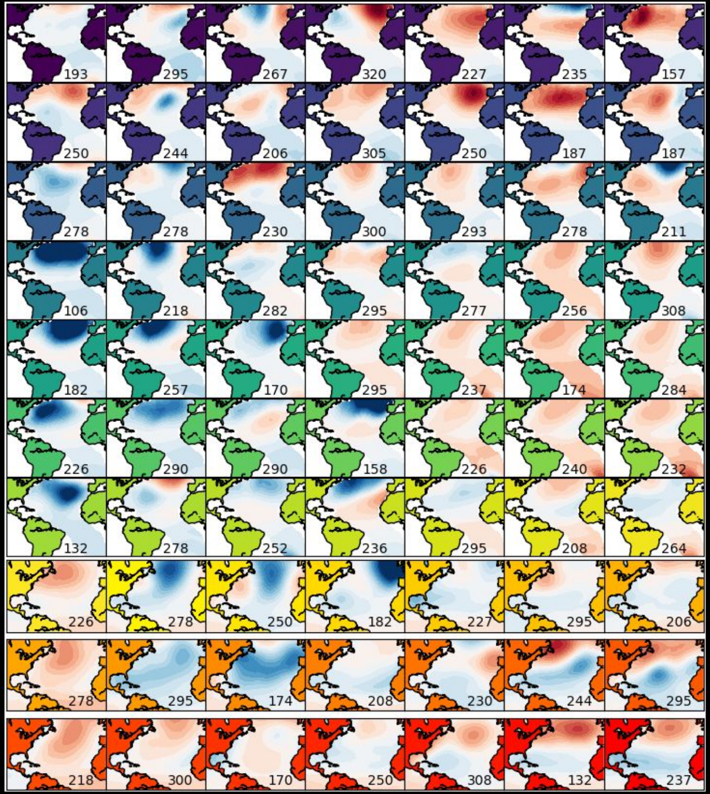


Methods: Auto-logistic Regression

Can make new weather pattern chronologies contingent on the large-scale climate indicators

Historical Weather





$$\mathbf{X}_t = \left(X^a_{1,t}, X^a_{2,t}, X^a_{3,t}, \cos\frac{2\pi t}{T_a}, \sin\frac{2\pi t}{T_a}, X^{MJO}_{1,t}, X^{MJO}_{2,t}\right)$$

$$\Pr\left(DWT_t = i \middle| DWT_{t-1},\ldots,DWT_{t-e},\mathbf{X}^a_t,\mathbf{X}^m_t,\mathbf{X}^{MJO}_t\right) = \\ = \frac{\exp\left(\alpha_i + \beta_i \mathbf{X}_t + \sum_{j=1}^{e} \gamma_{ij} DWT^d_{t-j}\right)}{\sum_{k=1}^{n_{DWT}} \exp\left(\alpha_k + \beta_k \mathbf{X}_t + \sum_{j=1}^{e} \gamma_{kj} DWT^d_{t-j}\right)}; \forall i = 1,\ldots,n_{DWT}$$

Guanche et al. (2013), Antolinez et al. (2017), Anderson et al. (2019)

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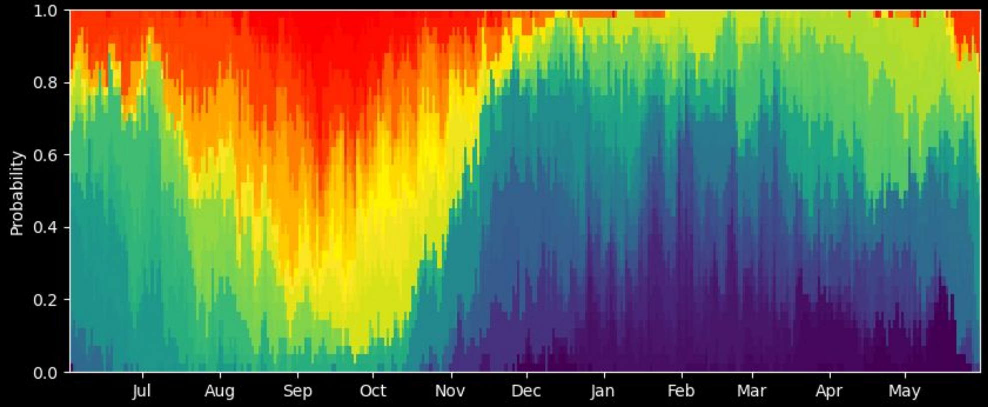
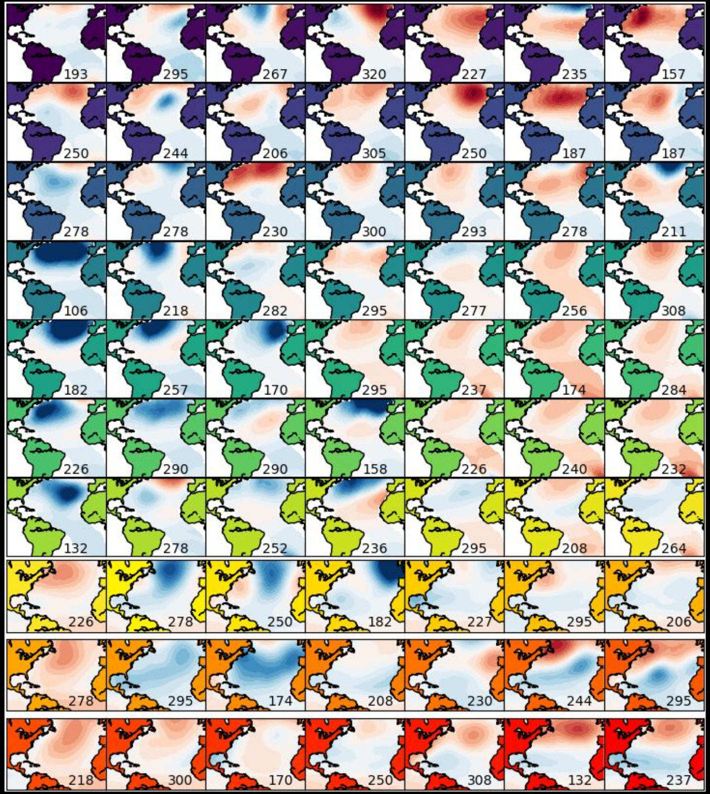
Simulated Weather





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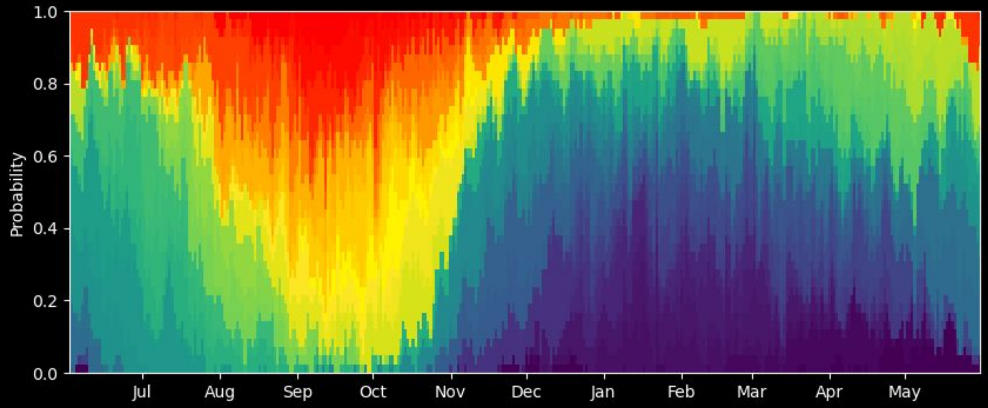

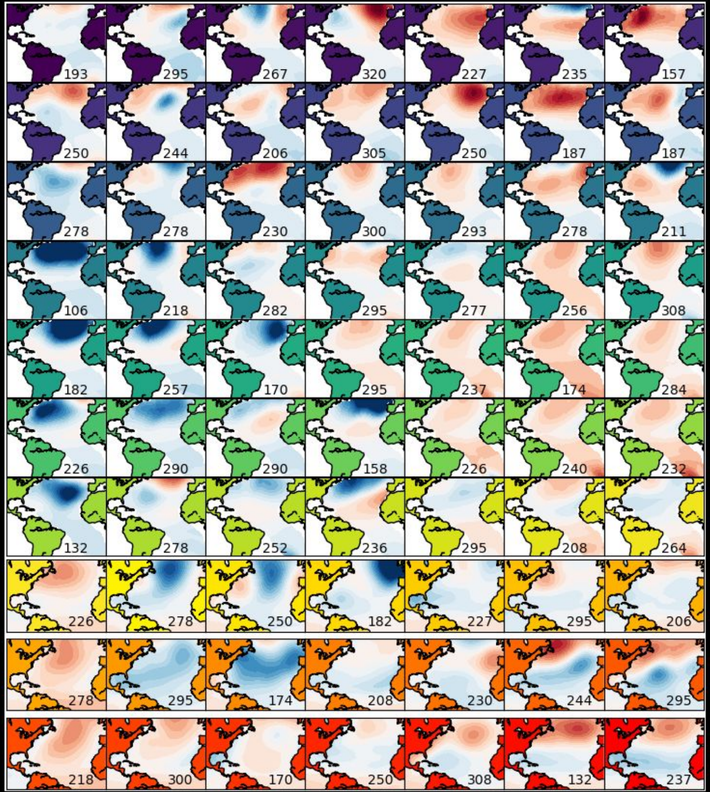

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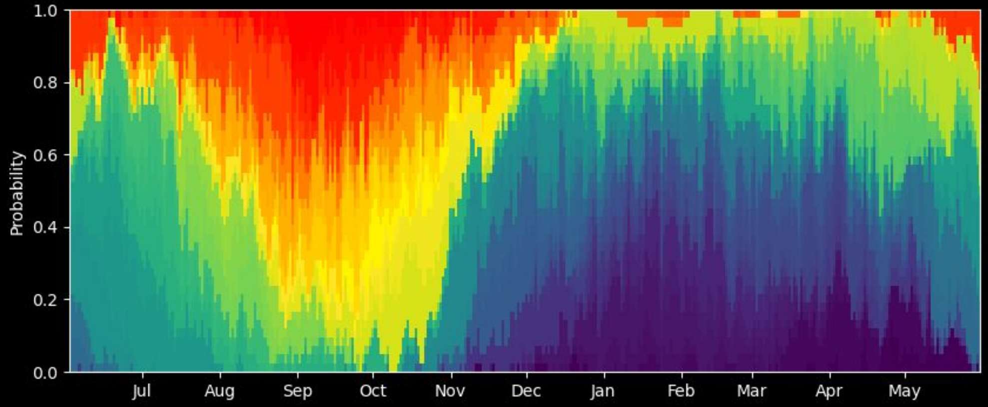

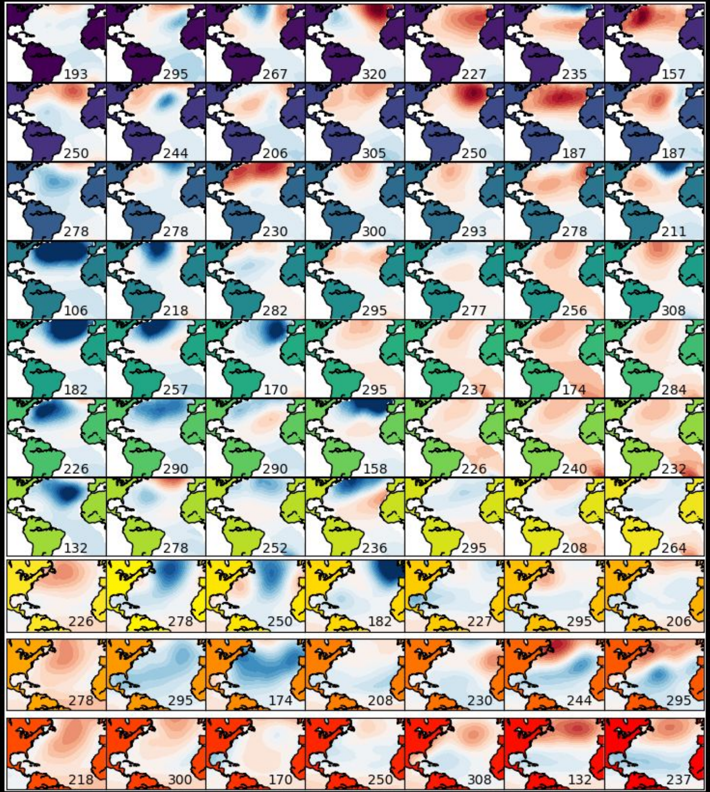

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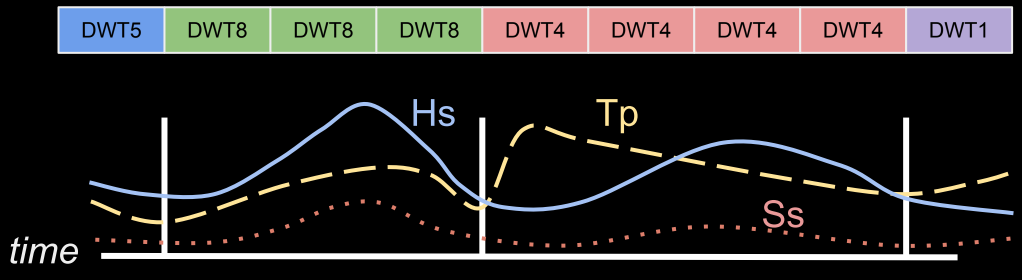
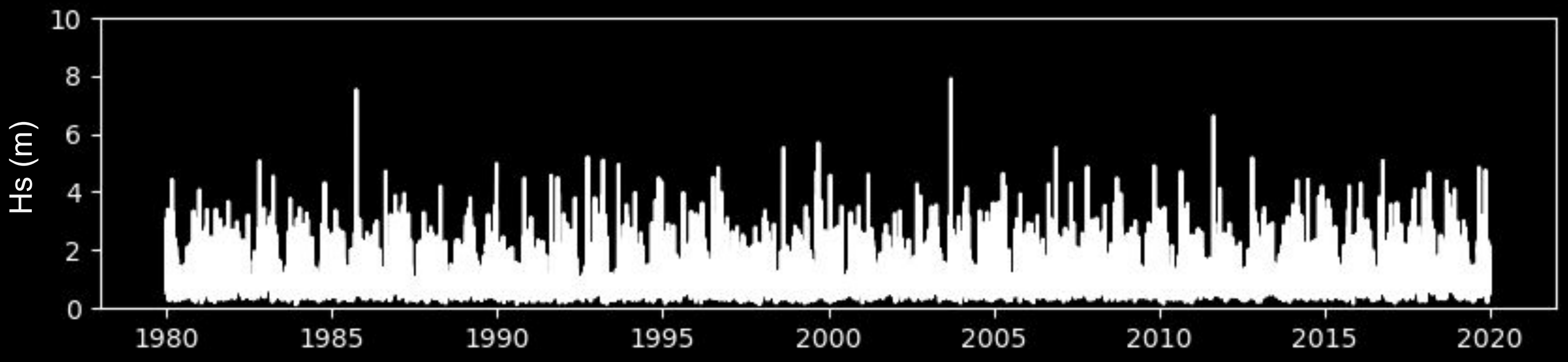
Guanche et al. (2013), Antolinez et al. (2017), Anderson et al. (2019)

Methods: Create wave "hydrographs" from historical record

Created a unique subset of normalized hydrographs for each DWT



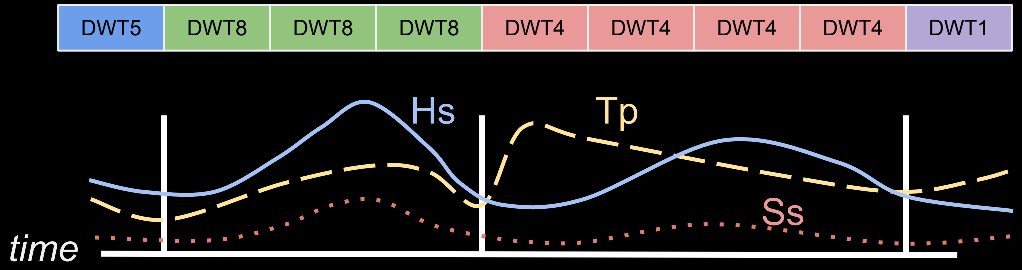


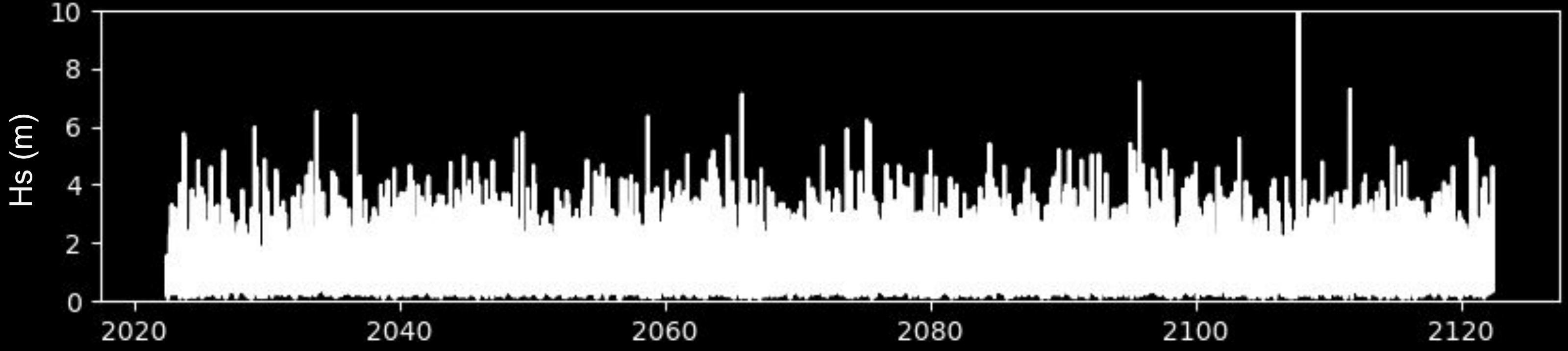
Cagigal et al. (2021)

Wave Information Studies Hindcast (2021)

Methods: Create wave "hydrographs" from historical record

Randomly sample a max Hs, Tp, SS and scale a random hydrograph to create synthetic hourly time series of storm parameters.





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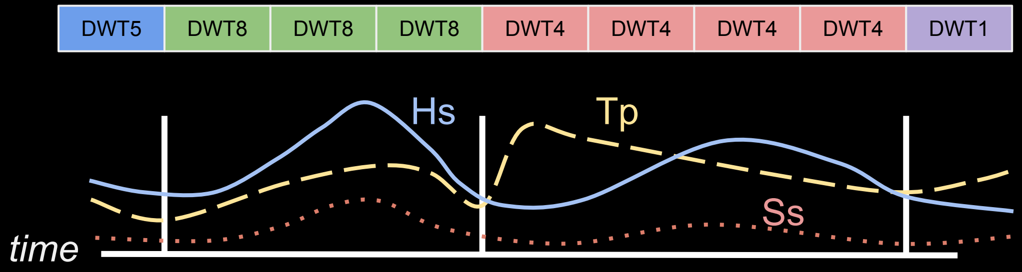

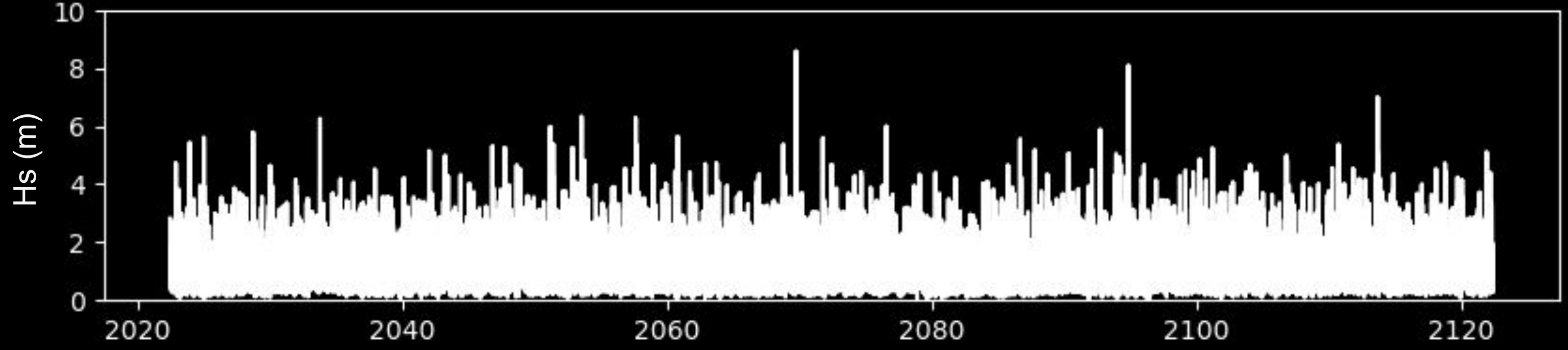

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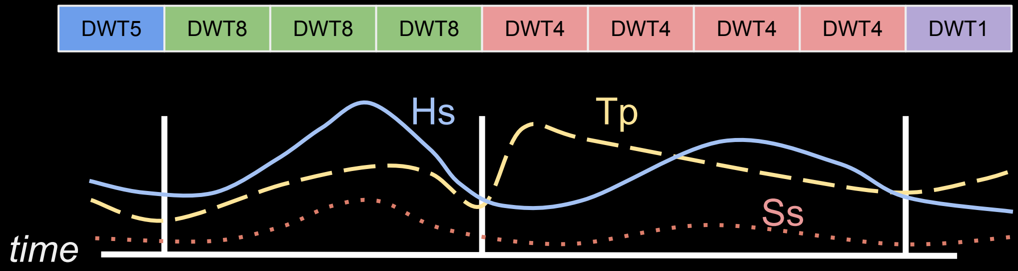
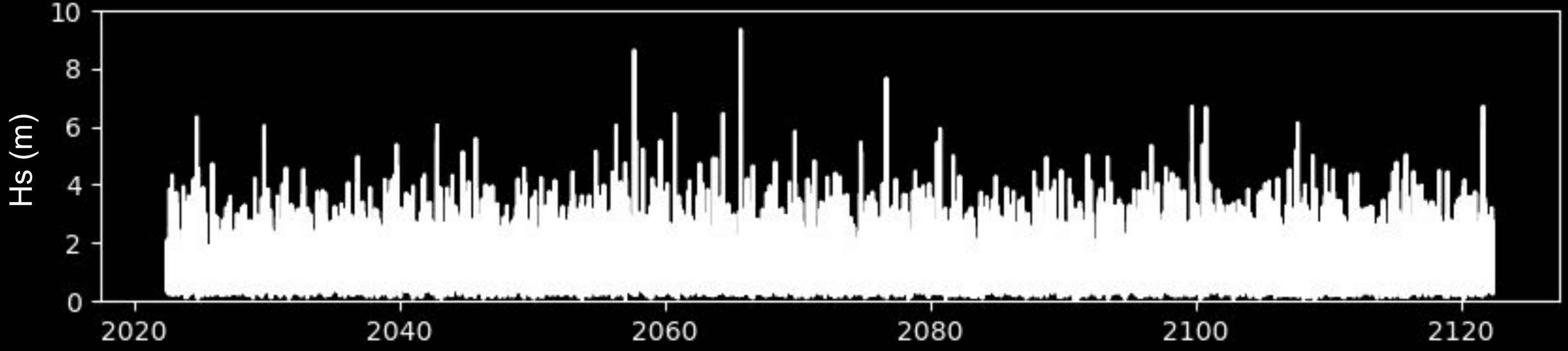
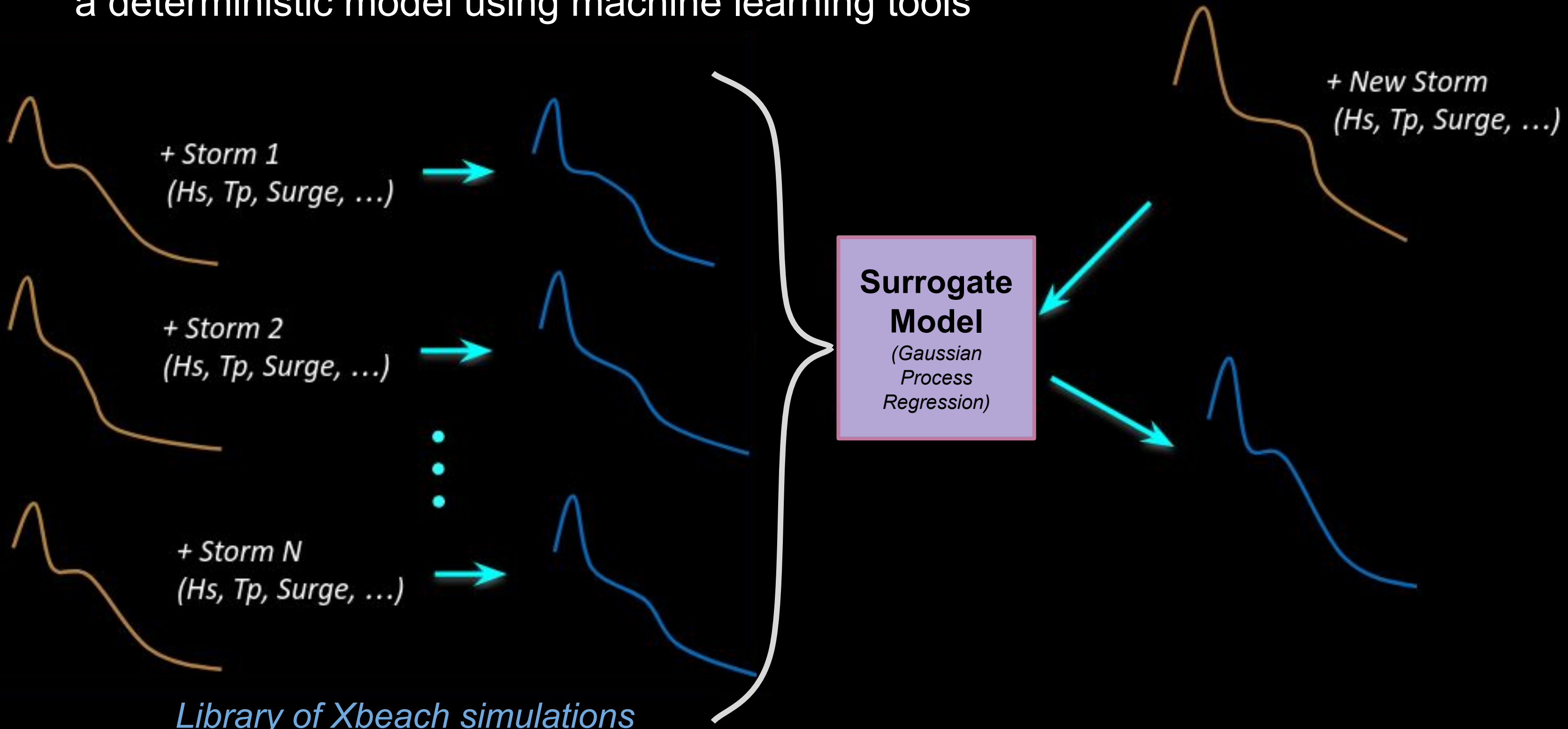




Cagigal et al. (2021)

2. Need to understand how engineered beaches respond to storm.

Surrogate Modeling: Statistical model that learns how to predict like a deterministic model using machine learning tools

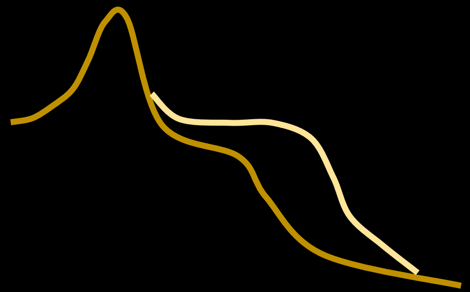


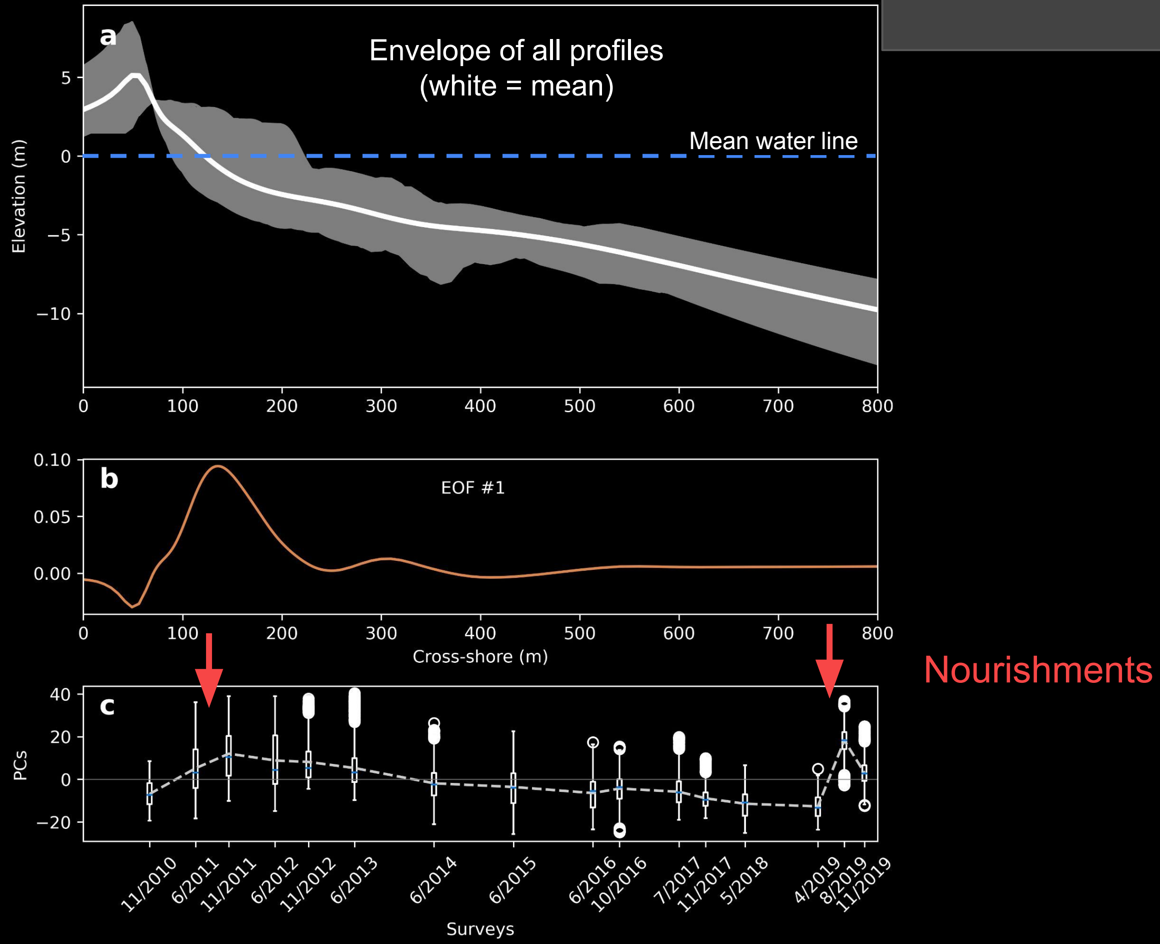
Library of Xbeach simulations

Gharagozlou et al. (submitted) *Emulator for Nourished Beach Scarping due to Storms*

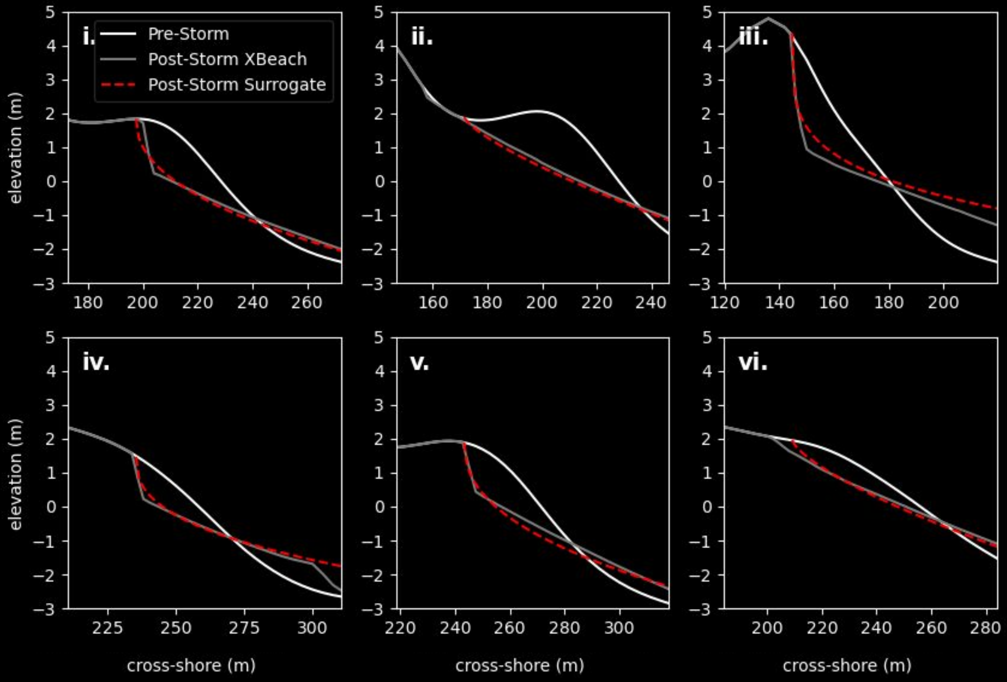
2. Predicting nourishment responses to synthetic waves

- 16 surveys of Nags Head evolution between 2010-2019





Methods: Efficient prediction of erosion from a hypothetical storm



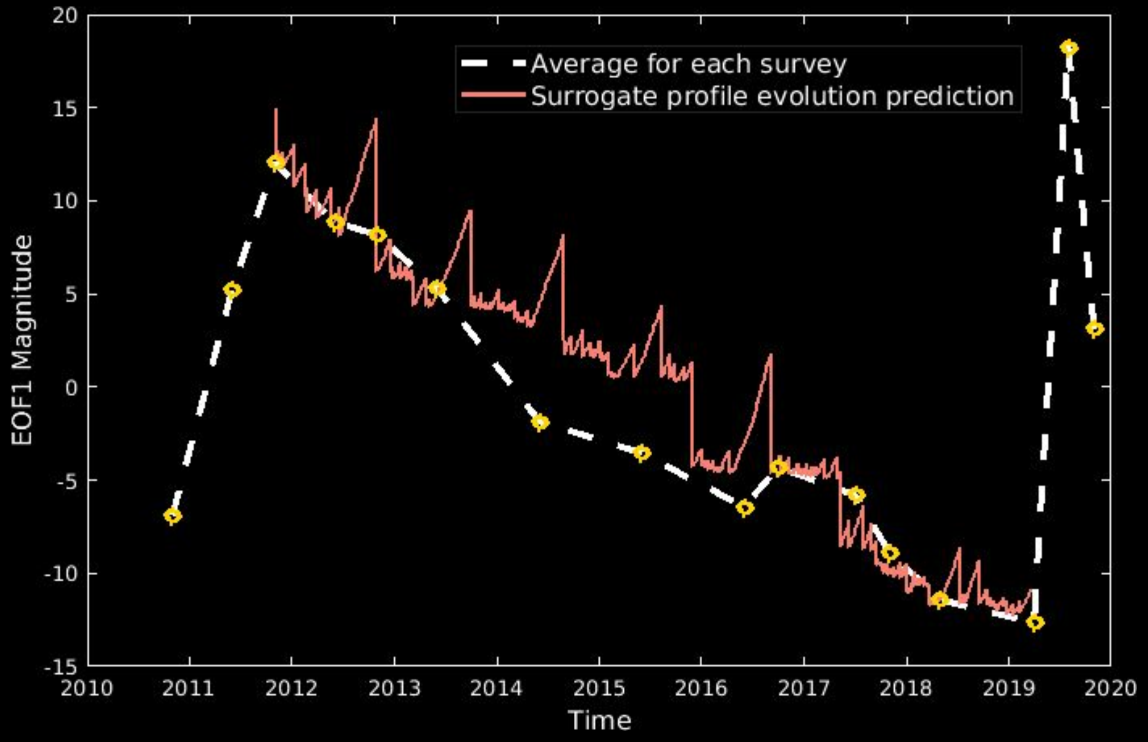
- Created 1250 synthetic storms using Wahl et al. (2016)
- Reduced dimensionality of the beach profile using EOF magnitudes.
- Predicted the scarp feature as defined by an exponential curve.

Gharagozlou et al. (submitted) *Emulator for Nourished Beach Scarping due to Storms*

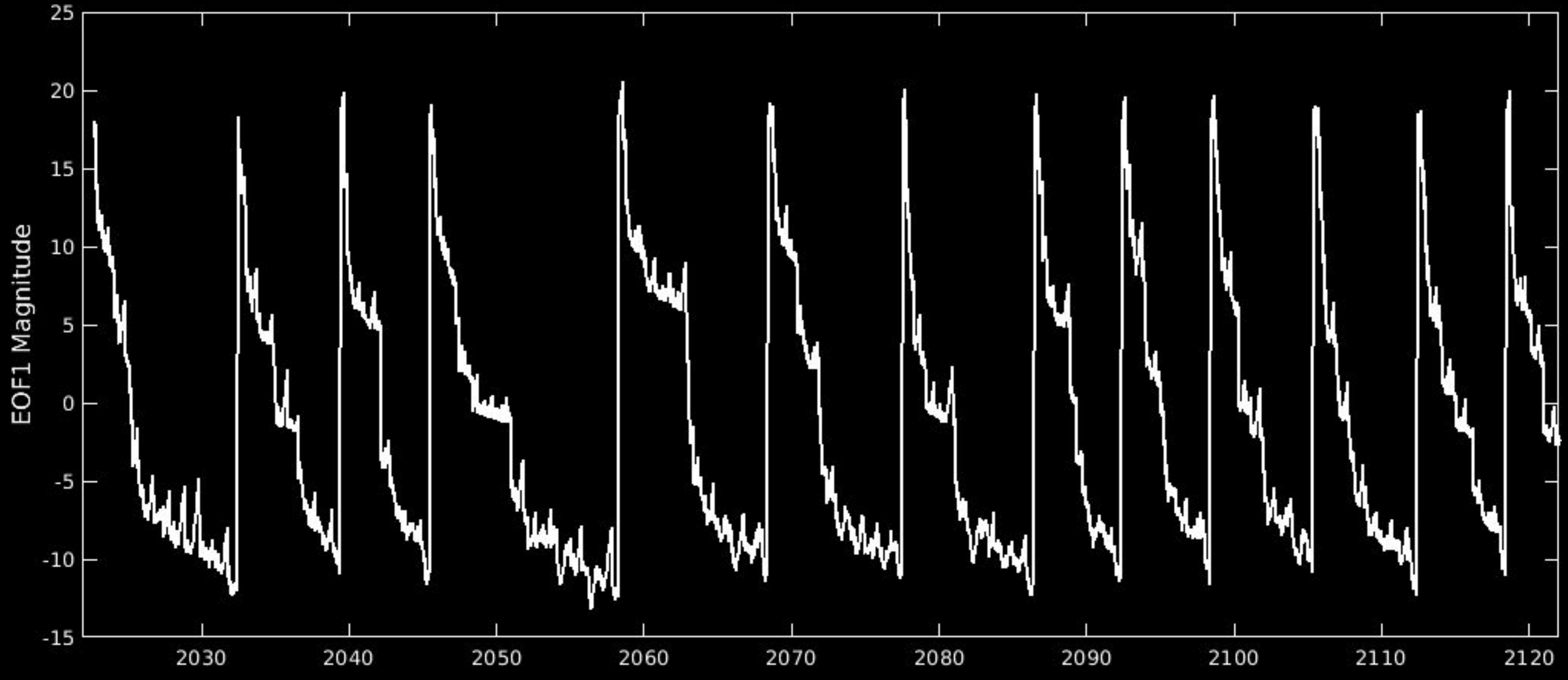
Methods: Assuming recovery between each storm is a function of non-dimensional fall velocity

$$\Omega = \frac{H_{s,b}}{w_s T_p}$$

- Any “storm” of >2m for >12 hours is evolved with the surrogate
- All other hours the EOF1 magnitude is adjusted by the non-dimensional fall velocity.



Results: **Applying the surrogate model to synthetic storm time series produces many realizations of nourishment evolution**



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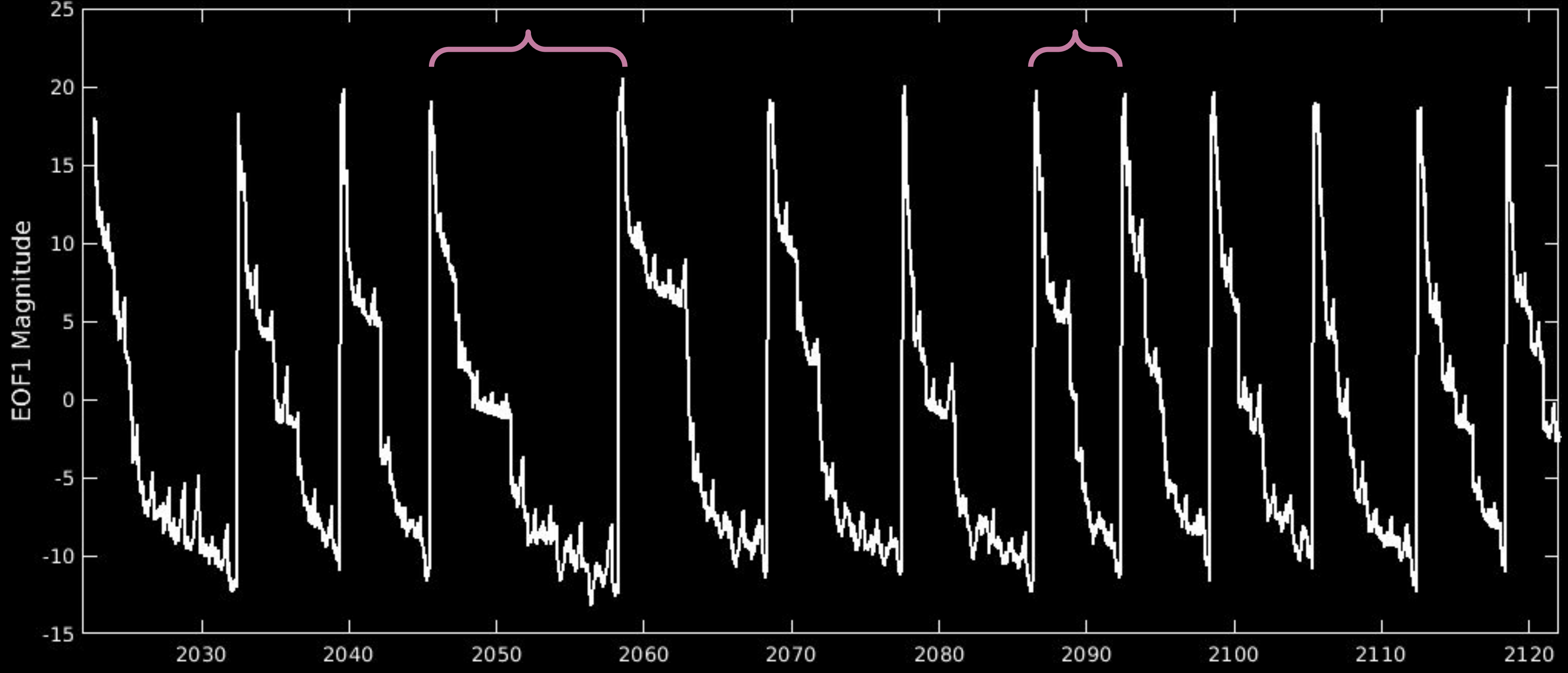

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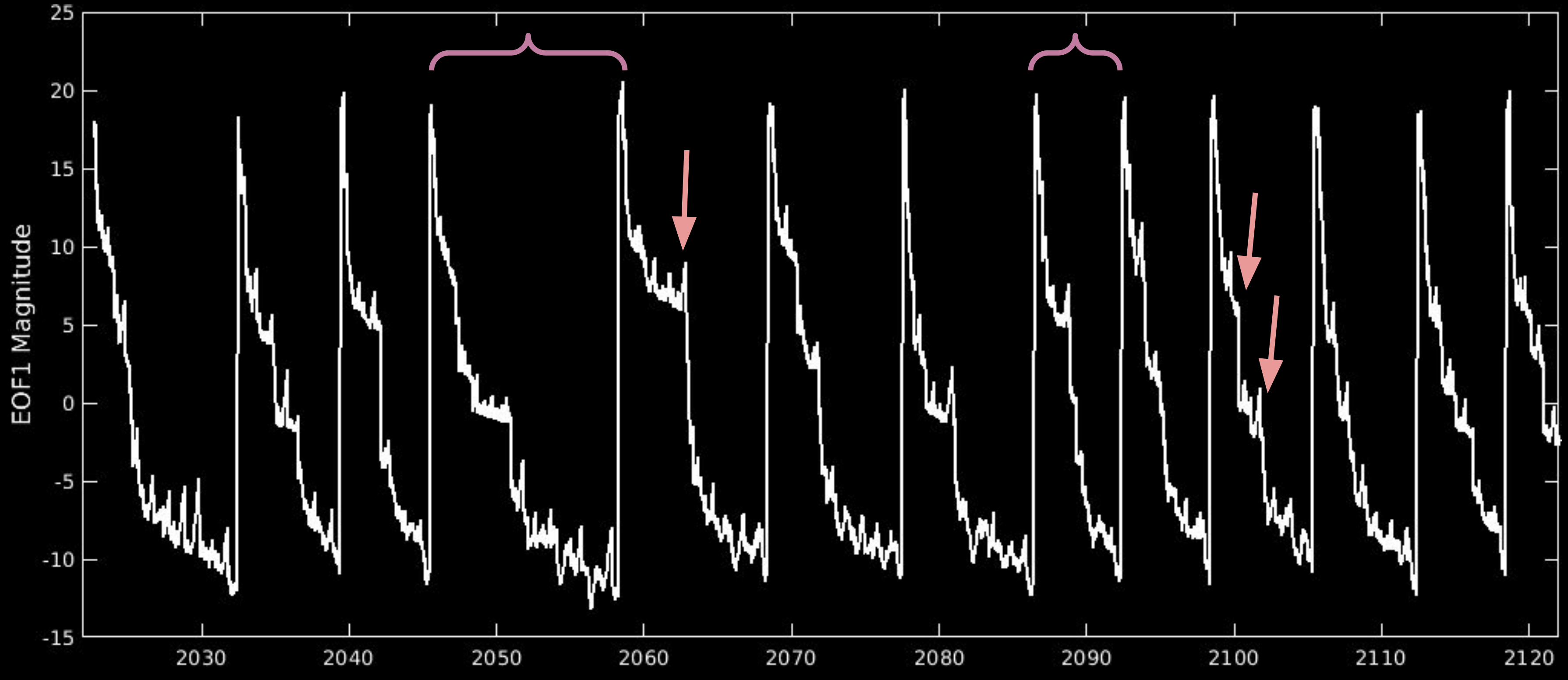
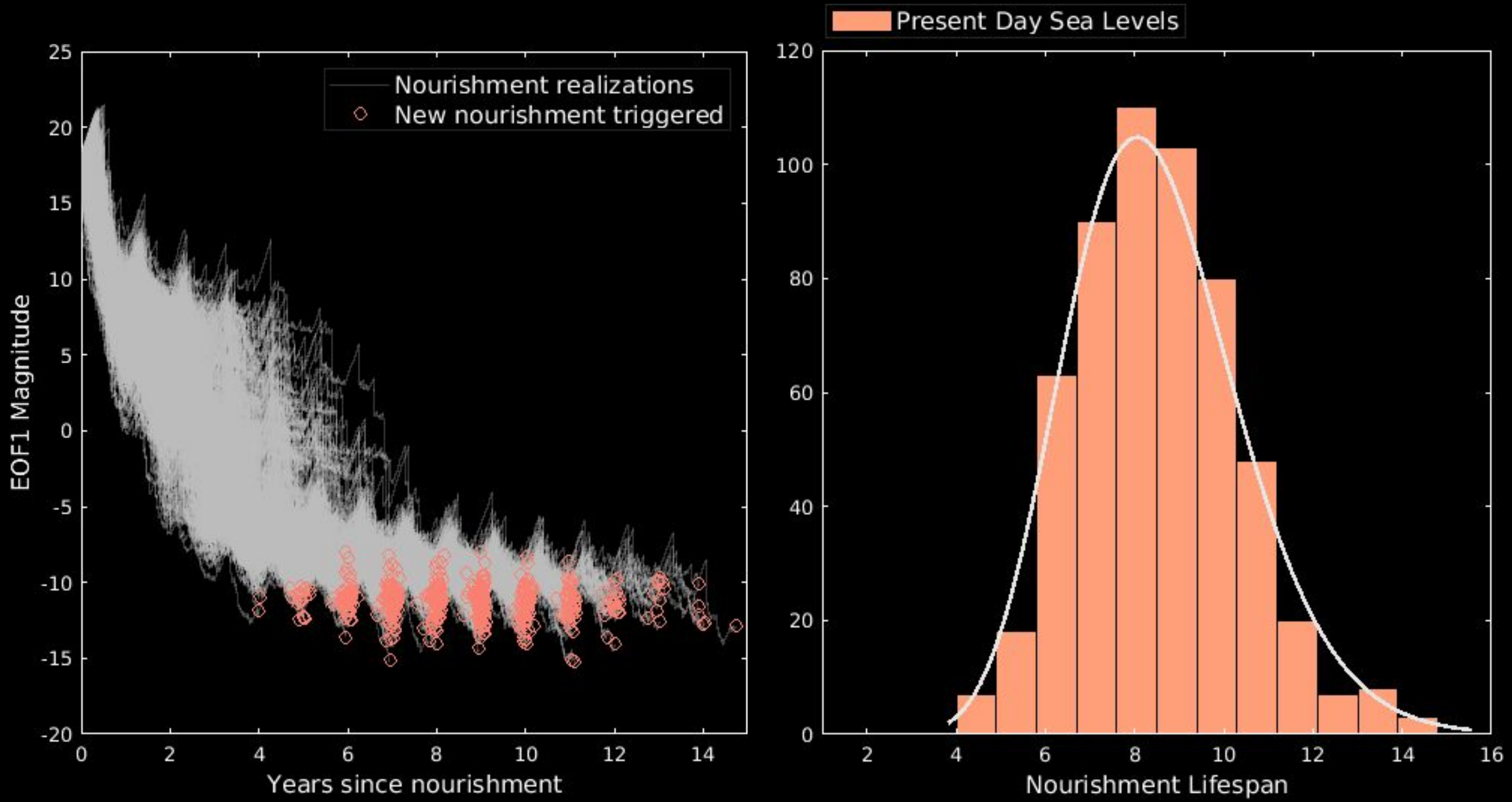


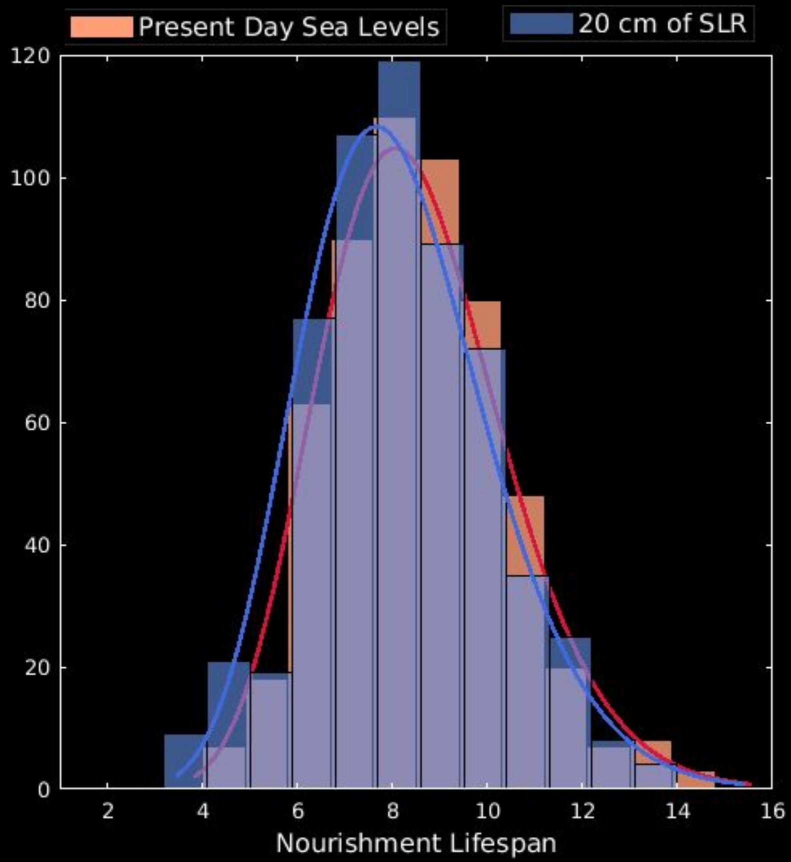
Simulated 5000 years of nourishment evolution: Can quantify the range of life spans that a community may experience



Simulated the exact same storms with 20 cm of SLR: begin to understand the effect of slightly higher sea levels

- Statistically significant different populations according to t-test

- Randomness of storm variability will remain the dominant determinant of nourishment lifespans during the next ~20 cm of SLR

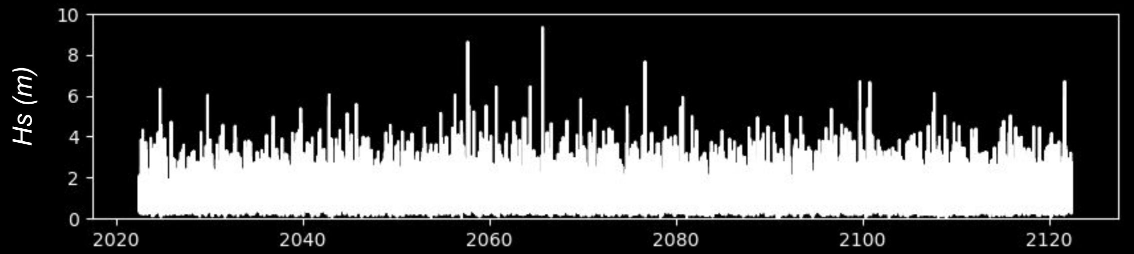


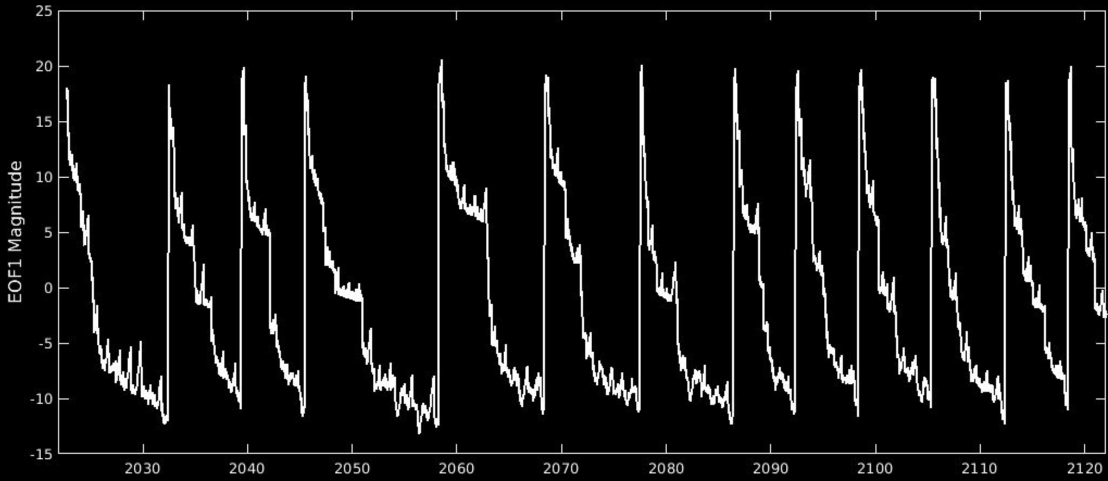
Created a framework to generate synthetic observations of nourishment life cycles contingent on storm chronologies.

- Developed stochastic storm climates for the Outer Banks, NC

- Developed a surrogate model to efficiently evolve the cross-shore profile of nourishment at any stage in its life cycle

- Initial results suggest that the randomness of storm variability will remain the dominant determinant of nourishment lifespans during the next ~20 cm of SLR





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Thank you to funding support for the United States Coastal Research Program and the US Army Corps of Engineers. Many thanks to the Town of Nags Head and Town Engineer David Ryan for sharing nourishment evolution data.

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