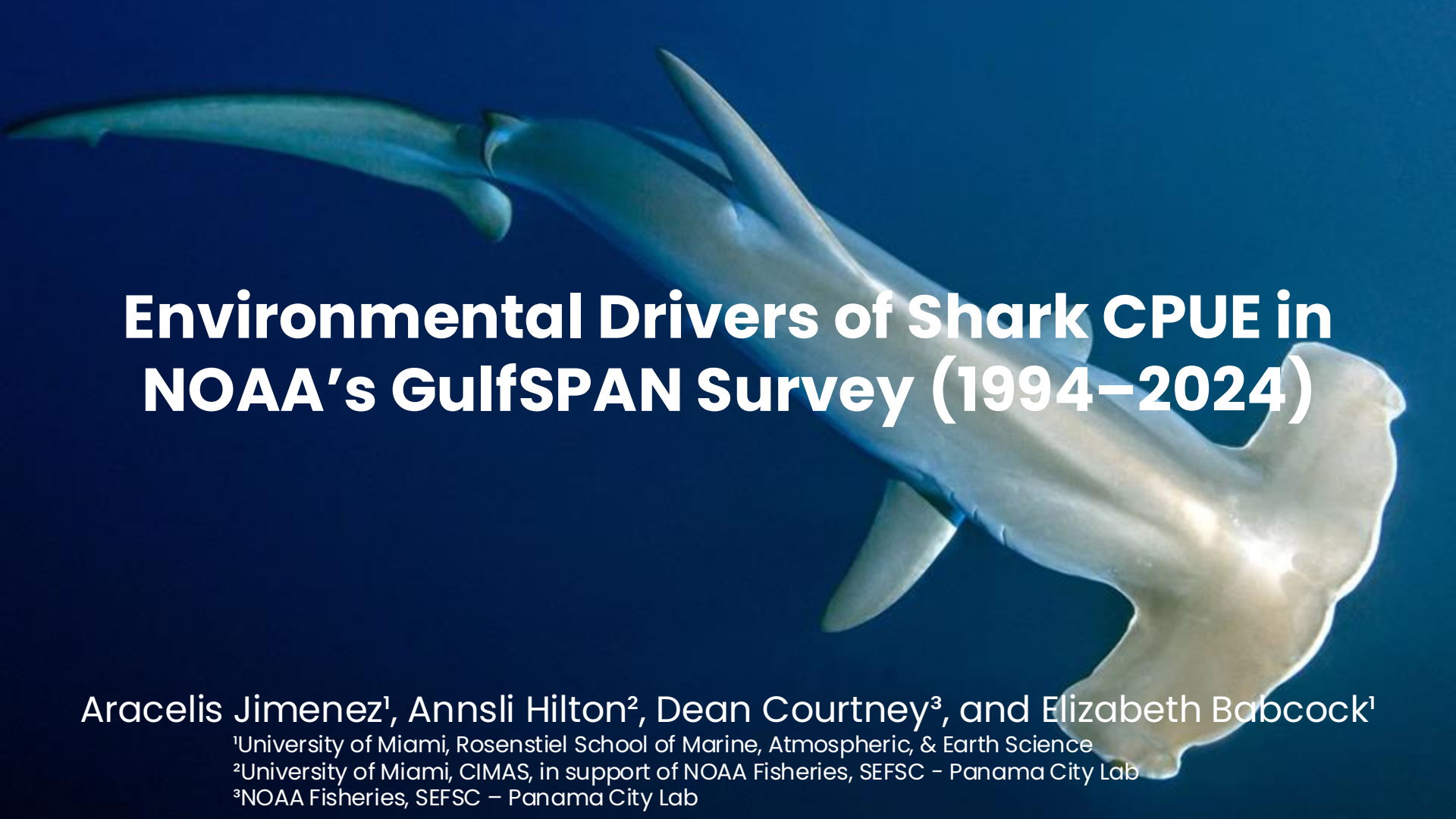


Environmental Drivers of Shark CPUE in NOAA's GulfSPAN Survey (1994–2024)

Aracelis Jimenez[1], Annsli Hilton[2], Dean Courtney[3], and Elizabeth Babcock[1]

[1]University of Miami, Rosenstiel School of Marine, Atmospheric, & Earth Science
[2]University of Miami, CIMAS, in support of NOAA Fisheries, SEFSC - Panama City Lab
[3]NOAA Fisheries, SEFSC – Panama City Lab

NOAA's GulfSPAN Survey (1994 - 2024)

Fishery-independent shark pupping and nursery survey

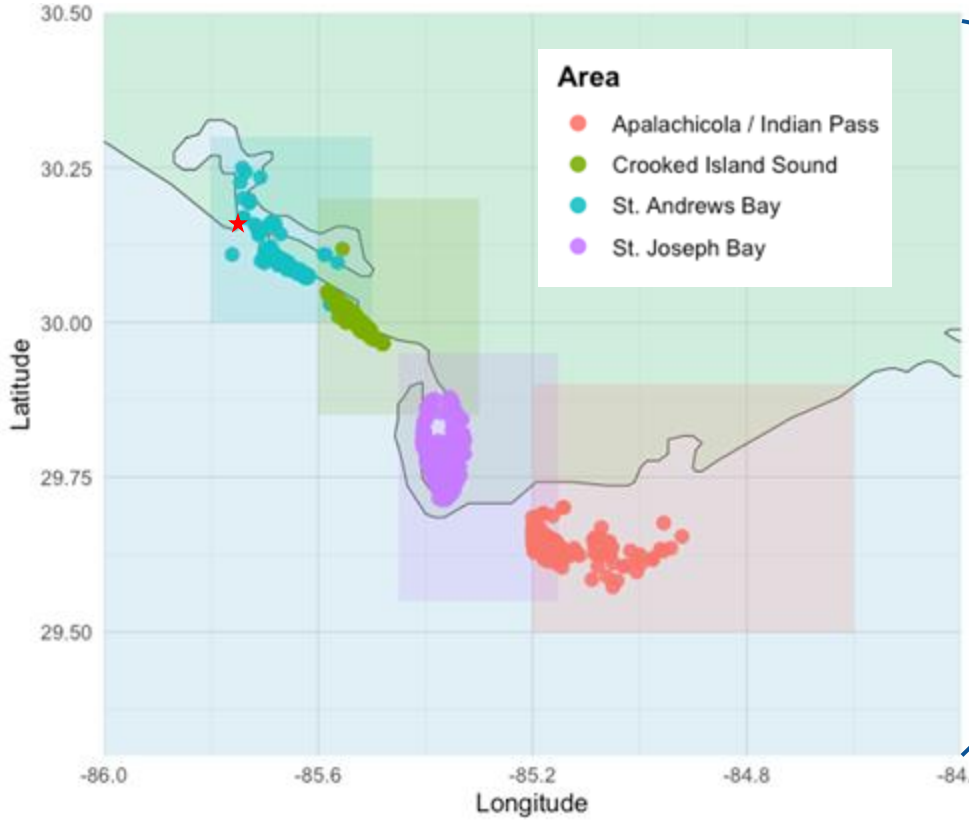
Runs from **April-November**

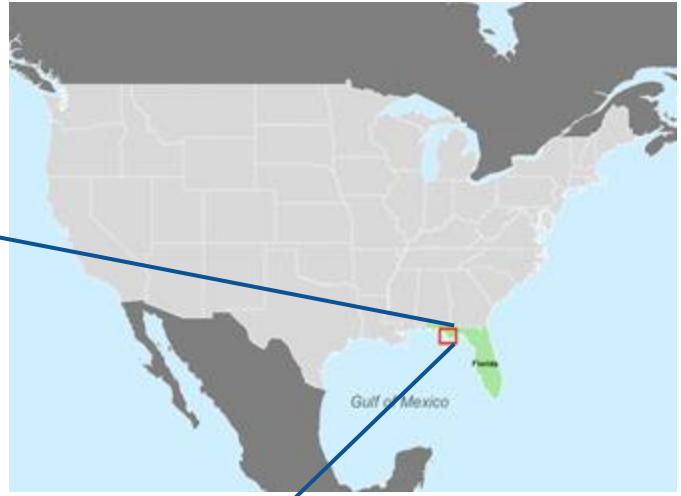
Crews sample coastal bays and estuaries using monofilament **gillnets**

Records soak time, environmental variables, and data on sharks captured

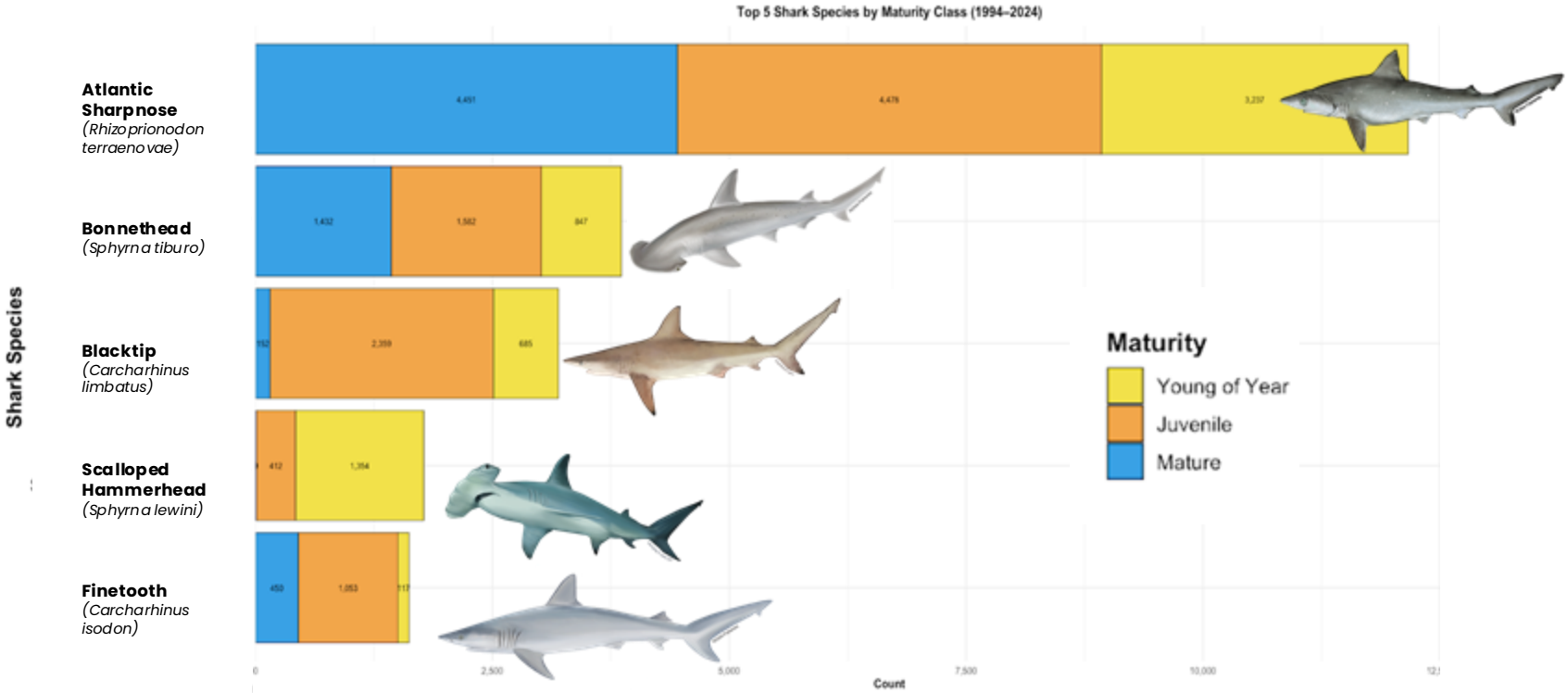
This data allows us to summarize CPUE per gillnet hour as a proxy for abundance in the area.

Areas Surveyed





Top 5 Most Caught Shark Species by Maturity Class (1994-2024)



RESEARCH QUESTIONS

(1.) Do any environmental variables predict CPUE?

(2) Do predictor–CPUE relationships differ by species?

(3) Does CPUE significantly change over time?

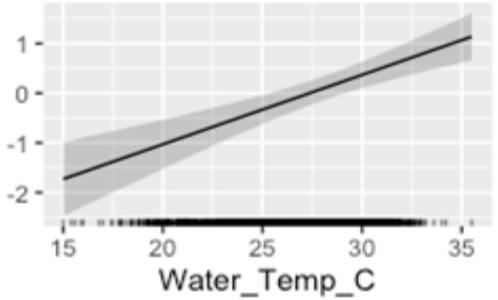
(4) Does CPUE differ by area—overall and over time?

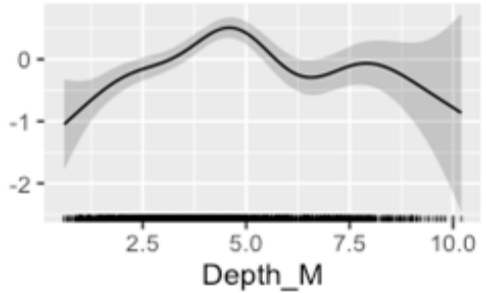
METHODS

Methods: Generalized Additive Models (GAMs)

mgcv

```
gam(CPUE ~
s(Water Temp) +
s(Salinity) +
s(Depth) +
s(Turbidity) +
s(Dissolved Oxygen) +
s(Year),
Data = Top-5_Sharks
Family = tw(link = "log")
method= "REML")
```





GAM checks

Histogram:

Positive, right-skewed; Tweedie(log)

Correlation Among Predictors:

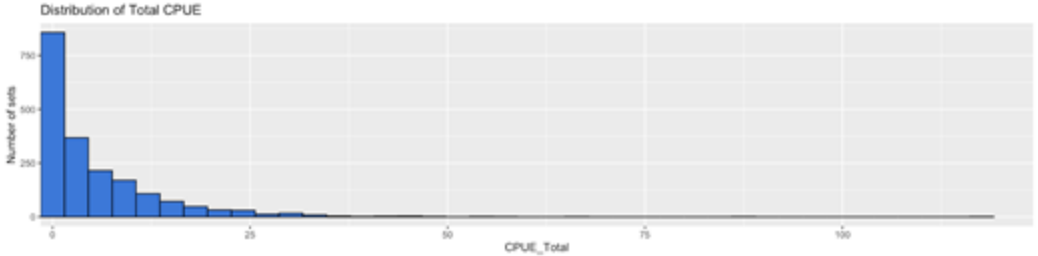
- Collinearity not a concern
- No predictors were correlated

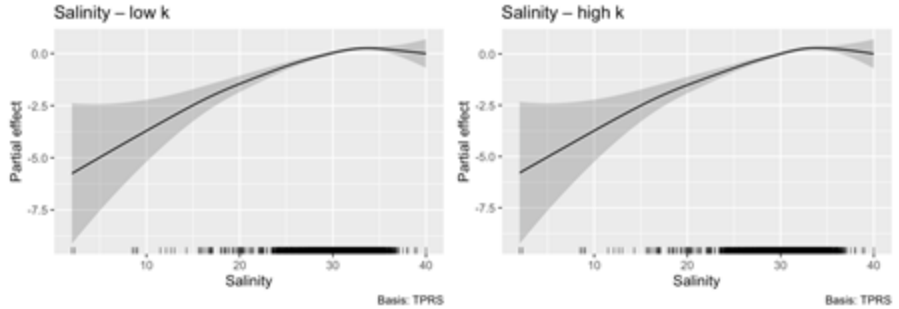
Fitting with REML and ML:

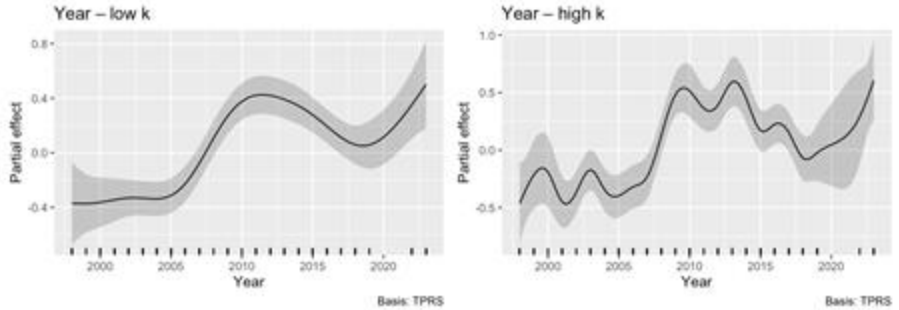
- REML for fitting GAMs
- ML for AIC model selection

Gam.check()

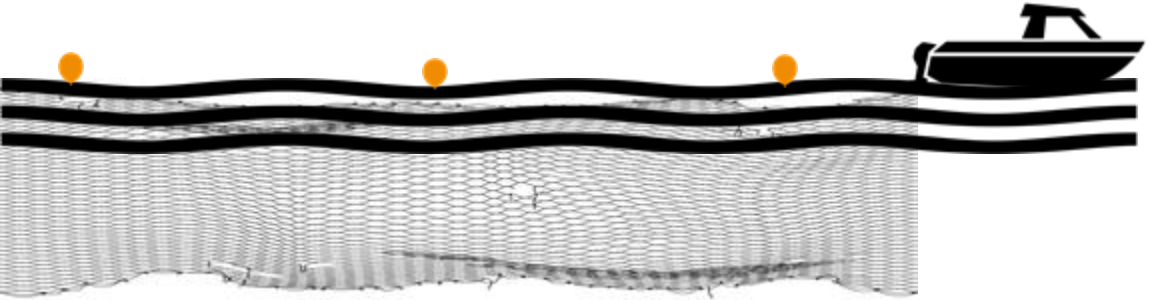
Checking available flexibility (k) to capture patterns in the data





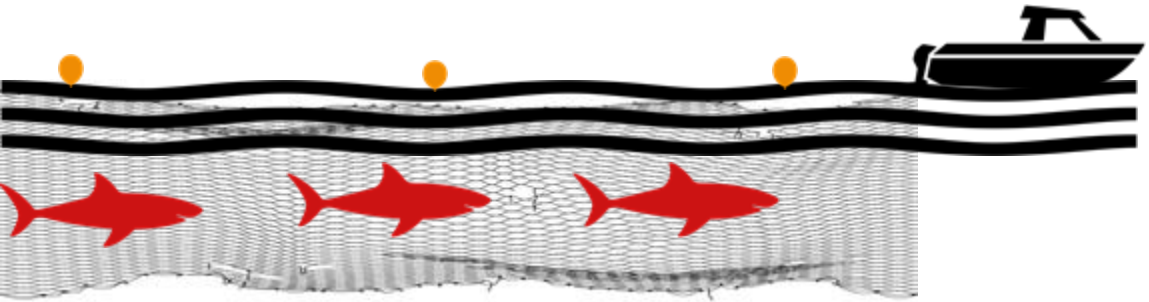


Methods: Data Preparation



Catch-Per-Unit-Effort (CPUE) =

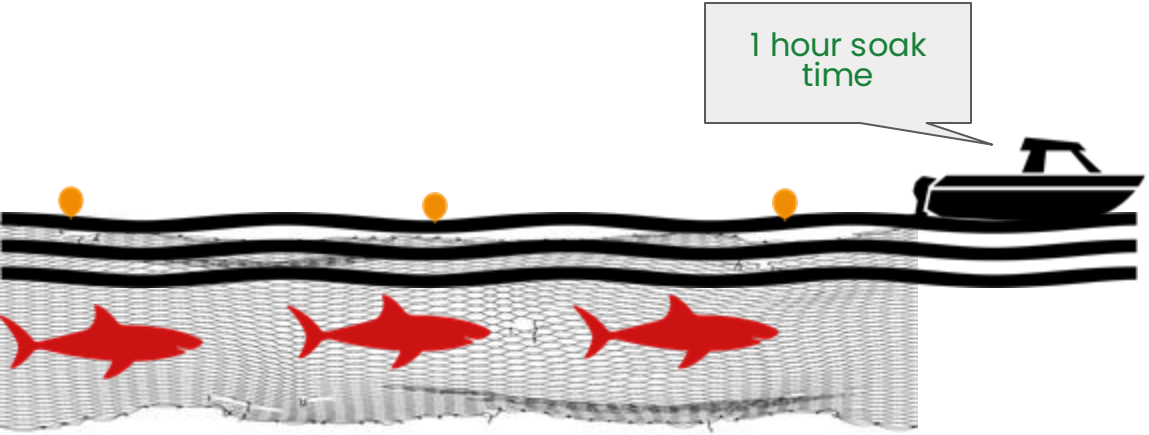
Methods: Data Preparation



Catch-Per-Unit-Effort (CPUE) =

Total Sharks Captured Per Haul

Methods: Data Preparation



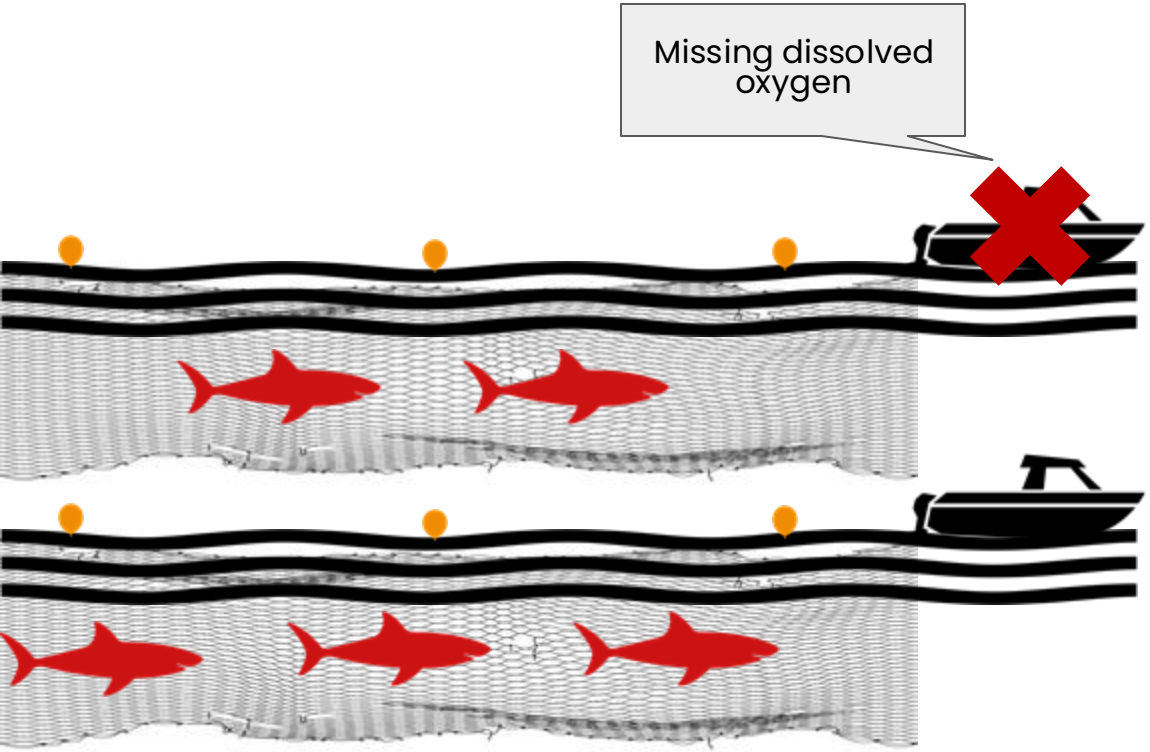
Catch-Per-Unit-Effort (CPUE) =

Total Sharks Captured Per Haul

÷

Soak Time (hours)

Methods: Data Preparation



Hauls missing ≥1 environmental variable were excluded

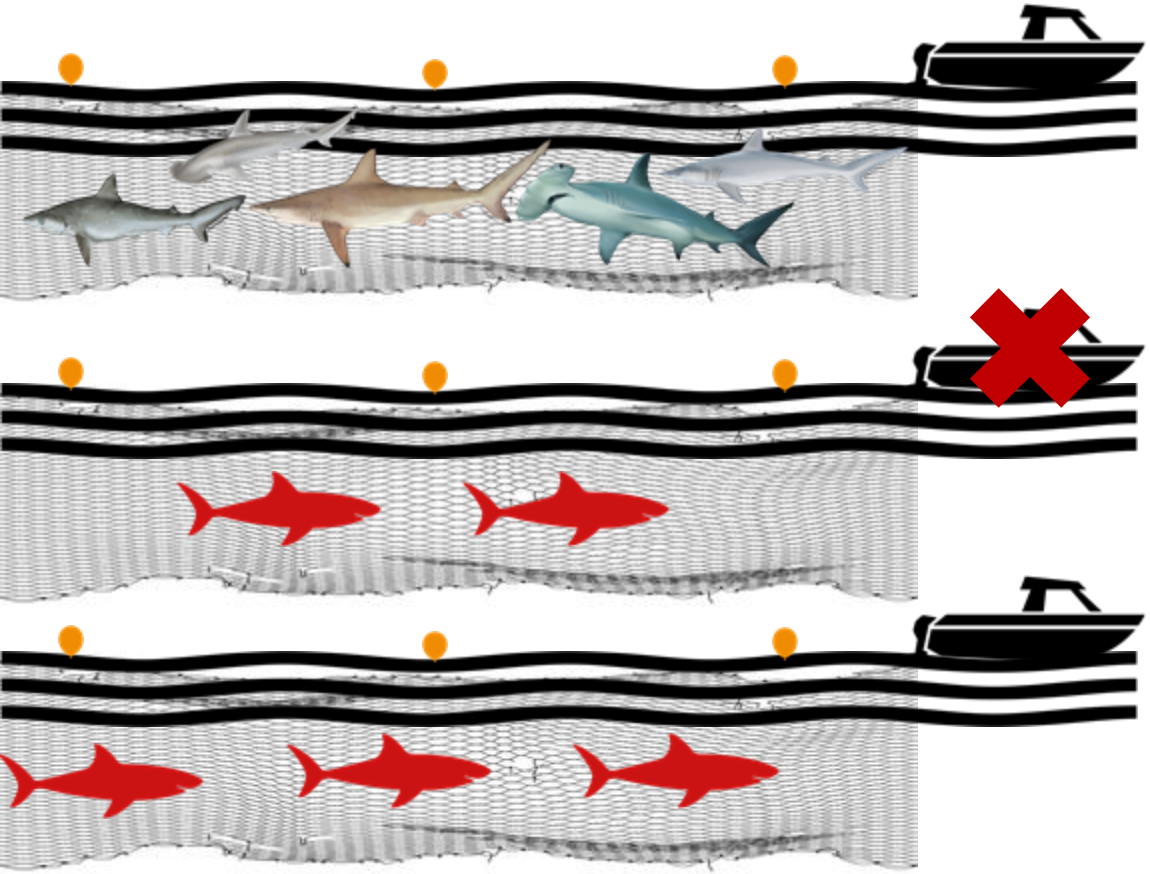
Catch-Per-Unit-Effort (CPUE) =

Total Sharks Captured Per Haul

÷

Soak Time (hours)

Methods: Data Preparation



n=1,960 unique hauls

Hauls missing ≥1 environmental variable were excluded

Catch-Per-Unit-Effort (CPUE) =

Total Sharks Captured Per Haul

÷

Soak Time (hours)

RESULTS

(1.) Do any environmental variables predict CPUE?

Variable	edf	df	F	Sig.
Water Temp (°C)	7.26	8.17	8.8	***
Salinity (ppt)	3.80	4.76	23.8	***
Depth (m)	6.01	7.16	32.1	***
Turbidity (m)	1.01	1.02	130.6	***
Dissolved Oxygen (mg/L)	1.74	2.23	2.7	*n.s.*
Year	6.14	7.24	14.8	***

n=1960

Deviance Explained: 23.7%

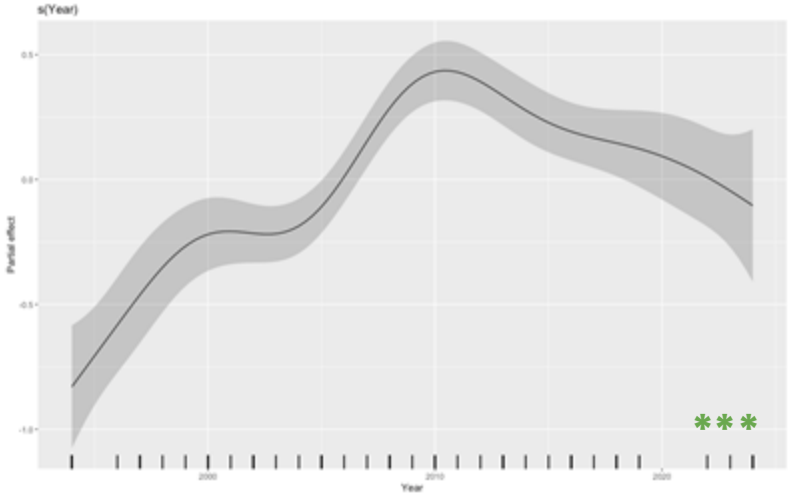
(2) Do predictor–CPUE relationships differ by species?

	Water Temp	Salinity	Depth	Turbidity	DO	Year	Deviance Explained
Atlantic Sharpnose	***	***	***	***		***	22.2%
Bonnethead	**	***	***	***			9.37%
Blacktip	***	**	***	***	**		22%
Scalloped Hammerhead	***	***	***	***		***	34.7%
Finetooth	✘	*	***	***	**	***	38%

(3) Does CPUE significantly change over time?

Year-Only Model

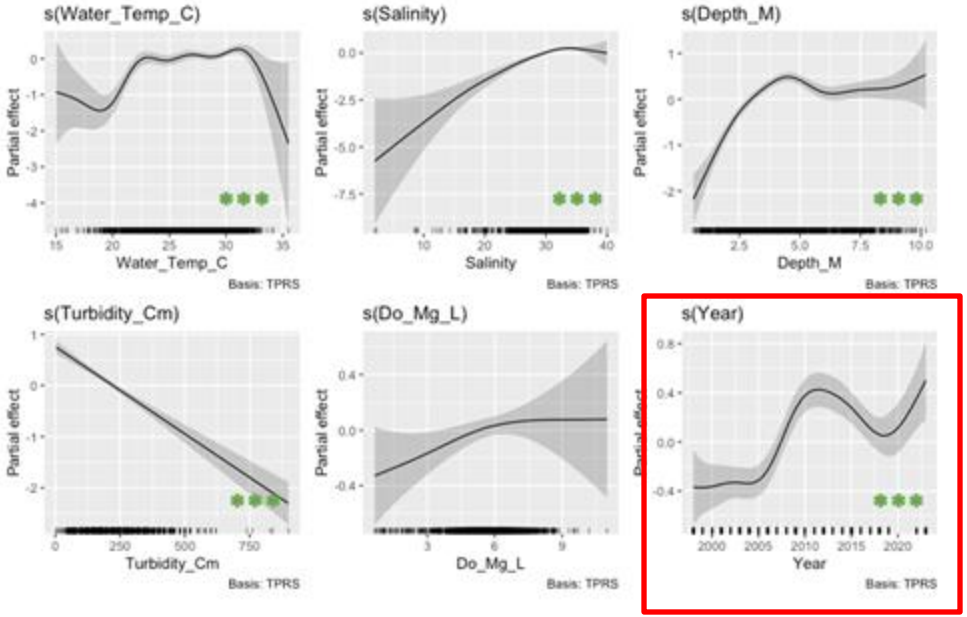
Variable	edf	df	F	Sig.
Year	6.204	7.30	18.26	***



n=2533

Deviance Explained: 4.36%

Full Model



n=1960

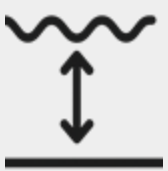
(4) Does CPUE differ by area—overall and over time?

KEY TAKEAWAYS & NEXT STEPS

Key Takeaways Across 30 Years

CPUE for the combined Top 5 Sharks *showed significant relationships with …*

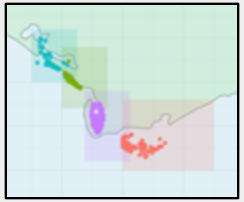

***


***


***


***


***

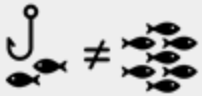

SAB
CIS
SJB
APL/IP
***

Predictor-CPUE relationships *of environmental variables* ***across species…***

**


9.3%

Limitations



Next Steps for NOAA, Management, & Future Research

Future SEDAR stock assessments should incorporate smooth environmental variables.

Details on SEDAR reports that have looked at Top 5 Sharks

What these results show for management →

- Thresholds for how species-specific environmental variables predict CPUE
- Highlight areas where more sampling is needed

Future research →

- Include variables that may influence CPUE:
  - Count of bycatch species per haul
  - Seasonal patterns
  - Time of day
- Test whether high-CPUE hotspots overlap with high shark depredation areas from fisher surveys

Acknowledgements

Committee:
Dr. Elizabeth Babcock
Dr. Manoj Shivlani
Dr. Catherine Macdonald

"Fishermen and scientists have recognized that the sum of their understanding of the fishery ecosystem is greater than their individual knowledge"

-West Coast Cooperative Research, 2005

This presentation was made possible by the National Oceanic and Atmospheric Administration, Office of Education Educational Partnership Program award number (NA21SEC4810005). Its contents are solely the responsibility of the award recipient and do not necessarily represent the official views of the U.S. Department of Commerce, National Oceanic and Atmospheric Administration.
Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the view of the U.S. Department of Commerce, National Oceanic and Atmospheric Administration.

Acknowledgements

Presenting at the PICES conference was also made possible by the generous contributions of the Marine Science Graduate Student Organization (MSGSO) at the University of Miami, and the US National Science Foundation (NSF)

MIAMI

NSF National Science Foundation

I want to also thank everyone at the NOAA SEFSC Panama City lab (**Dr. John Carlson**, **Chris Gardner**) and **Dr. Stephen Kajiura** at FAU for their support in this research.

Works Cited

Arnold, T. W. (2010). Uninformative Parameters and Model Selection Using Akaike's Information Criterion. *The Journal of Wildlife Management*, *74*(6), 1175–1178. https://doi.org/10.1111/j.1937-2817.2010.tb01236.x

Burnham, K. P., & Anderson, D. R. (2004). Multimodel Inference: Understanding AIC and BIC in Model Selection. *Sociological Methods & Research*, *33*(2), 261–304. https://doi.org/10.1177/0049124104268644

Chiarini, M., Guicciardi, S., Angelini, S., Tuck, I. D., Grilli, F., Penna, P., Domenichetti, F., Canduci, G., Belardinelli, A., Santojanni, A., Arneri, E., Milone, N., Medvešek, D., Isajlović, I., Vrgoč, N., & Martinelli, M. (2022). Accounting for environmental and fishery management factors when standardizing CPUE data from a scientific survey: A case study for Nephrops norvegicus in the Pomo Pits area (Central Adriatic Sea). *PLOS ONE*, *17*(7), e0270703. https://doi.org/10.1371/journal.pone.0270703

Courtney, D. (2025). *SEDAR Reports & Notes on Top 5 Shark Species—NOAA SEFSC (Panama City)*. Google Sheets. https://docs.google.com/spreadsheets/d/1F4HO0vxArspNVgh-rPK6le5INkSIt25YNFDzj6eBx9g/edit?usp=sharing&usp=embed_facebook

García-Fernández, C., Ciércoles, C., Urra, J., Marina, P., Serna-Quintero, J. M., & Baro, J. (2024). Influence of environmental conditions on the abundance of the striped venus Chamelea gallina in the northern Alboran Sea (Western Mediterranean Sea). *Regional Studies in Marine Science*, *76*, 103601. https://doi.org/10.1016/j.rsma.2024.103601

Gomez-Rubio, V. (2018). Generalized Additive Models: An Introduction with *R* (2nd Edition). *Journal of Statistical Software*, *86*(Book Review 1). https://doi.org/10.18637/jss.v086.b01

Han, H., Yang, C., Zhang, H., Fang, Z., Jiang, B., Su, B., Sui, J., Yan, Y., & Xiang, D. (2022). Environment variables affect CPUE and spatial distribution of fishing grounds on the light falling gear fishery in the northwest Indian Ocean at different time scales. *Frontiers in Marine Science*, *9*, 939334. https://doi.org/10.3389/fmars.2022.939334

Kloese, S. (2022, December 2). *Generalized Additive Models* [PDF]. P/C Rate Modeling Actuary.

Lai, J., Tang, J., Li, T., Zhang, A., & Mao, L. (2024). Evaluating the relative importance of predictors in Generalized Additive Models using the gam.hp R package. *Plant Diversity*, *46*(4), 542–546. https://doi.org/10.1016/j.pld.2024.06.002

Maunder, M. N., & Punt, A. E. (2004). Standardizing catch and effort data: A review of recent approaches. *Fisheries Research*, *70*(2–3), 141–159. https://doi.org/10.1016/j.fishres.2004.08.002

R Core Team. (2025). *R: The R Project for Statistical Computing* (Version Version 4.4.2) [Compter Software]. https://www.R-project.org/

Sheridan, P., & Davenport, G. (2010). A Brief History of Time at the National Marine Fisheries Service Panama City Laboratory (Apologies to Stephen Hawking). *Gulf of Mexico Science*, *28*(1). https://doi.org/10.18785/goms.2801.16

Southeast Fisheries Science Center. (2025). *SEFSC Elasmobranch Tag and Recapture Database (longterm capture and recapture data)*. https://www.fisheries.noaa.gov/inport/item/8658

Venables, W. N., & Dichmont, C. M. (2004). GLMs, GAMs and GLMMs: An overview of theory for applications in fisheries research. *Fisheries Research*, *70*(2–3), 319–337. https://doi.org/10.1016/j.fishres.2004.08.011

Ward-Paige, C. A., Britten, G. L., Bethea, D. M., & Carlson, J. K. (2015). Characterizing and predicting essential habitat features for juvenile coastal sharks. *Marine Ecology*, *36*(3), 419–431. https://doi.org/10.1111/maec.12151

Whitlock, M. C., & Schluter, D. (2020). *The Analysis of Biological Data* (3rd ed.). Macmillan Learning.

Wood, S. (2000). *mgcv: Mixed GAM Computation Vehicle with Automatic Smoothness Estimation* (p. 1.9-3) [Dataset]. https://doi.org/10.32614/CRAN.package.mgcv


Thank You!

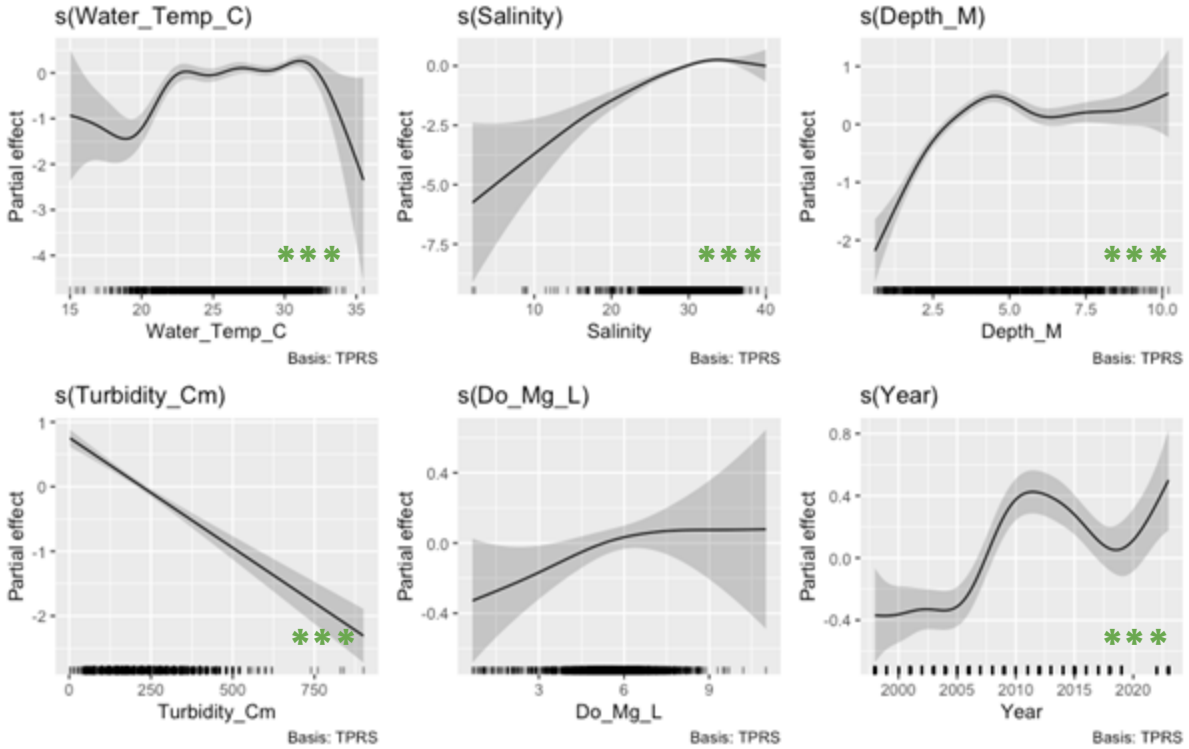

Thank You!

(1.) Do any environmental variables predict CPUE?

Variable	edf	df	F	Sig.
Water Temp (°C)	7.26	8.17	8.8	***
Salinity (ppt)	3.80	4.76	23.8	***
Depth (m)	6.01	7.16	32.1	***
Turbidity (m)	1.01	1.02	130.6	***
Dissolved Oxygen (mg/L)	1.74	2.23	2.7	*n.s.*
Year	6.14	7.24	14.8	***

n=1960

Deviance Explained: 23.7%



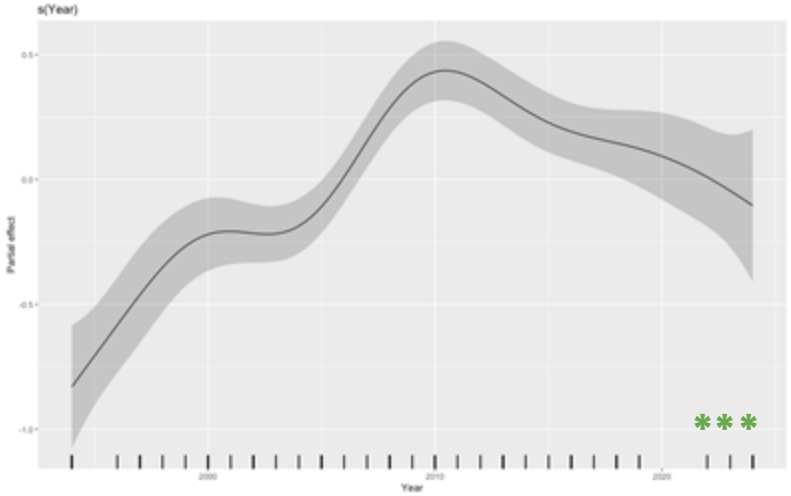
(2) Do predictor–CPUE relationships differ by species?

	Water Temp	Salinity	Depth	Turbidity	DO	Year	Deviance Explained
Atlantic Sharpnose	***	***	***	***	***	***	22.2%
Bonnethead	**	***	***	***			9.37%
Blacktip	***	**	***	***	**		22%
Scalloped Hammerhead	***	***	***	***		***	34.7%
Finetooth		*	***	***	**	***	38%

(3) Does CPUE significantly change over time?

Year-Only Model

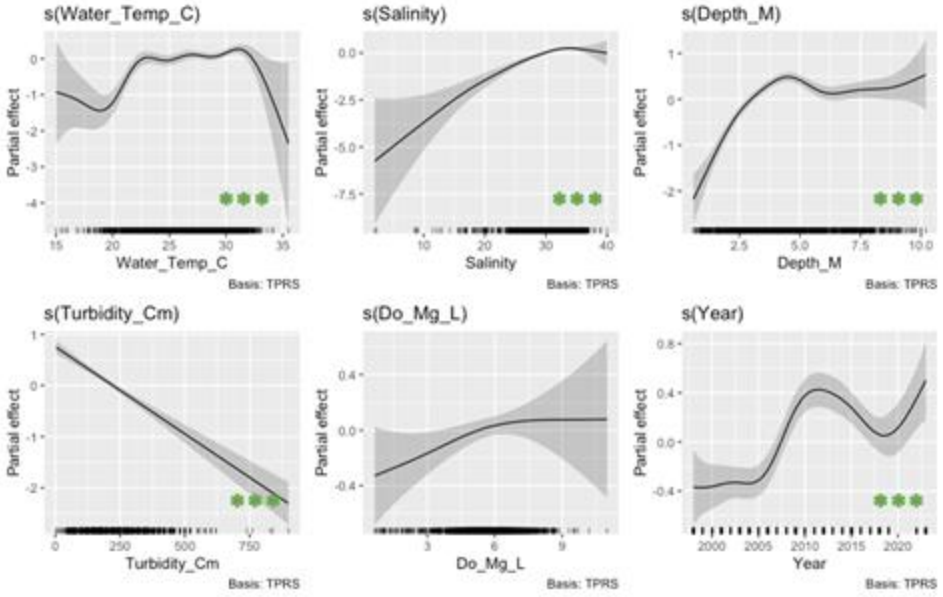
Variable	edf	df	F	Sig.
Year	6.204	7.30	18.26	***



n=2533

Deviance Explained: 4.36%

Full Model



n=1960

(4) Does CPUE differ by area—overall and over time?

Area	Mean diff by Area	edf	df	F	Sig.
APL/IP	*Intercept*	8.383	10.08	4.10	***
CIS	*n.s*	8.939	10.71	26.54	***
SAB	***	6.366	7.72	5.73	***
SJB	***	5.756	7.05	13.11	***

n=2533

Deviance Explained: 33.6%