

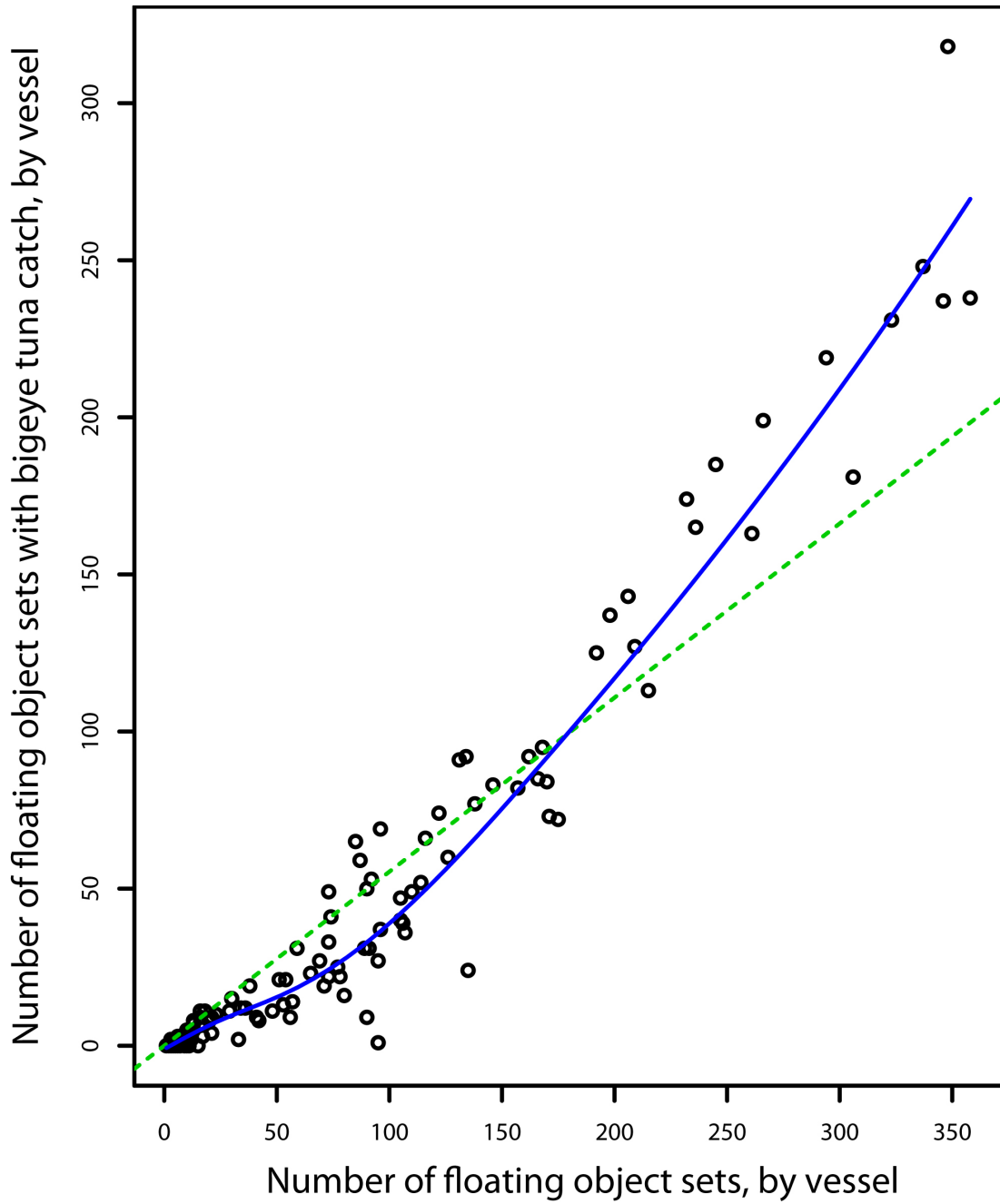
# An analysis of gear effects on the presence of bigeye tuna catches in floating object sets

(SAR-8-09c)

# Objectives of analysis

To determine:

- how well we can predict the presence of bigeye tuna catch from data on environmental conditions, fishing operations and gear characteristics;
- the importance and structure of gear effects;
- if there exist additional ‘vessel effects.’



# Analytical approach

- How well can we predict the presence of bigeye catch from data on environmental conditions, fishing operations and gear characteristics?
  - build classification algorithm on subset of data
  - compute misclassification error
- What is the importance and structure of gear effects?
  - compute the utility of each variable for predicting the occurrence of bigeye catch
  - estimate the relationship between the probability of catching bigeye tuna and gear characteristics, accounting for the average effects of other predictors

# Analytical approach

- Do there exist additional ‘vessel effects’?
  - apply classification algorithm to test data and identify sets where bigeye was caught, but none was predicted
  - group sets catching bigeye by vessel
  - compute the probability for each vessel of obtaining  $r$  or more misclassified sets out of  $n$  sets catching bigeye tuna (based on binomial distribution)

# Gear/operational predictors

Vessel capacity (median: 1,089mt; range: 397-2,833mt)

**Hanging depth of purse-seine net** (median: 120f; range: 72-180f)  
(‘net depth’)

**Purse-seine mesh size** (median: 4.25in; range: 3.5-12.0in)

**Presence of dolphin safety panel** (~55% of sets)

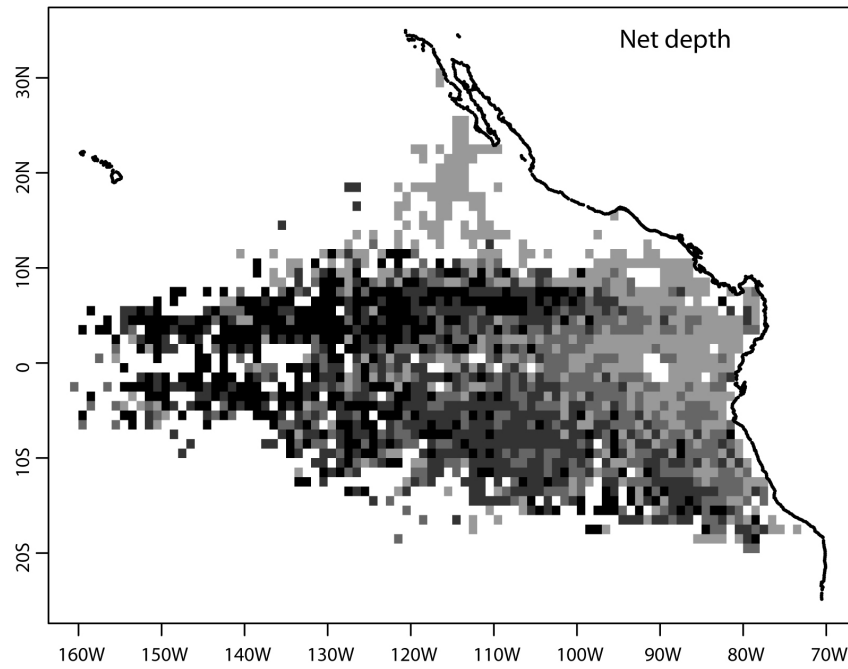
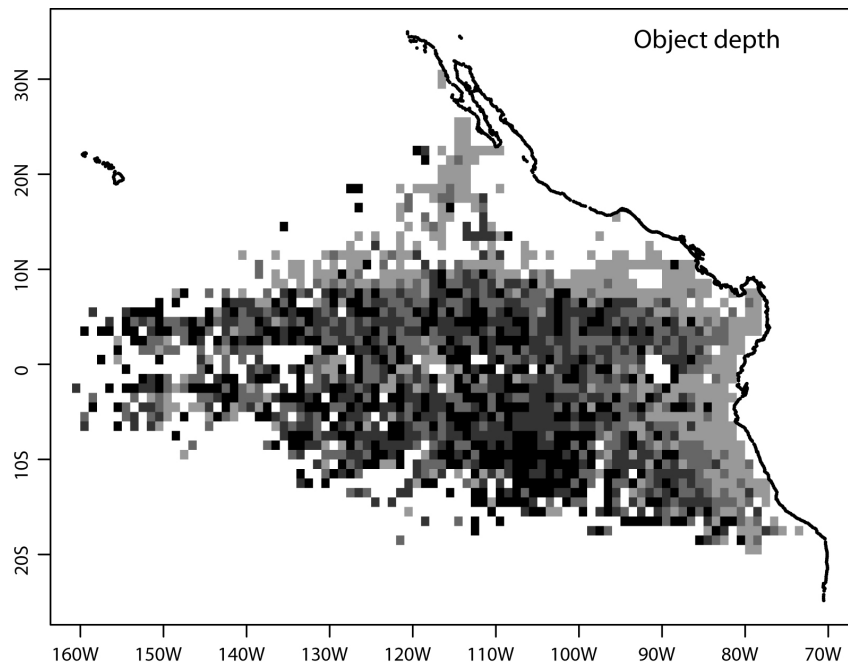
**Maximum object depth below surface** (median: 18.1m; range: 0.01-130m)  
(‘object depth’)

Percent object covered with fouling organisms (median: 40%; range: 0-100%)

Start time of the set (median: ~06:40; range: 04:45 –19:00)

# Environmental/other predictors

Sea surface temperature (SST)
Probability of SST fronts
Mixed layer depth (MLD)
Bathymetry
Presence strong currents
Sea surface height anomaly (SSH)
Slope of SSH
Chlorophyll-a density
Location (latitude, longitude)
Month, Year
Proxy for the size of non-tuna community at the object
Proxy for local object density





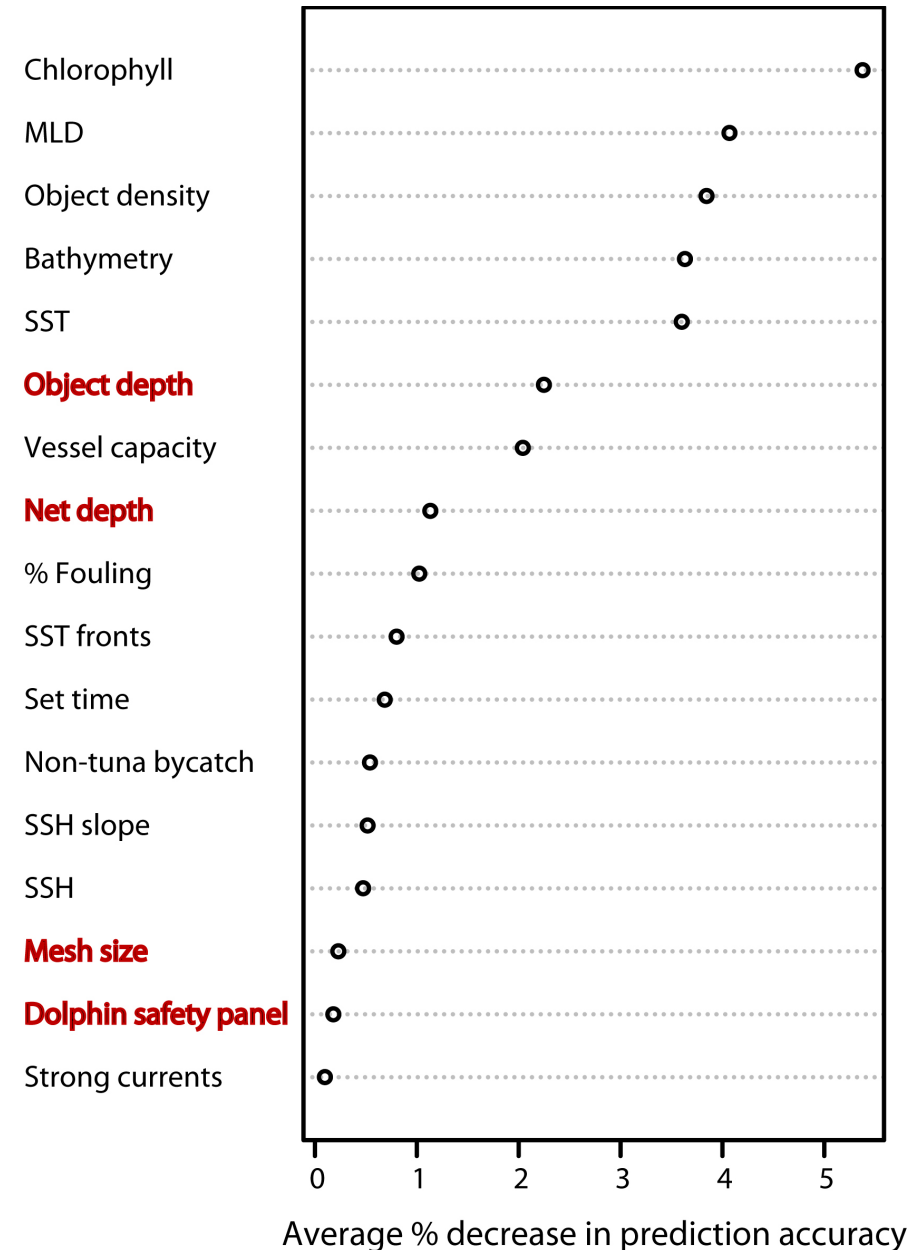
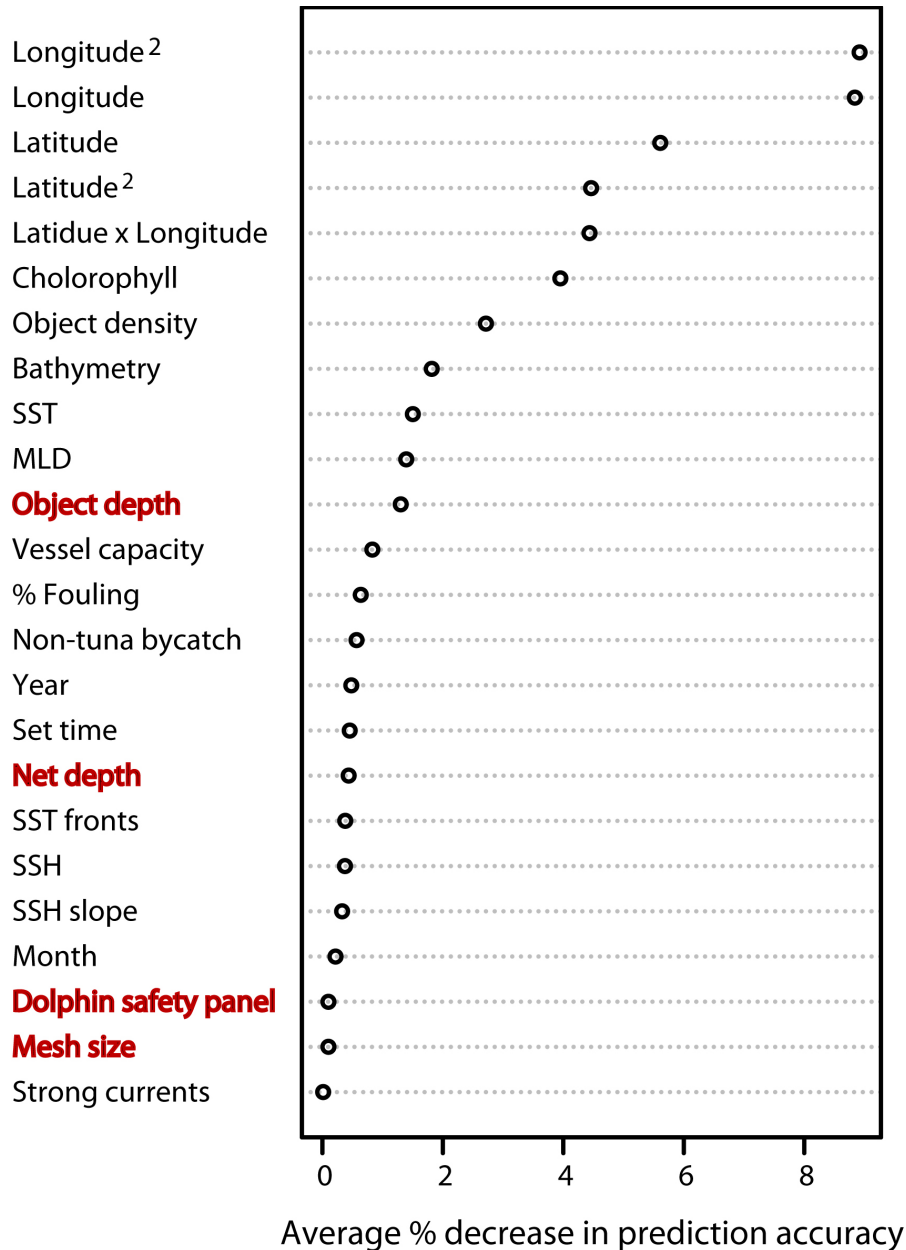
# Data

- 10,425 floating objects sets (IATTC observer data), 2001-2005
  - Limited data to first sets with some catch of yellowfin, skipjack or bigeye.
  - Split data into a training set (5,212 sets) and a test set (5,213 sets).
- 21 predictors
- Response variable: presence/absence of any amount bigeye tuna catch

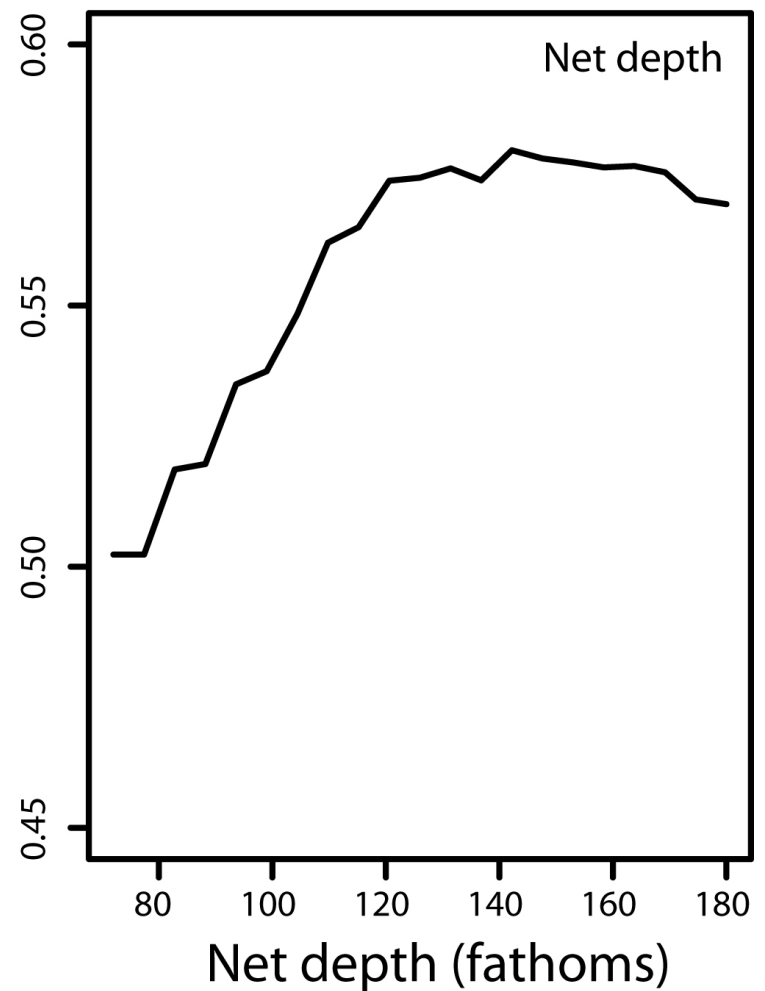
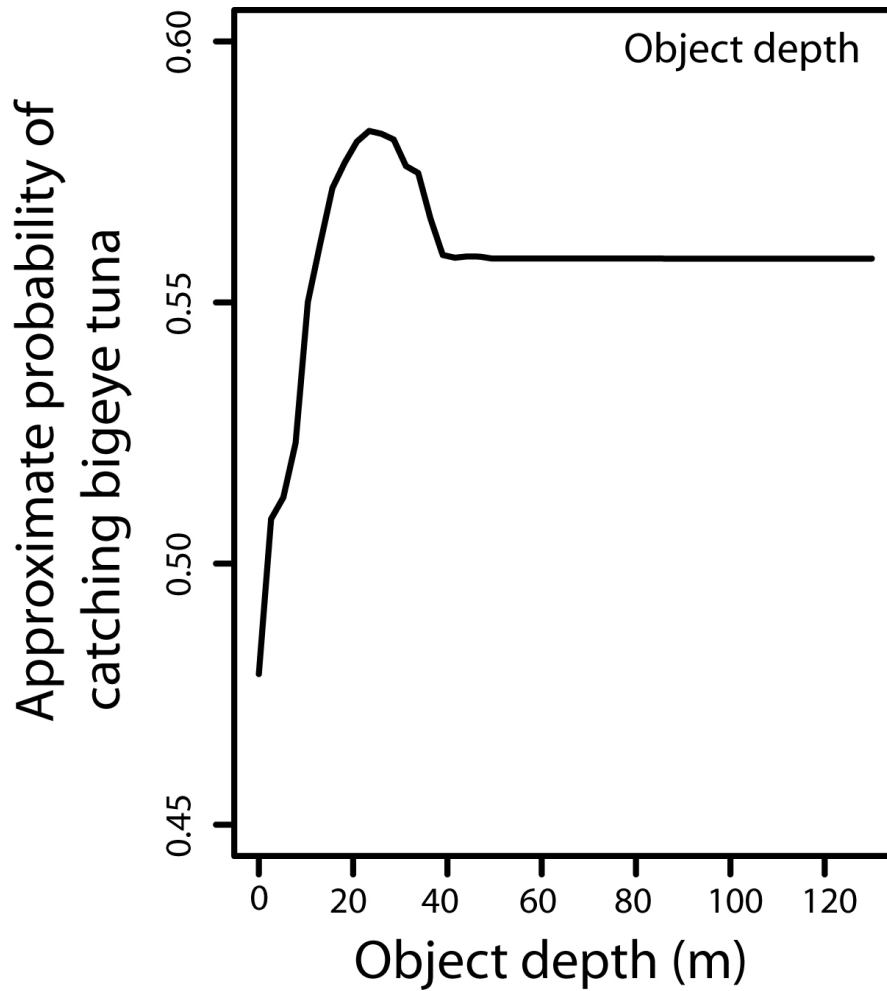
# Misclassification errors

	Observed class	Predicted class		Misclassification error
		0 (no bigeye)	1 (bigeye)	
(a)	0 (no bigeye)	1952	433	0.182
	1 (bigeye)	430	2397	0.152
(b)	0 (no bigeye)	1745	640	0.268
	1 (bigeye)	213	2614	0.075

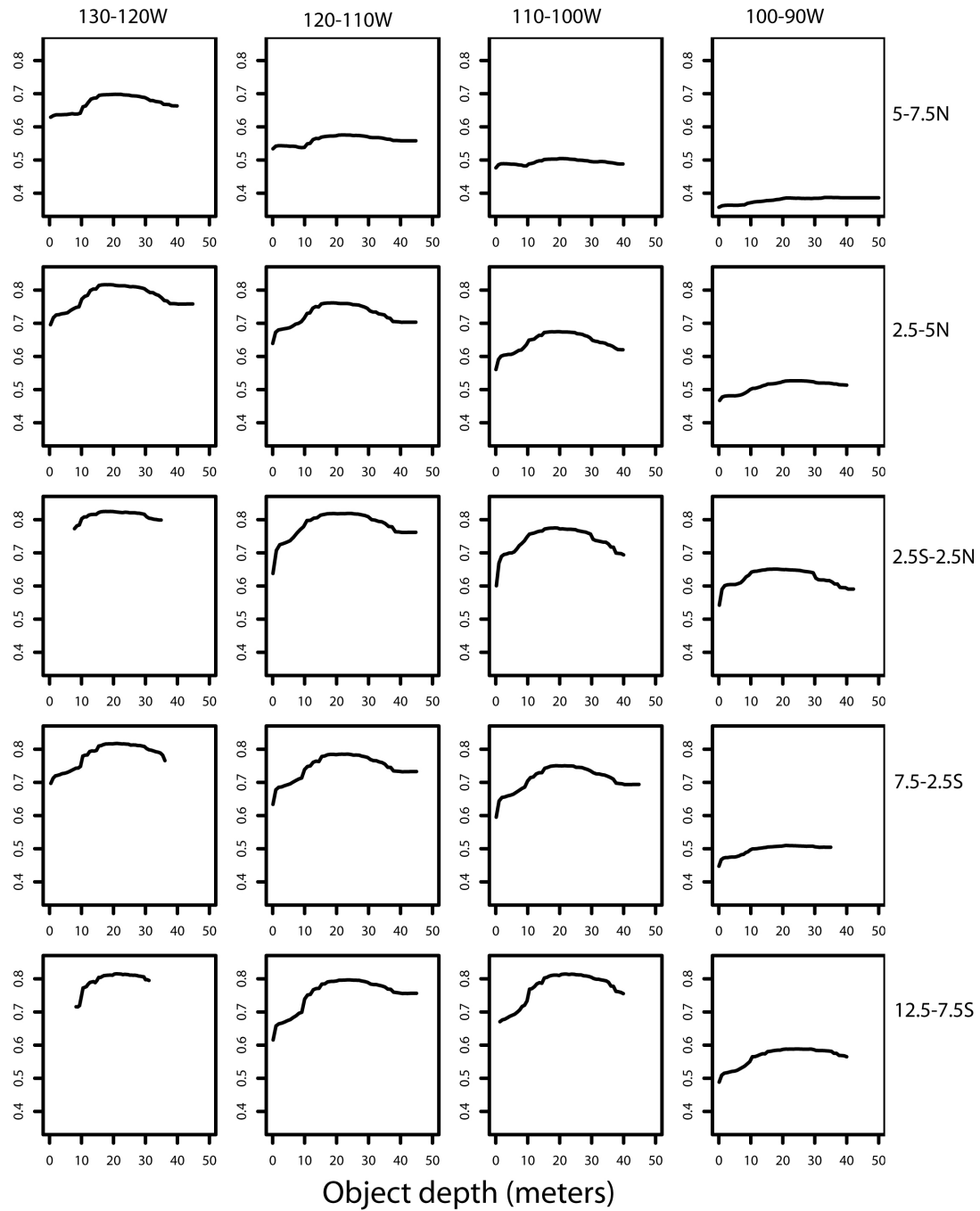
# Predictor importance for presence of bigeye



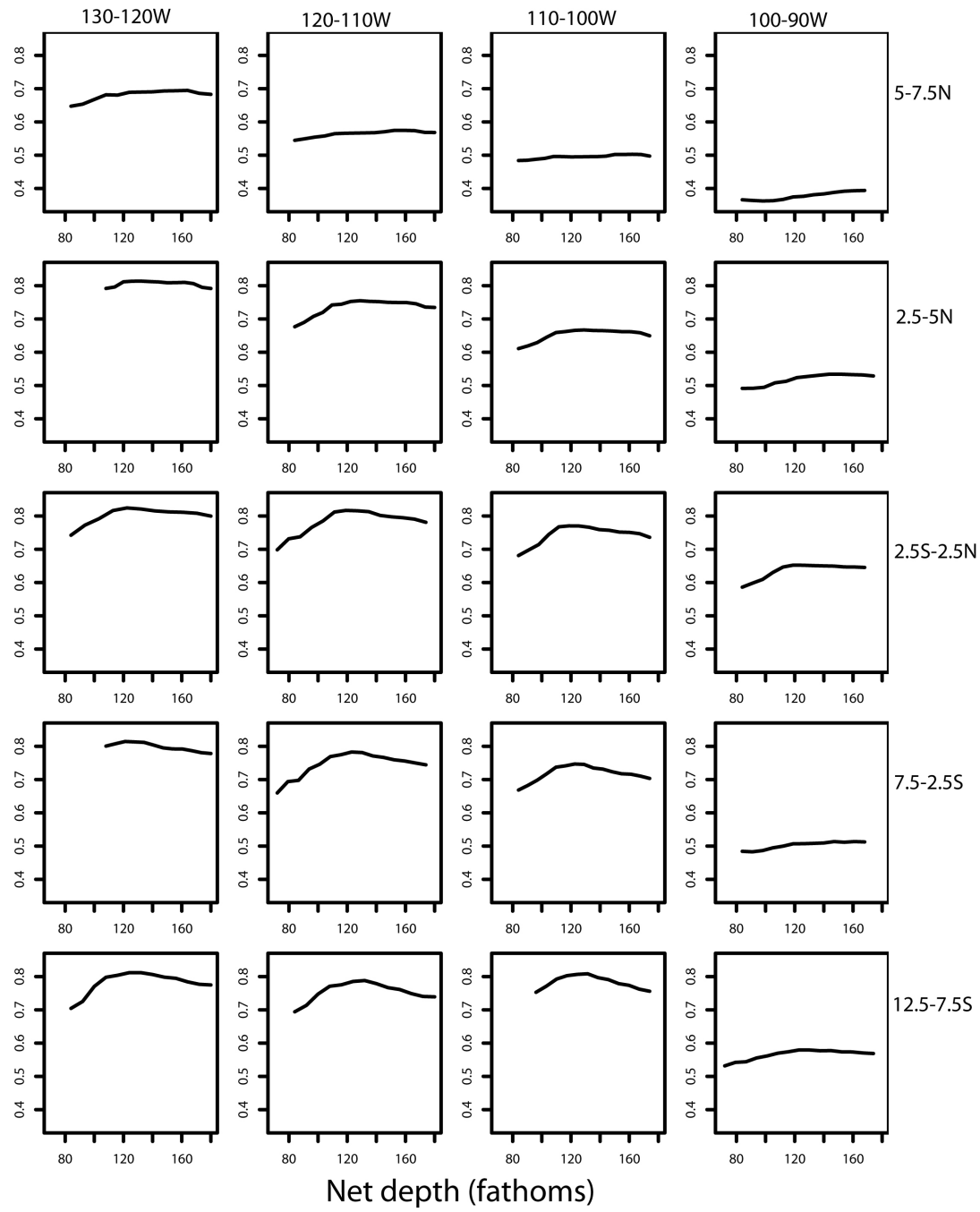
# Probability of bigeye catch versus gear



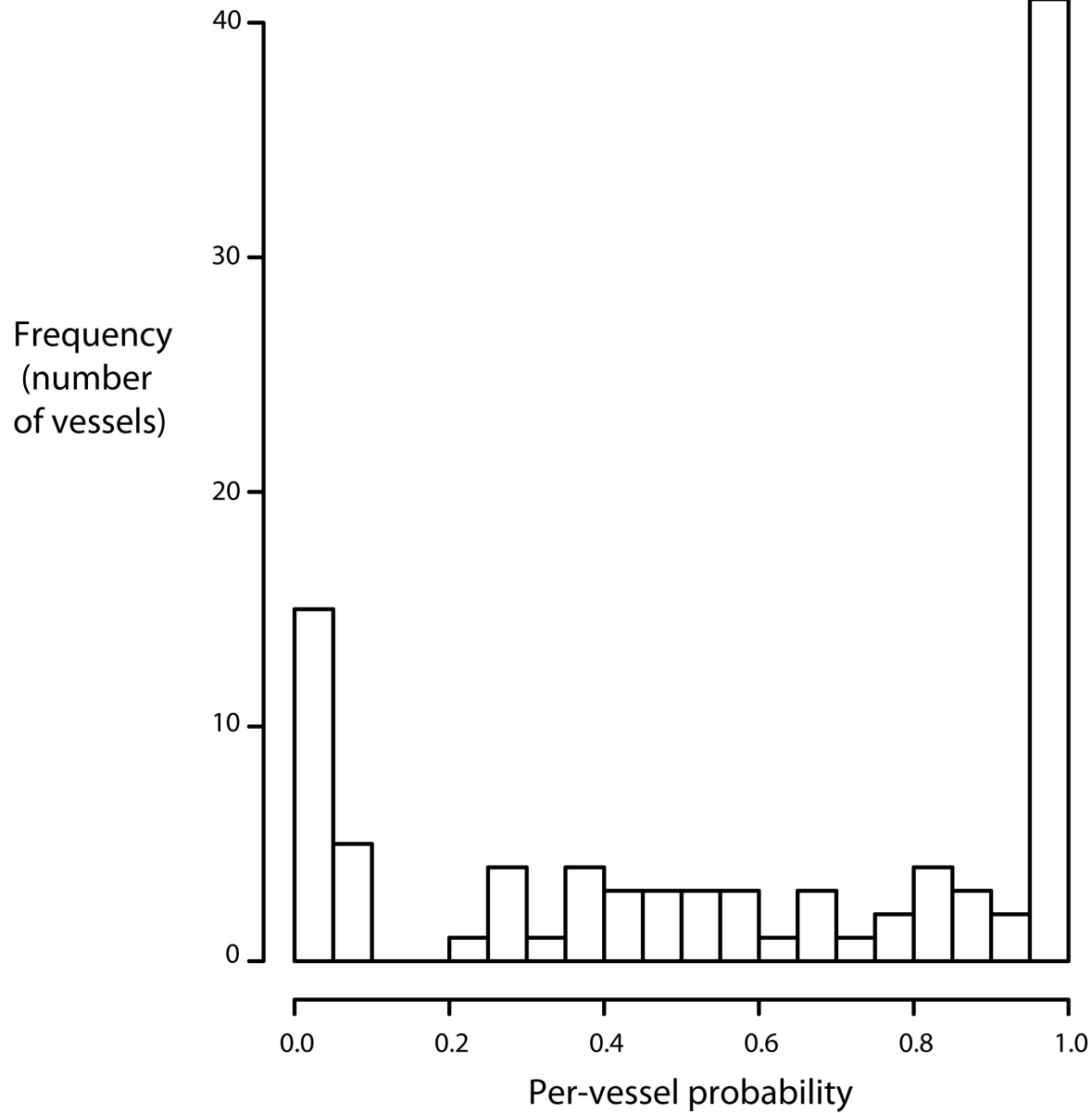
Approximate probability of catching bigeye tuna



Approximate probability of catching bigeye tuna



# Per-vessel probabilities



# Summary

- The occurrence of bigeye tuna catch in floating object sets is consistent with some level of fishermen control:
  - 46% of floating object sets and 29% of vessels making floating object sets caught no bigeye tuna;
  - the presence of bigeye tuna was reasonably predicted from set location, environmental conditions, and gear/operational characteristics;
  - some important features of the classification algorithm:
    - set location was the most important predictor
    - object depth effects varied spatially
  - failure to predict the presence of bigeye tuna was concentrated within certain vessels, possibly indicating additional ‘vessel effects.’



# Implications

- Fishermen have options for avoiding catching bigeye tuna, including:
  - in certain areas, changing the in-water depth of the floating object and fishing depth of the purse-seine net;
  - changing their fishing location.