Applications of statistics and machine learning in environmental science

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2025-01-10

Stats

Research 51%

60+ peer-reviewed articles

4 R packages

80+ pubs total

$16M+ research funding

Teaching and student advising 49%

43 credit hours taught (61 with co-instructors)

400+ students

20+ undergraduates supervised

15 graduate committees

Outline

Scientific discovery

Integration

Application

Teaching

Future directions

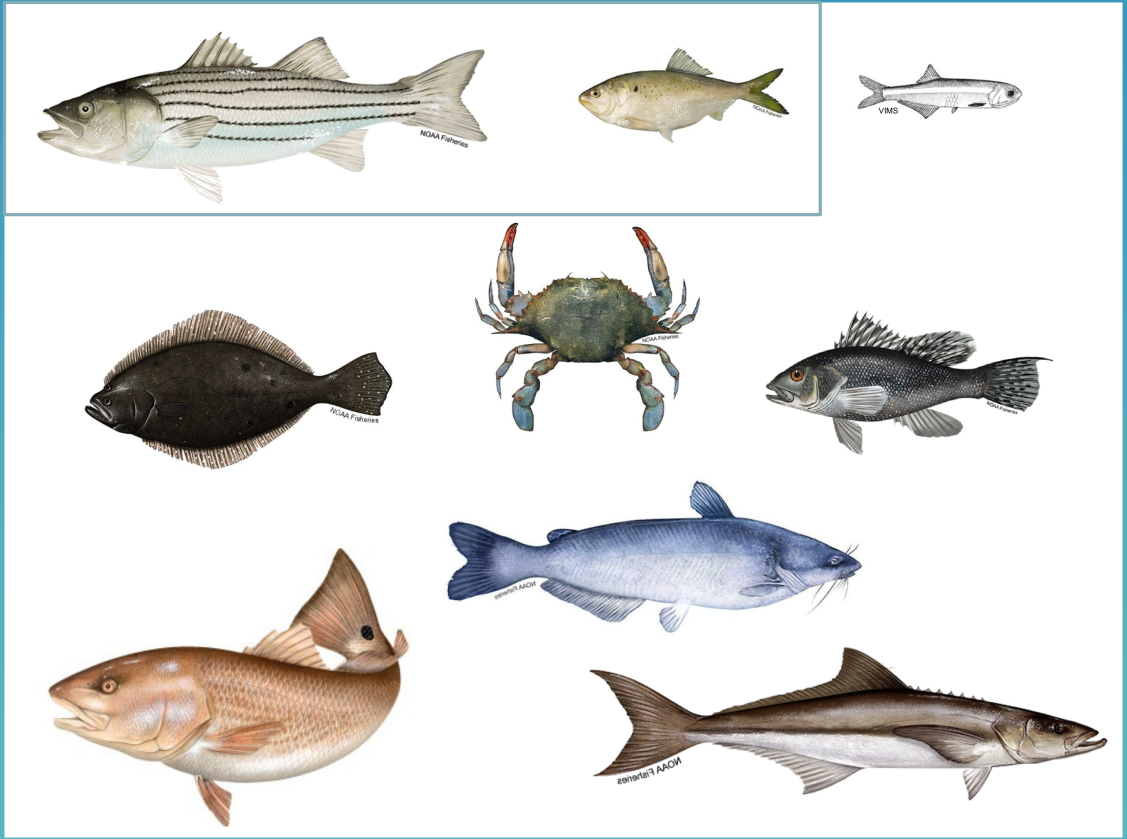
Scientific discovery:
Quantifying linked rare events in fish and environmental time series

with
Genny Nesslage (CBL, UMCES), Eric Durell (MD DNR),
Troy Tuckey (VIMS) & Mary C. Fabrizio (VIMS)

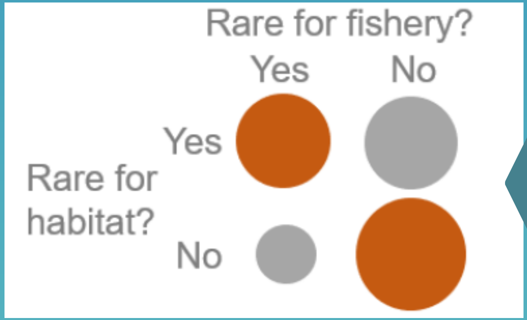
FY23 Chesapeake Bay Fisheries Research Program
NOAA Chesapeake Bay Office

Goals:

1) Identify linkages between fish catch-per-unit-effort and environmental **<u>rare events</u>** in Chesapeake Bay using time series analysis and machine learning techniques
2) Explore performance of predictive models that quantify the impact of rare environmental events on fish/shellfish stocks



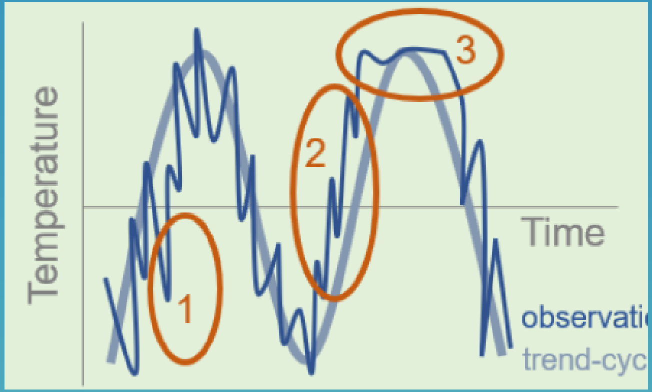
Methods

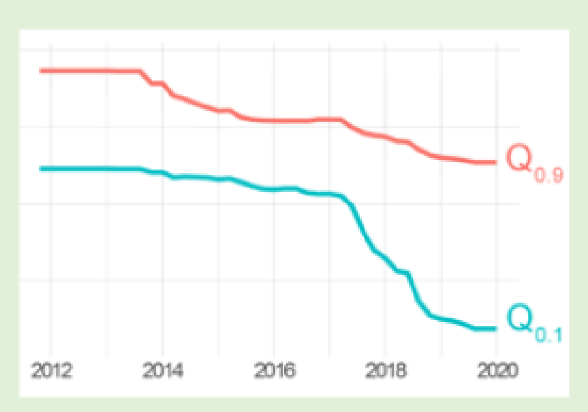


Identify rare events

Identify linkages

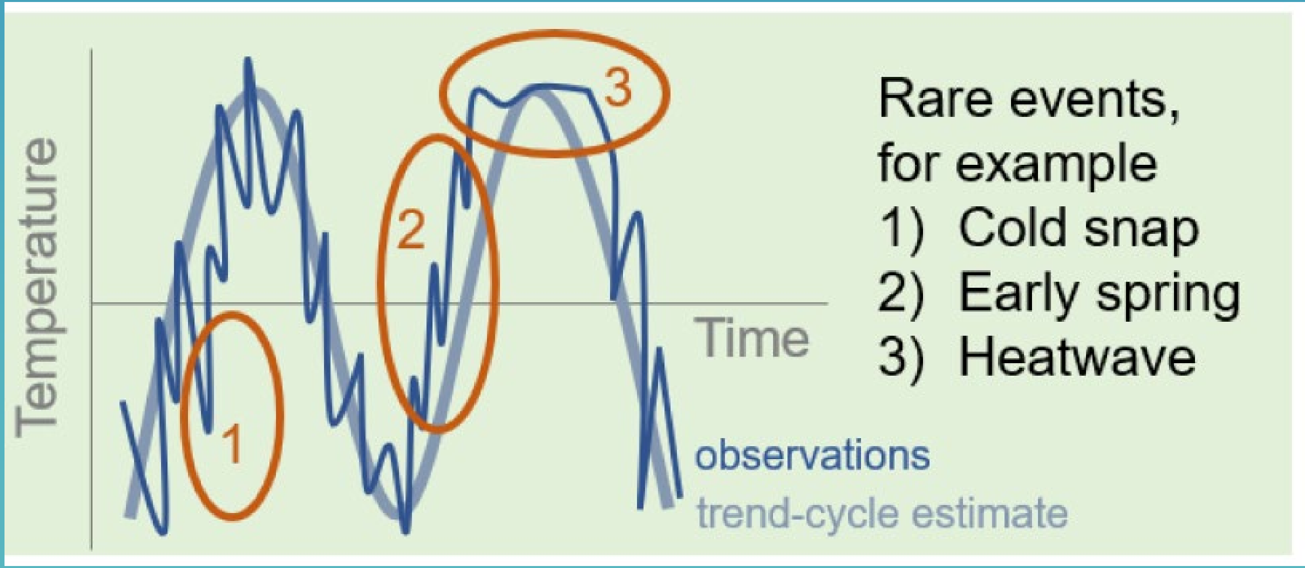
Develop predictive models





Identify rare events

Seldom occurring and inherently happening in the time domain (Carreño et al. 2020)



Time series decomposition

Trend-seasonal model for environmental data (no seasonality for fish time series)

$$Y_t = M_t + S_t + \epsilon_t$$

- Non-parametric estimates of trend and seasonality using loess

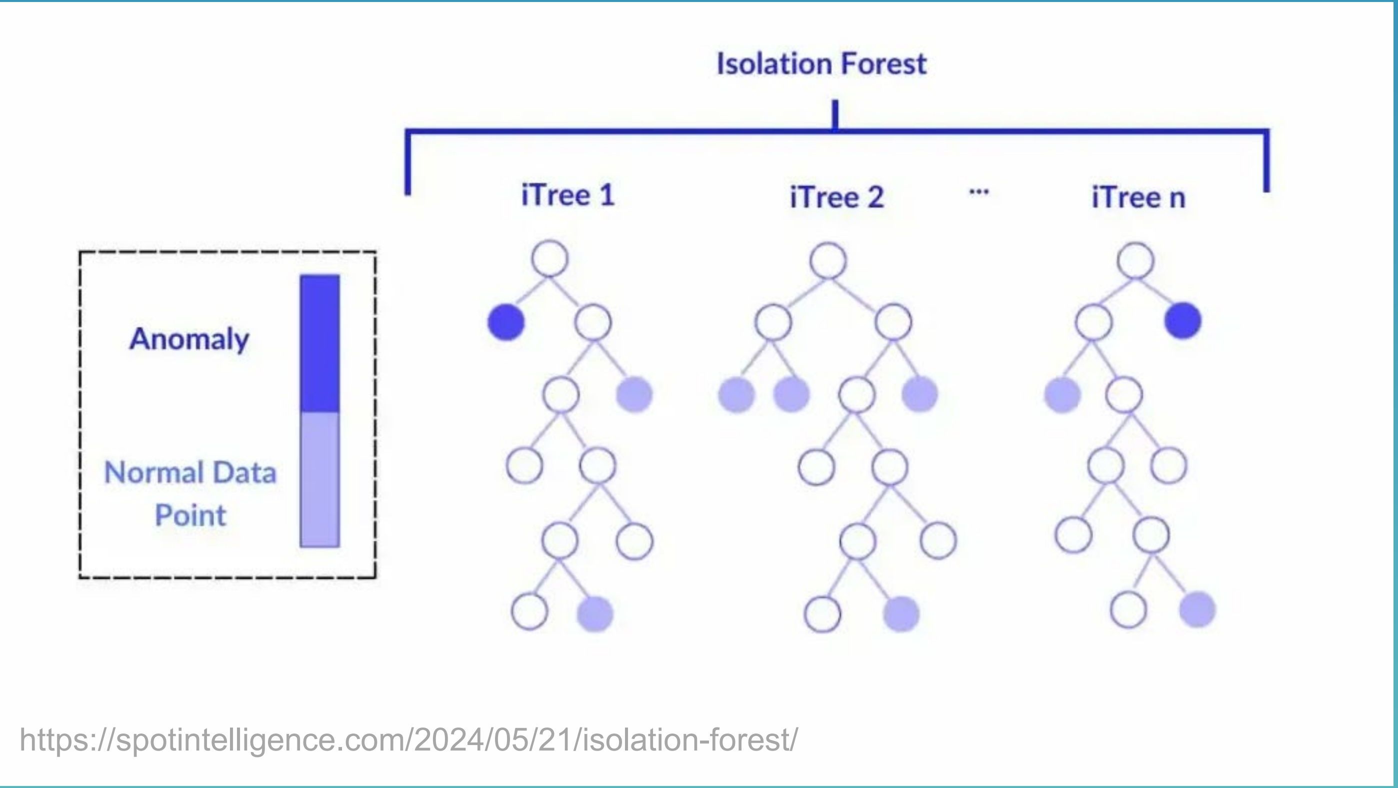
Compare seasonality estimates

- Parametric quadratic trends and two pairs of Fourier series with periods 12 and 6 months

$$M_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2$$

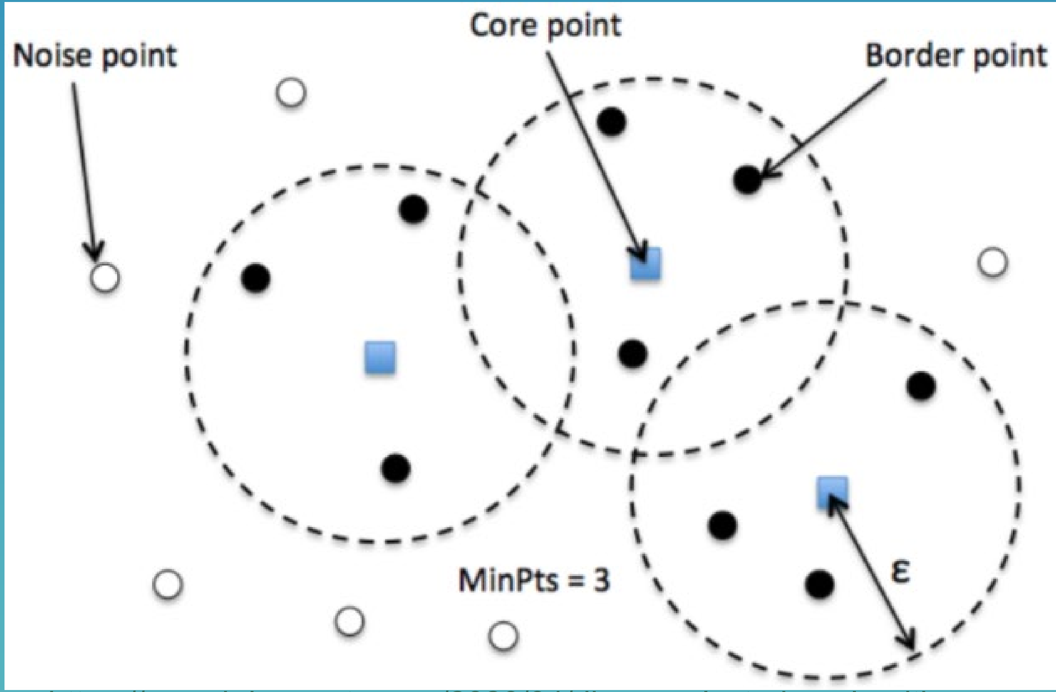
$$S_t = \beta_1 cos_{1,t} + \beta_2 sin_{1,t} + \beta_3 cos_{2,t} + \beta_4 sin_{2,t}$$

Individual event identification: RF

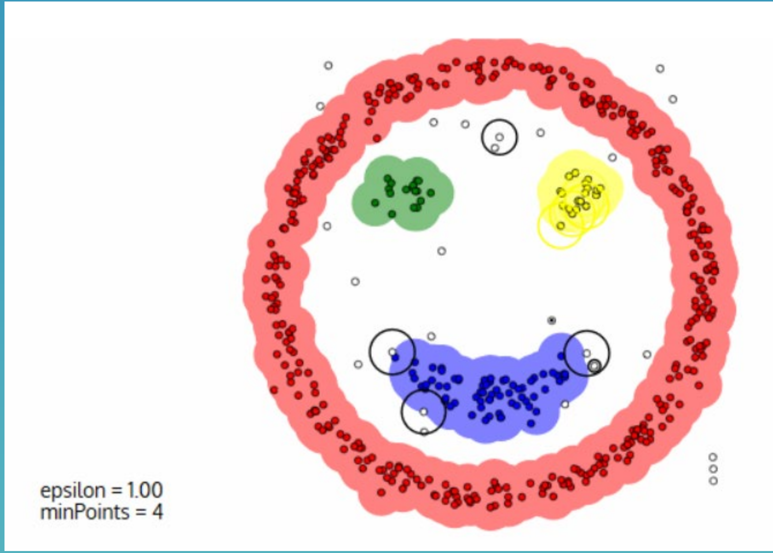


Average path length (number of splits to isolate an observation within a tree) is the anomaly score

Individual event identification: DBSCAN



https://www.kdnuggets.com/2020/04/dbscan-clustering-algorithm-machine-learning.html



https://www.digitalvidya.com/blog/the-top-5-clustering-algorithms-data-scientists-should-know/

Select the noise points

Identify linkages

Time series lags used to consider delayed effects (during fish spawning) of environmental variables on corresponding fisheries.

X(April) + X(May) + X(June) ~ Y

Run a chi-square test on positive and negative anomalies detected by each algorithm.

Data sources

Fish/shellfish

- Maryland DNR

  -Seine Survey

  -Striped Bass Spawning Stock Survey
- VIMS

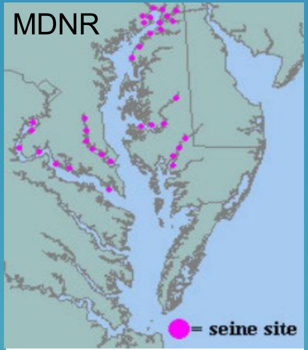
  -Seine Survey

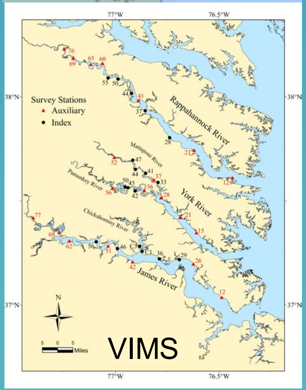
  -Juvenile Trawl Survey

  -ChesMMAP
- Maryland DNR & VIMS

  -Blue crab Winter Dredge Survey

  -Blue crab Trawl Survey
- CBSAC & ASMFC landings



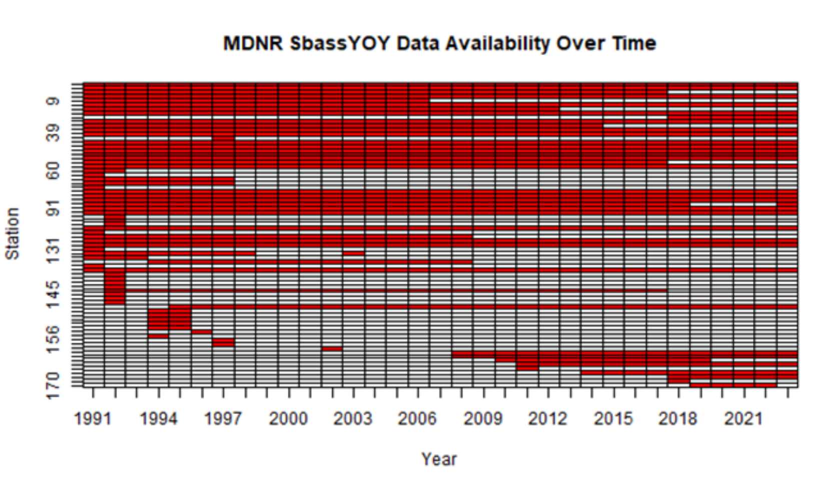


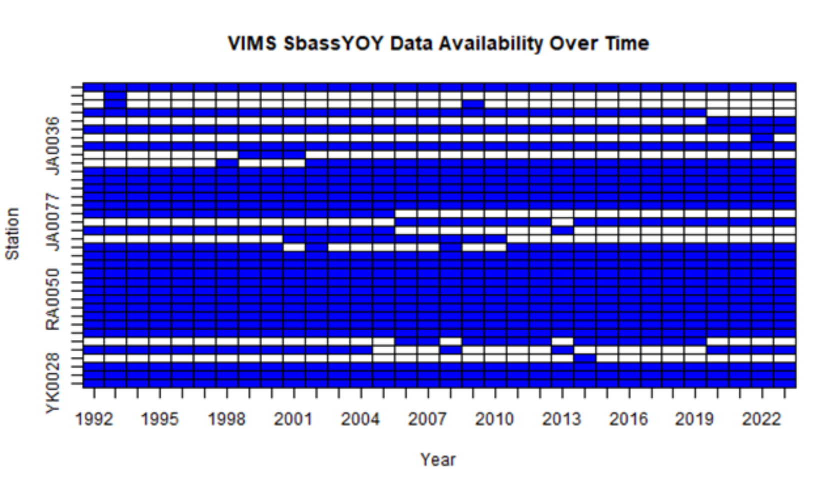
Environmental

- NASA Daymet – min/max temp & precipitation
- Chesapeake Bay Environmental Forecast System (CBEFS)
- Chesapeake Bay Interpretive Buoy System (CBIBS)
- VIMS Submerged Aquatic Vegetation Program

Data treatment 1

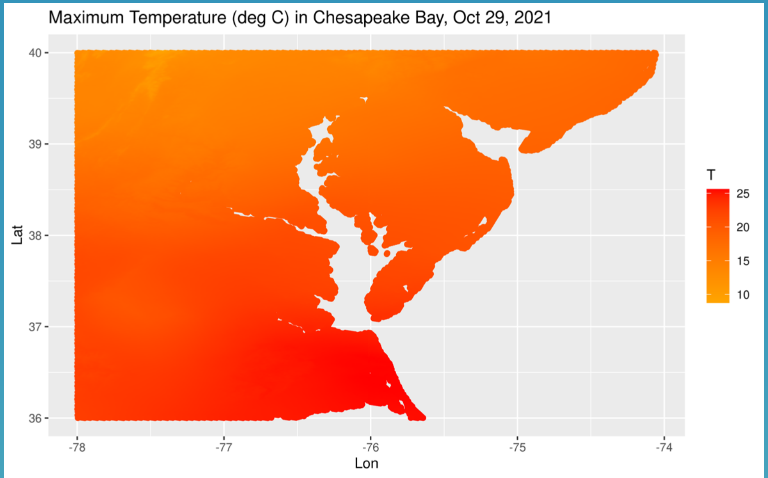
- Fish seine survey effort data collection consistent from 1991+, so time series spanned 1991-2023
- Stations with sampling in >80% of years were used in analyses
- 27 stations in Maryland and 22 stations in Virginia

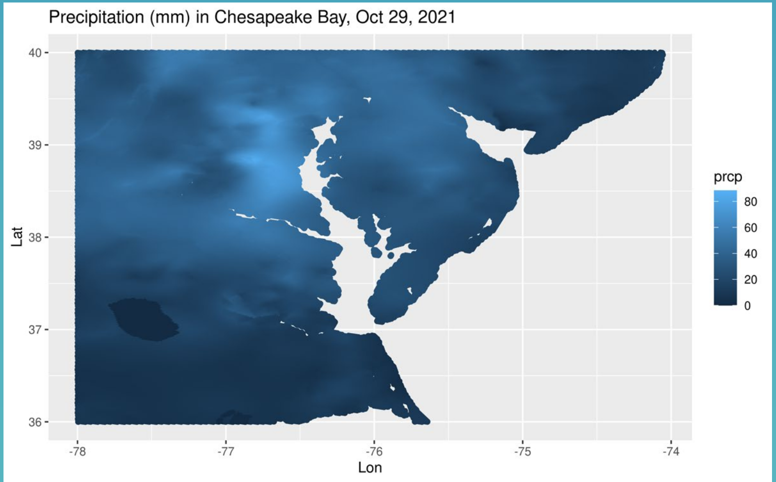




Data treatment 2

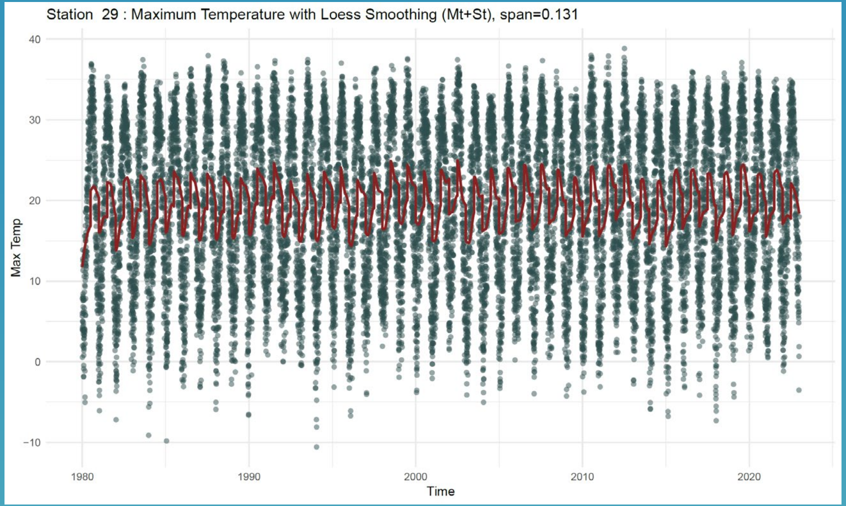
- Selected Daymet cell nearest to each fish sampling station to represent nearby weather conditions
- At each individual fish sampling station, both environmental and fish CPUE rare events were tallied across the time series
- To identify relationships between environmental and fish CPUE, we tallied Daymet rare events March-June annually and all sampling events in a year for fish seine surveys

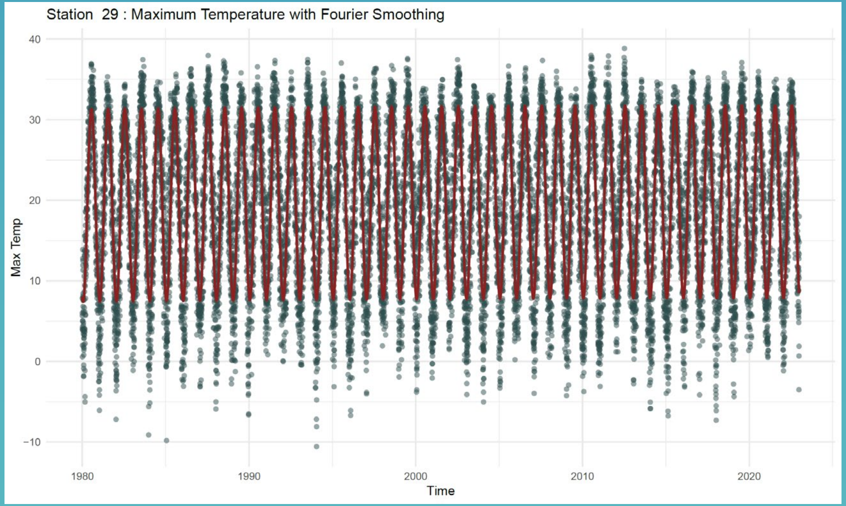




Implementation

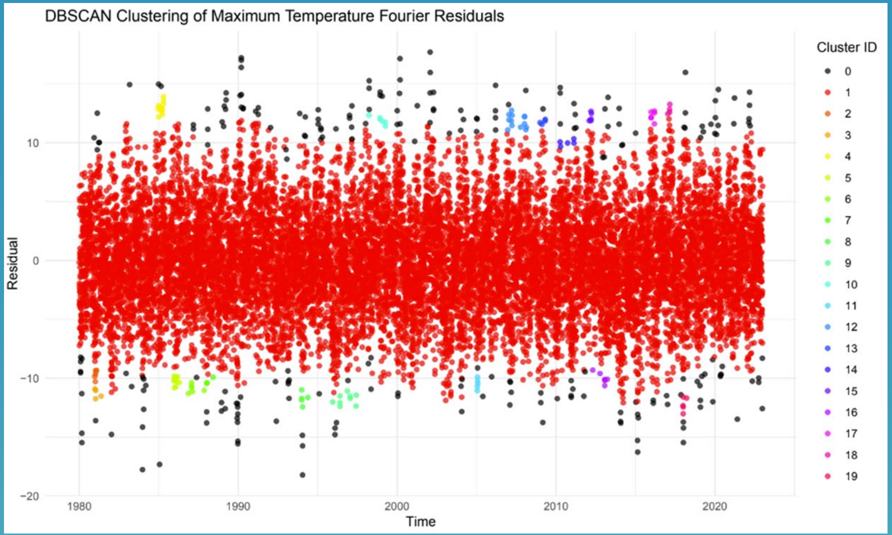
1. Smoothed all fish and environmental time series using locally weighted smoothing (loess) or trend + Fourier series

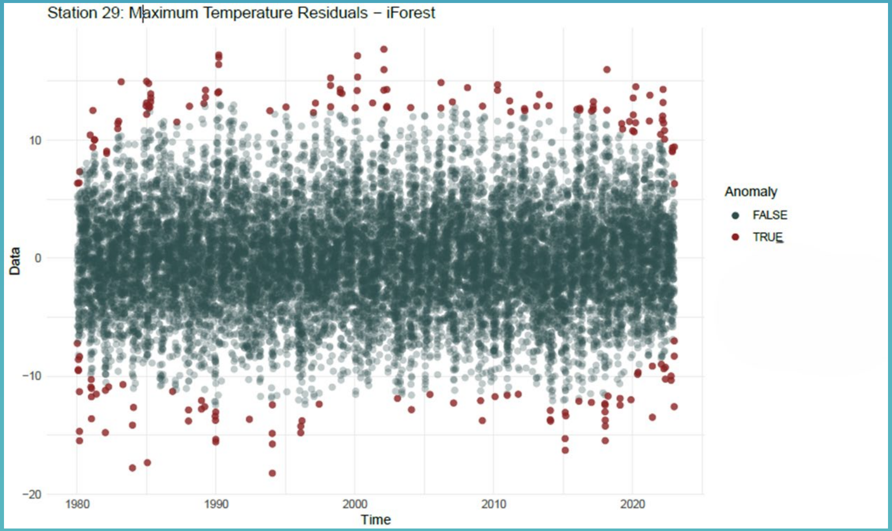




Implementation

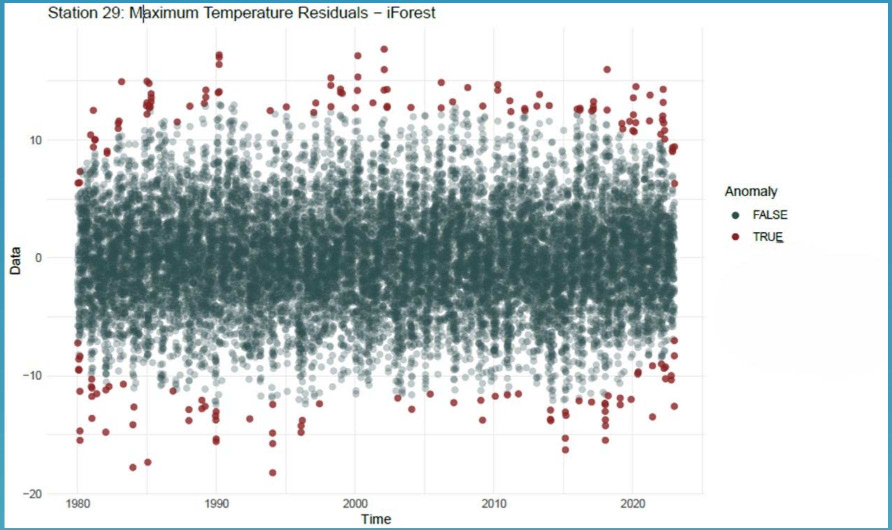
1. Smoothed all fish and environmental time series using locally weighted smoothing (loess) or trend + Fourier series
2. Identified rare events in both fish and environmental residuals using isolation forest and density-based clustering (DBSCAN) algorithms

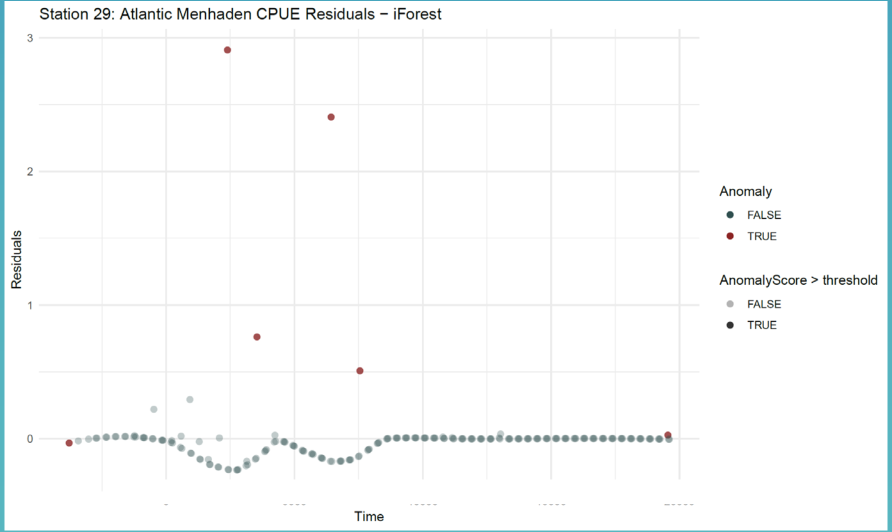




Implementation

1. Smoothed all fish and environmental time series using locally weighted smoothing (loess) or trend + Fourier series
2. Identified rare events in both fish and environmental residuals using isolation forest and density-based clustering (DBSCAN) algorithms
3. Quantified significance of relationships between rare fish events and rare weather events (March-June) using chi-square tests



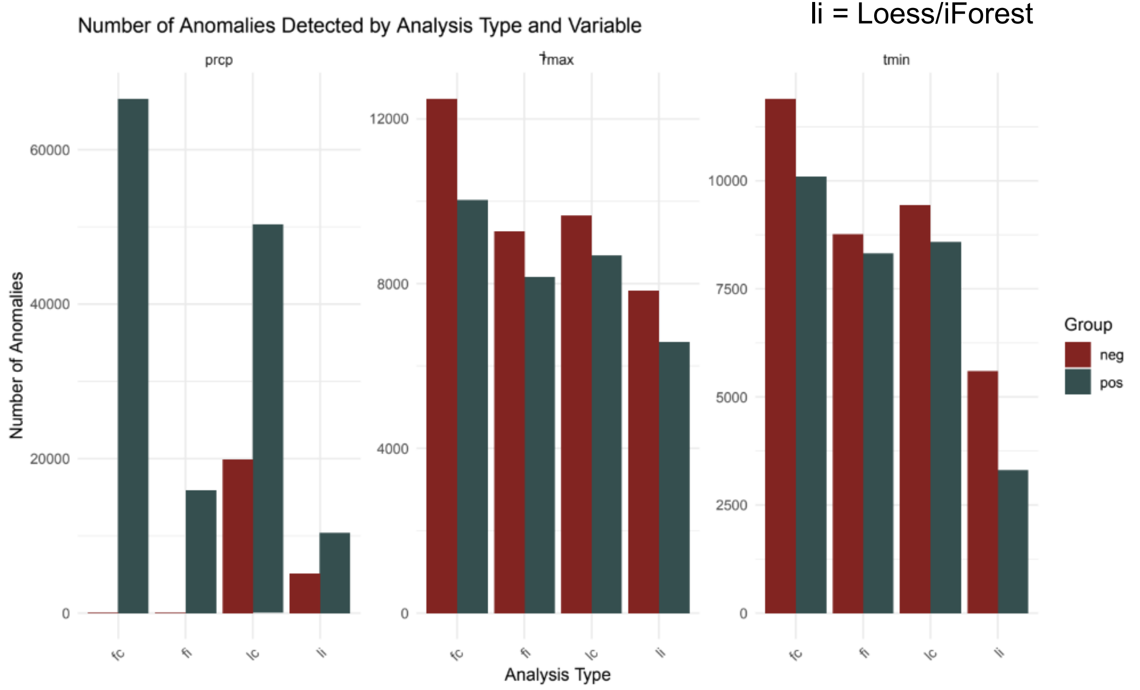


Preliminary results

Rare event detection

- More precipitation rare events, more high than low
- Similar number of pos/neg temperature rare events
- Smoothing method (Fourier vs loess) had minimal effect on rare event detection
- DBSCAN identified more rare events than Isolation Forest
- In general, most sensitive combination of methods was FC and least was LI

Method
fc = Fourier/Clustering
fi = Fourier/iForest
lc = Loess/Clustering
li = Loess/iForest



Preliminary results

- For both species, more relationships identified between CPUE and min temperature than max temperature or precipitation
- Depending on algorithms used, ~20-39% of relationships between CPUE and min temperature rare events were significant
- Higher proportion of significant relationships identified when # rare events was lower. Focus on more strict methods to yield fewer false positives.

Atlantic menhaden

Proportion of Significant Relationships and Number of Anomalies Detected by Test - Menhaden

	Fourier-iForest	Fourier-Clustering	Loess-iForest	Loess-Clustering
Precipitation	0.027/15953	0.14/66662	0.013/15444	0.127/70237
Maximum Temperature	0.14/17442	0.14/22533	0.247/18337	0.24/14424
Minimum Temperature	0.353/17093	0.267/22003	0.207/18022	0.347/8909

[1] p significant Relationships/n weather anomaly detected
[2] P<0.05

Striped bass

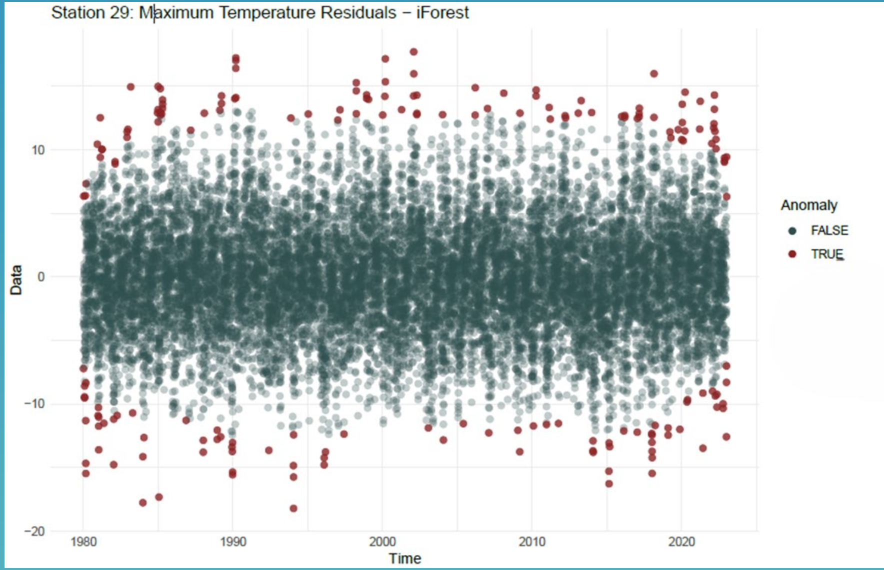
Proportion of Significant Relationships and Number of Anomalies Detected by Test - Striped Bass

	Fourier-iForest	Fourier-Clustering	Loess-iForest	Loess-Clustering
Precipitation	0.1/15953	0.12/66662	0.107/15444	0.113/70237
Maximum Temperature	0.12/17442	0.12/22533	0.26/18337	0.267/14424
Minimum Temperature	0.333/17093	0.267/22003	0.28/18022	0.387/8909

[1] p significant Relationships/n weather anomaly detected
[2] P<0.05

Next steps

- Summarize rare event results by pos/neg anomalies
- Identify rare events in CBEFS hindcast estimates of water temp, salinity, DO, attenuation depth, and wave height
- Refine methods and apply to all YOY and adult fish and environmental data sources
- Develop predictive models
- Data analysis tools



Integration:
Ecological monitoring and inference for wind energy development

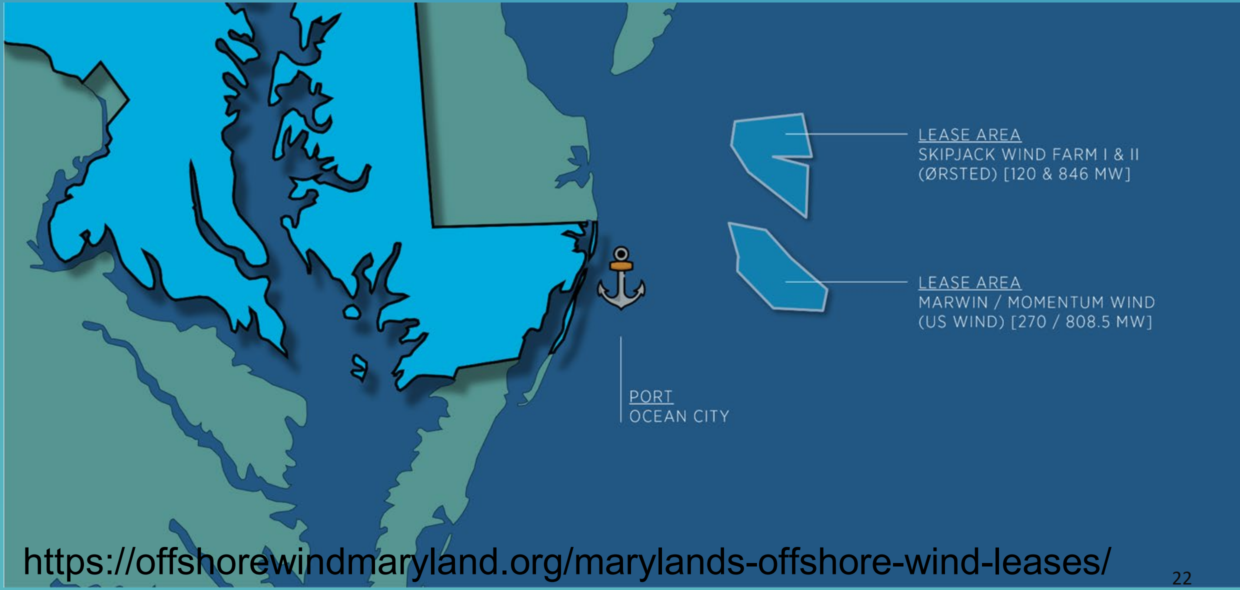
with

TailWinds

Team for **A**ssessing **I**mpacts to **L**iving resources from offshore **WIND** turbine**S** (UMCES, https://tailwinds.umces.edu/),
Annamaria DeAngelis (NOAA), Bruna Pagliani (Fed. U. of Rio de Janeiro, Brazil)

Motivation

- Conduct a passive acoustic monitoring (PAM) study within the area of potential effect for the Maryland Lease Area
- Improve marine mammal acoustic call detectors (distinguish between bottlenose and common dolphins)
- Ecological understanding, biodiversity monitoring



https://offshorewindmaryland.org/marylands-offshore-wind-leases/

Data processing: PamGuard + ROCCA

Data were processed in PamGuard using the Real-time Odontocete Call Classification Algorithm (ROCCA), a random forest classifier that measures 50 features of each whistle contour

- ROCCA groups individual whistles into different encounters
- Encounters are given unique IDs representing collections of whistles assumed to be from a discrete individual or group of dolphins
- Whistle features measured by ROCCA, grouped by encounter IDs, were exported and used to train the models

ROCCA was originally trained on whistles of 8 delphinid species in the tropical Pacific Ocean

- Whistle structure has been shown to vary across region and population
- Training classification algorithms on data from the region and/or species of interest are most effective

Data processing: PamGuard + ROCCA

Acoustic files included either confirmed only common dolphin or most probable only bottlenose dolphin whistles in the Atlantic Ocean

Common dolphin whistles from:

- NW Atlantic (NOAA AMAPPS)
- SW Atlantic off Brazil (Dr. Bruna Pagliani)
- Sable Island, Canary Island, and an unknown location (Watkins Marine Mammal Sound Database)

Bottlenose dolphin whistles from subset of data

- Mid-Atlantic region (previous Maryland DNR/BOEM study)

Number of whistles available from each source and year along with the event counts

Source	Dolphin species	1958	1975	1987	2014	2016	2017	2018	Whistle, count	Whistle, %	Event, count	Event, %
Brazil	Common	0	0	0	3580	0	0	0	3580	24.153	29	2.241
NOAA	Common	0	0	0	0	2637	0	0	2637	17.791	9	0.696
T1C	Bottlenose	0	0	0	0	5251	2049	1075	8375	56.504	1225	94.668
Watkins	Common	131	97	2	0	0	0	0	230	1.552	31	2.396
Total	–	131	97	2	3580	7888	2049	1075	14822	100	1294	100.001

VS

Methods

BANTER (Rankin et al. 2017)

NN + GLM

RF + Boruta (variable selection; Kursa & Rudnicki 2010) + GLM

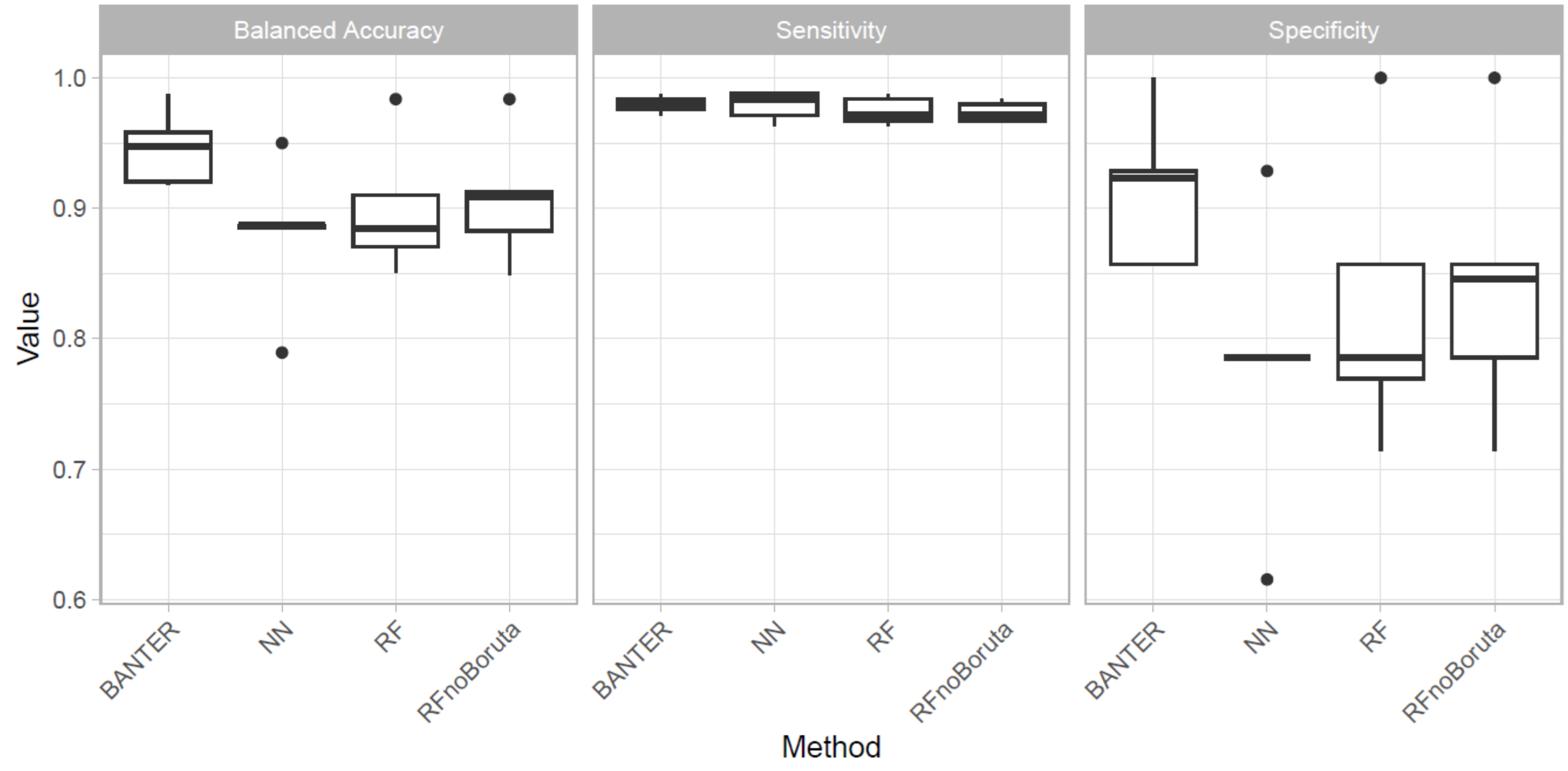
RF + GLM

Model assessment

5-fold cross-validation applied 5 times

Performance metrics: balanced accuracy, sensitivity, specificity

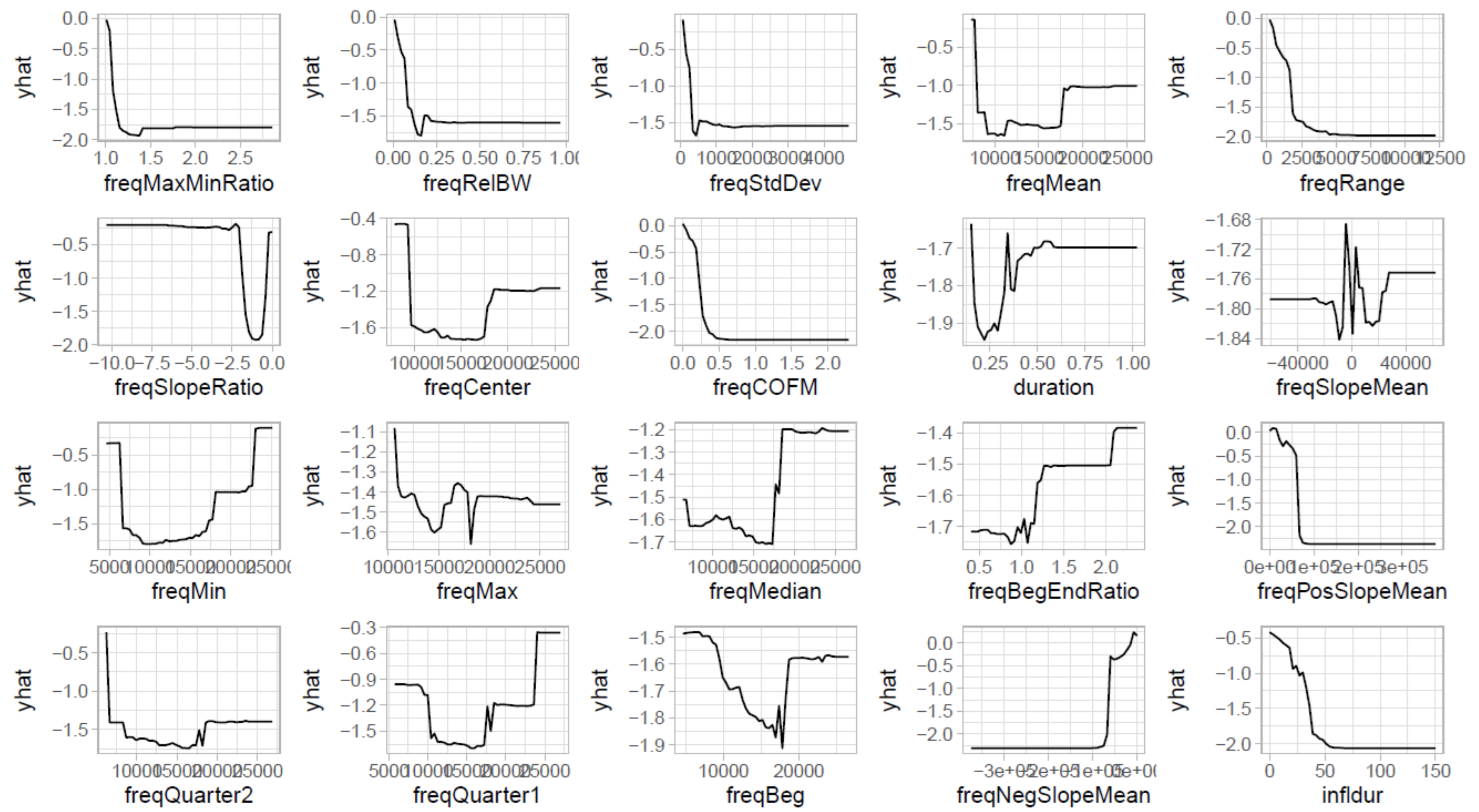
Classification performance in cross-validation



Accuracy (%) at different levels of retrained BANTER

Species	Whistle	Event
Bottlenose	91.5	97.7
Common	82.6	91.3
Overall	87.7	97.4

Partial dependence plots for the most important variables



Conclusions

- A retrained BANTER model outperformed other models by classifying events with bottlenose dolphins more accurately
- Partial dependence plots help to identify thresholds for distinguishing the two species of dolphins
- Classification of unlabeled (without ground truth) recordings from the Maryland Wind Energy Area reveals predominantly bottlenose dolphins and a few common dolphins in the winter, mainly December to May

Application:
Machine learning of factors for improving oyster hatchery production

with

Mathew Gray (HPL, UMCES), Greg Silsbe (HPL, UMCES)

https://vlyubchich.github.io/OysterHatcheryYield/

Teaching and advisement

Courses

Environmental statistics 1 (MEES 613, 3 credits)

Environmental statistics 2 (MEES 713, 3 credits)

R programming basic (MEES 602, 1 credit) – self-paced with open-source materials (thanks to UMD TLC grant)

R programming advanced (MEES 702, 1 credit)

Students

400+ students taught

15 graduate committees (10 completed)

20+ undergraduate interns (Maryland Sea Grant NSF REU, College of Southern Maryland, St. Mary’s College of Maryland, etc.)

Future directions

Data-driven solutions to environmental problems

- Causality
- Machine learning for PAM recordings
- High-dimensional inference

Questions?

lyubchich@umces.edu

Thank you!