Comparing machine learning to ratio-based estimates of protected species bycatch

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Objective

Evaluate the use of machine learning techniques for estimation of bycatch

Photo: Michael Patrick O'Neill/SWOT

Study system: shallow-set longline

- Hawaii shallow-set longline fishery has 100% observer coverage
- This allows us to estimate bycatch and compare estimates to true take

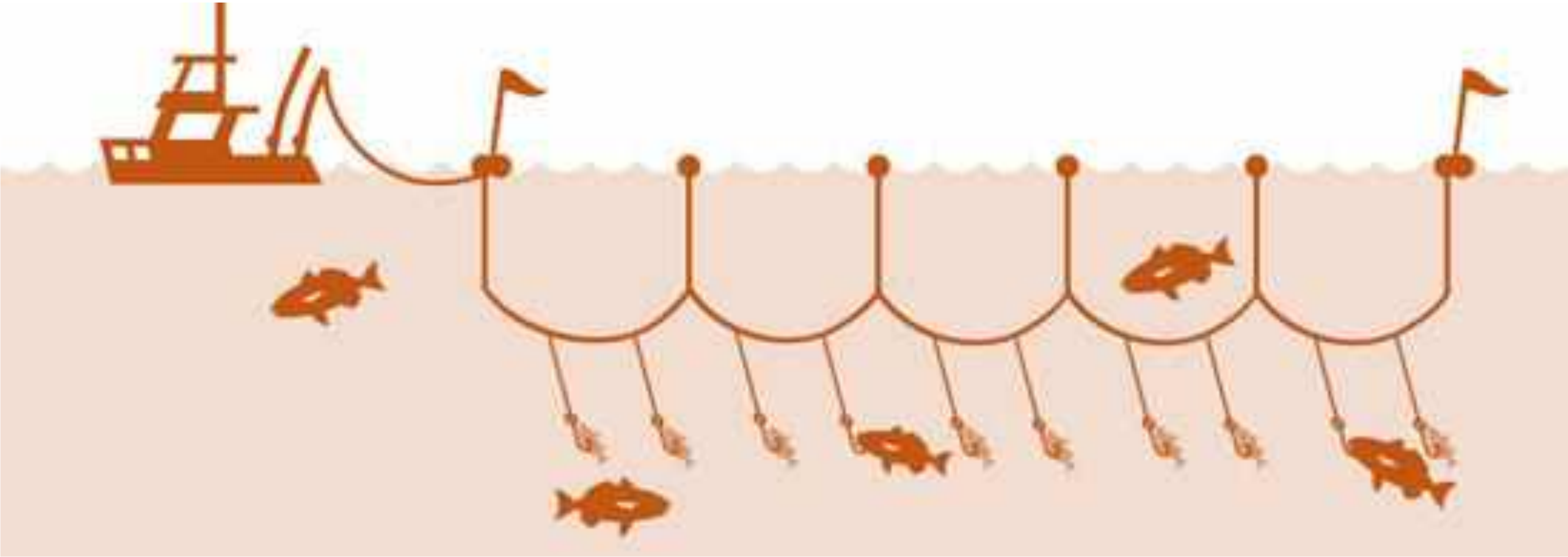


Photo: NOAA

Methods

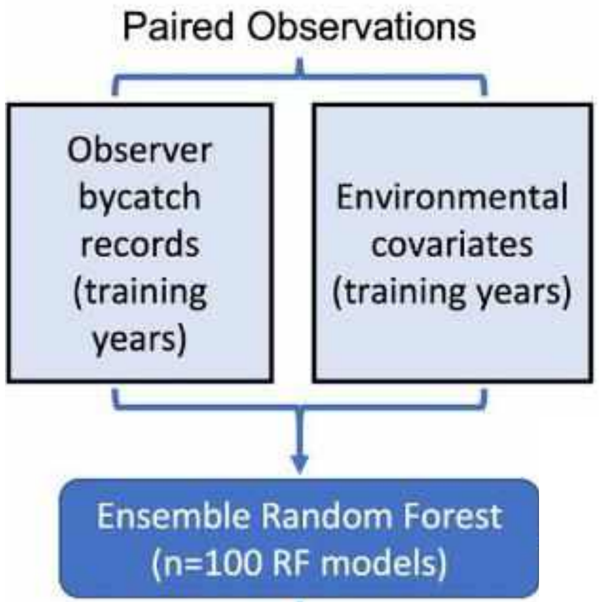
- Developed Ensemble Random Forest method using all 2005-2021 shallow-set longline data (n=18,988 sets)
- Leave one out approach (16 years training, 1 test)
- Focused on 5 protected species:
  - Oceanic whitetips (n=667 sets with interaction)
  - Laysan albatross (n=417)
  - Black-footed albatross (n=354)
  - Loggerheads (n=204)
  - Leatherback (n=105)
- Used a set of 26 environmental covariates derived from GPS coordinates of longline set and retrieve locations

Environmental Covariates						
Bathymetry	SST	Current (meridonal)	Current speed	Chl a front	Wind speed	Dist. to wind front
Lunar phase	SST front	Current flow	Current vorticity	Dist. to chl a front	Wind vorticity	Log(dist. to wind front)
Dist. to seamount	Dist. to SST front	Current front	Current divergence	Wind (zonal)	Wind divergence	
SLA	Current (zonal)	Log(current front)	Log(chl a)	Wind (meridonal)	Wind direction	

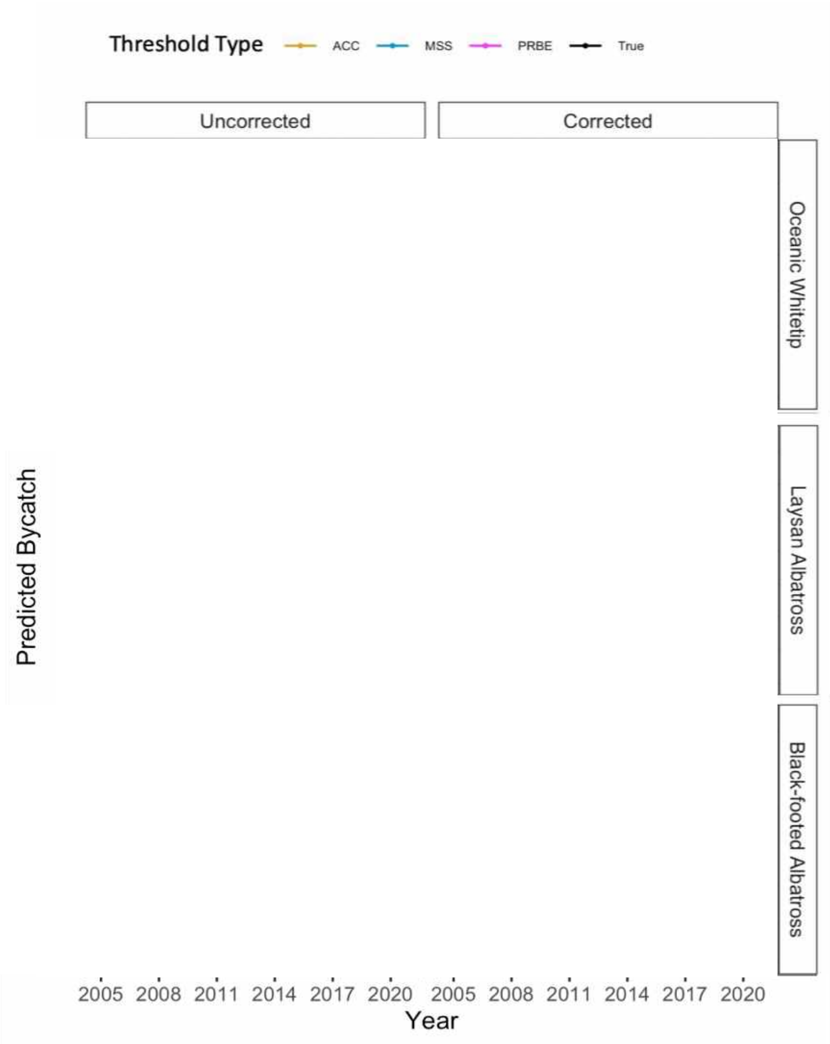


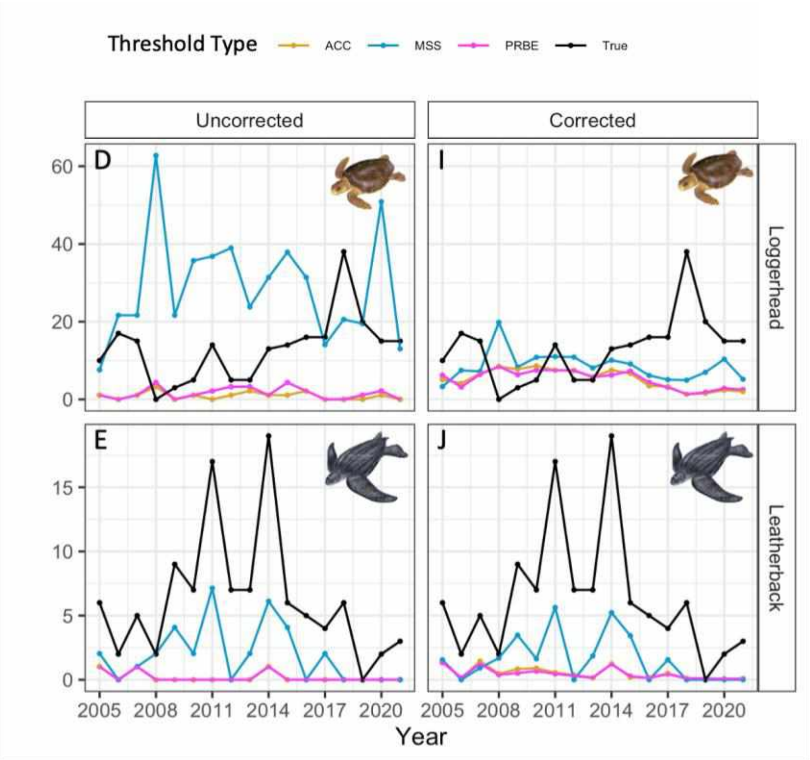


ERF framework



Leave-one-out results

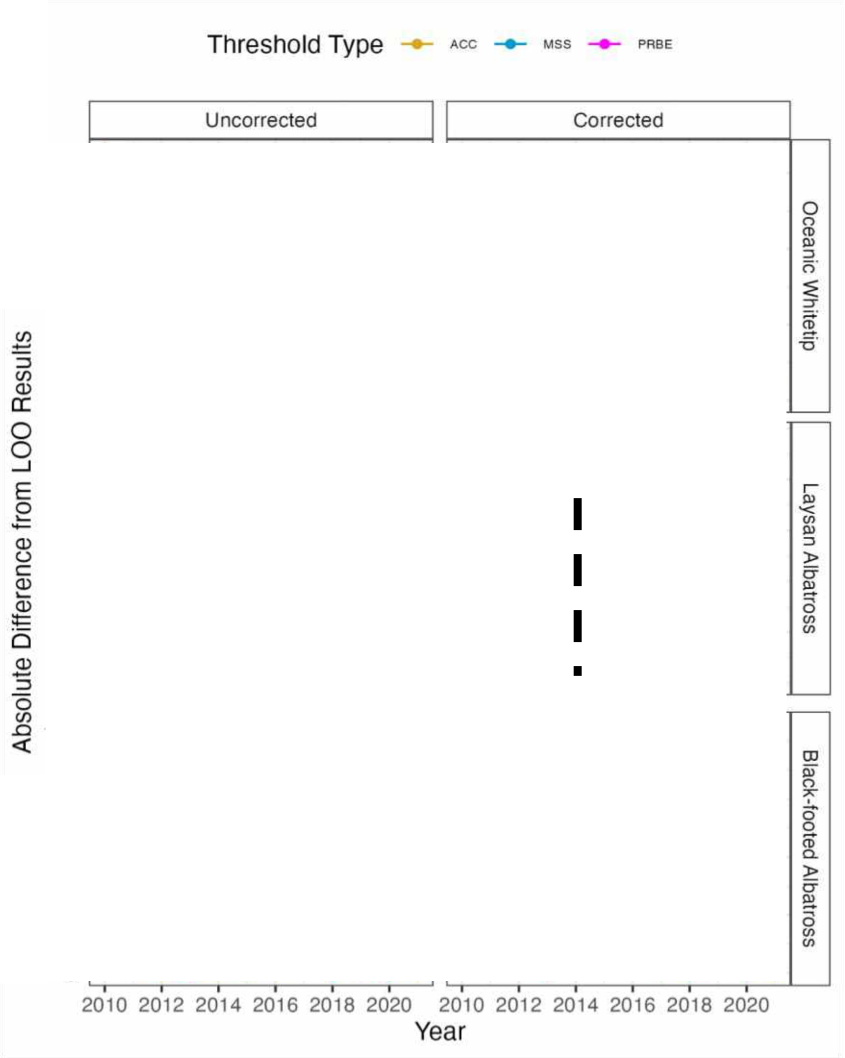


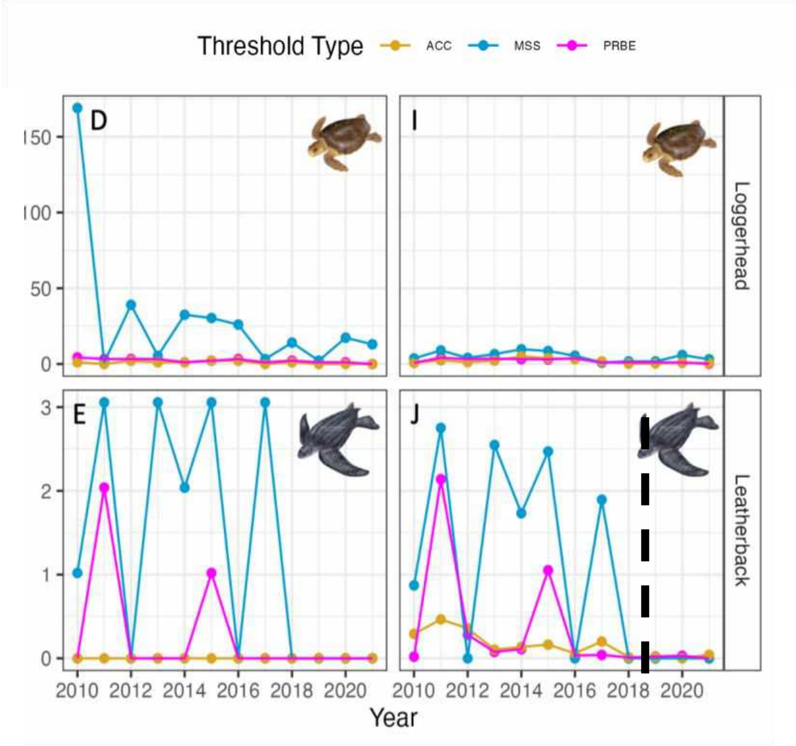


Sequential addition

- Attempting to assess training data needs
- For 2010-2021: compared models that only used previous years and those that used all data
  - Examples:
  - For 2010, used 2005-2009
  - For 2017, used 2005-2016

Sequential addition results



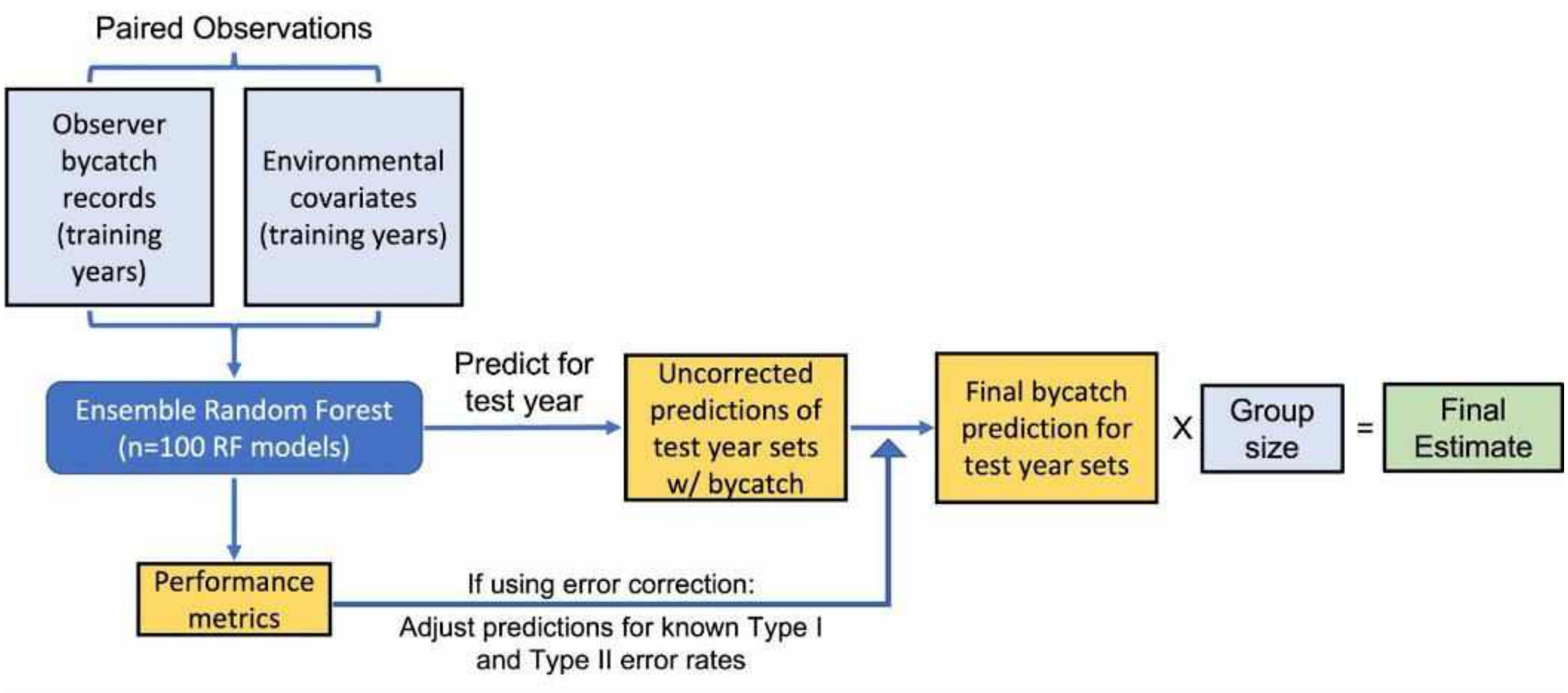


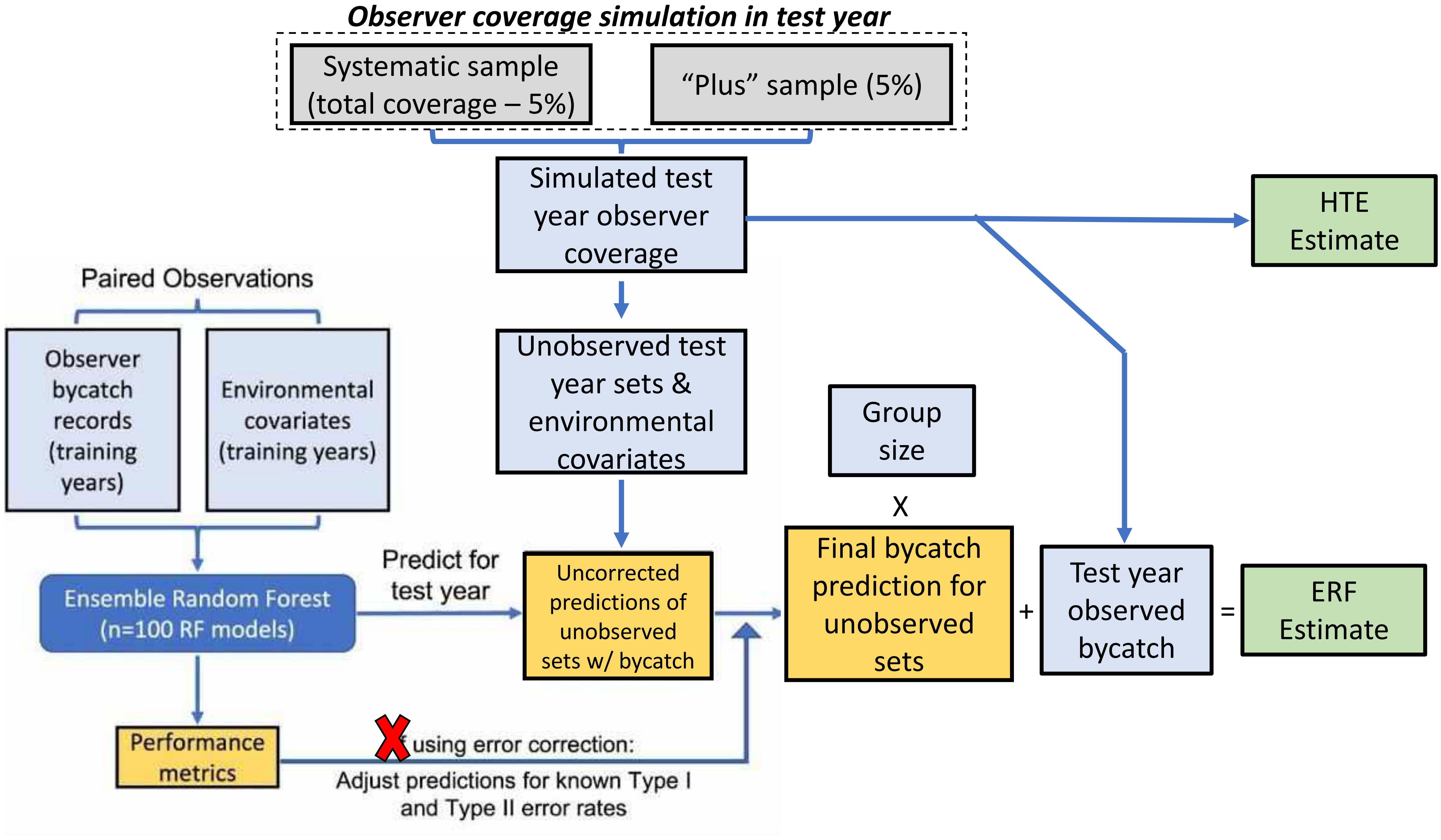
Takeaways

- Method works best for species above 2% interaction rates
  - Whitetips, Laysan albatross, Black-footed albatross (sort of)
- Error-corrected results generally better, especially over the long term
- Training data needs vary, but approximately 7-12 years for most species
  - 7,000 - 12,000 sets

Comparing to ratio-based estimators

Can ERF method help reduce observer coverage needs?





Observer coverage simulation in test year
Systematic sample (total coverage – 5%)
"Plus" sample (5%)
Simulated test year observer coverage
HTE Estimate
Paired Observations
Observer bycatch records (training years)
Environmental covariates (training years)
Unobserved test year sets & environmental covariates
Group size
X
Ensemble Random Forest (n=100 RF models)
Predict for test year
Uncorrected predictions of unobserved sets w/ bycatch
Final bycatch prediction for unobserved sets
+
Test year observed bycatch
=
ERF Estimate
Performance metrics
using error correction:
Adjust predictions for known Type I and Type II error rates

Methods

- For each test year (2005-2021), we repeated this procedure for each species at many coverage levels
- Leave-one-out only
- Observer coverage in training years: always 100%
- Observer coverage in test year: 5% to 95%
  - 25 replicates at each coverage level
- Compared by 4 metrics

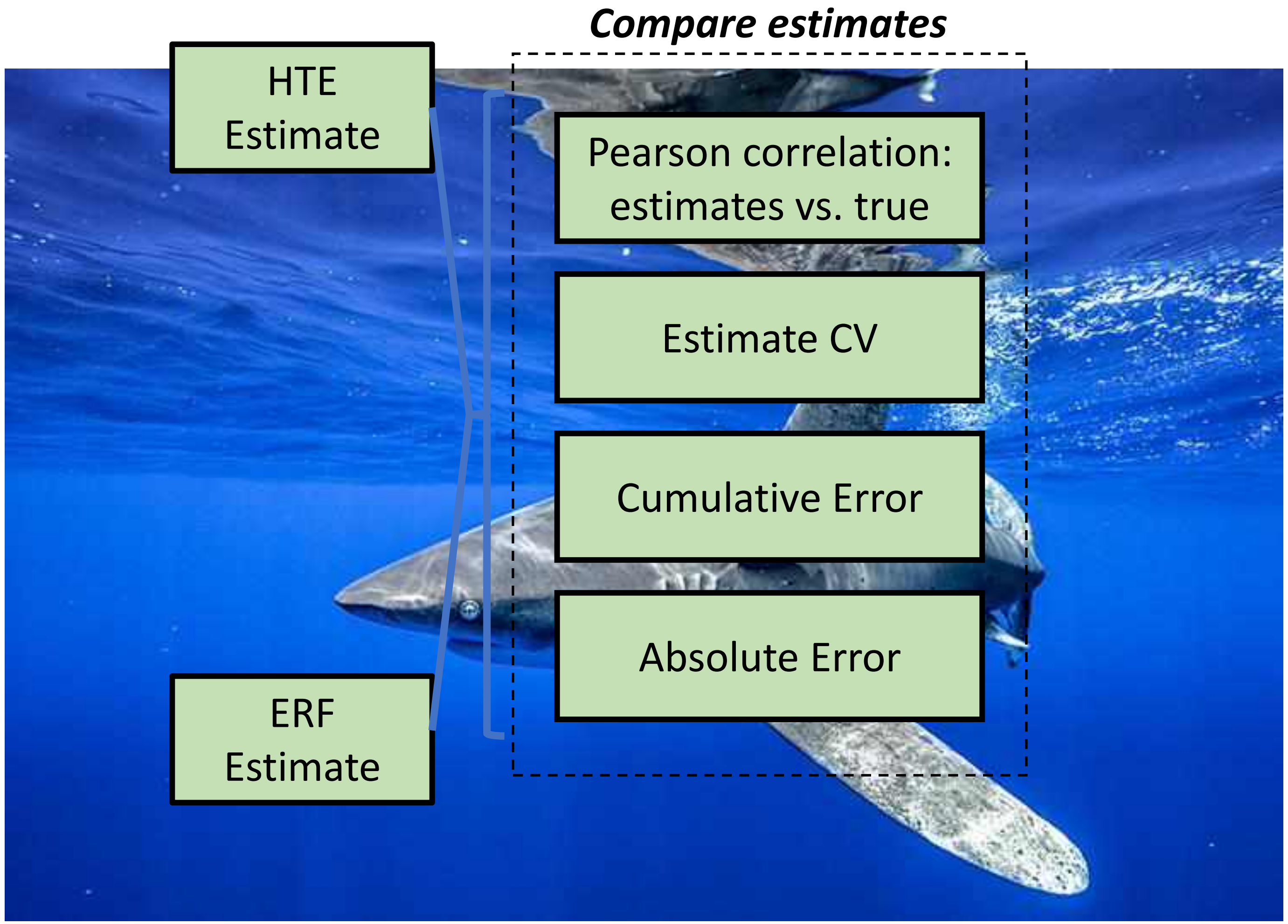
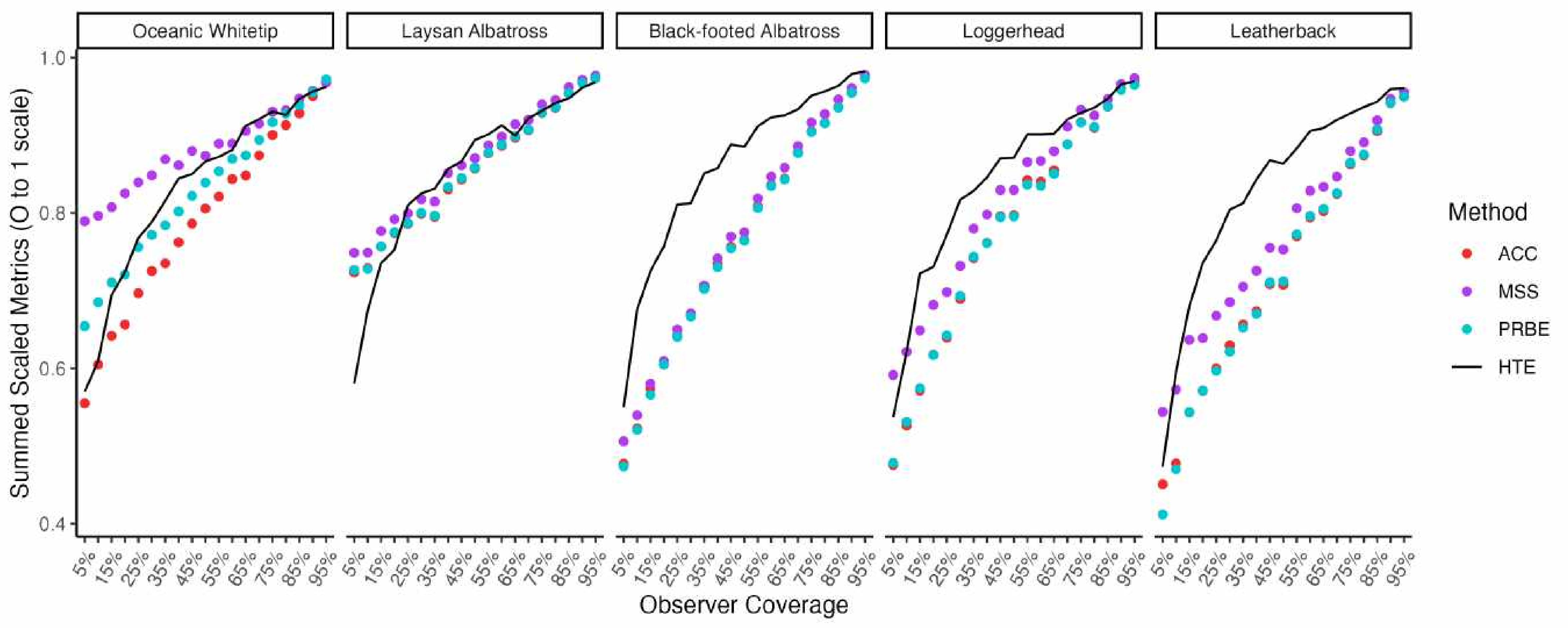


Photo: NOAA Fisheries


Mean Pearson Correlation: Estimate vs. Actual
5%
15%
25%
35%
45%
55%
65%
75%
85%
95%
Observer Coverage
Observer Coverage
Observer Coverage
Observer Coverage
Method
ACC
MSS
PRBE
HTE

What happens if you combine all of these metrics?



Summary

- ERF framework can produce biased estimates while ratio-based estimator is unbiased
- However, variability of bycatch estimates is substantially reduced at low coverage levels
- Combining all metrics, ERF method preferable for oceanic whitetips and Laysan albatross
- How much bias is acceptable if observer costs and estimate variation can be reduced?

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Thank you for listening!