

Predictions of the Presence of Coastal Pelagic Fishes off Georgia, USA, from Local Oceanographic and Biological Conditions

Predicciones sobre la Presencia de Peces Pelágicos Costeros en Georgia, USA, Basadas sobre Condiciones Oceanográficas y Biológicas

Prédictions de la Présence de Poissons Pélagiques Côtiers au Large de la Géorgie, aux États-Unis, à partir des Conditions Océanographiques et Biologiques Locales

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ABSTRACT

Understanding how specific environmental variables affect the presence of coastal pelagic fishes can improve the ecological understanding of and ability to sample these species. We provide a description of environmental conditions that were associated with the presence of Blue Runner (*Caranx crysos*), reef sharks (*Carcharinus* sp.), scads (*Decapterus* sp.), Little Tunny (*Euthynnus alletteratus*), Ocean Sunfish (*Mola mola*), Greater Amberjack (*Seriola dumerili*), Almaco Jack (*S. rivoliana*), and Great Barracuda (*Sphyraena barracuda*) off the Southeastern USA coast. We used generalized linear models and a suite of environmental variables (forage fish presence, salinity, temperature, time of day) to predict the presence of pelagic species at a human-made reef at a mid-shelf location, over eight years, as characterized by hourly ultra-short videos. We used Akaike's information criterion to evaluate candidate model fit for each species. *C. crysos*, *S. dumerili*, *S. rivoliana*, and *E. alletteratus* were more likely to be present when forage fish (*Decapterus* sp.) were present. The probability of presence of all species increased with increasing temperatures, except *E. alletteratus* and *M. mola*, for which the probability of presence decreased 1.2 - 1.4 times with each 1 °C temperature increase. Probability of presence was positively associated with salinity for *Decapterus* sp. and *S. rivoliana* and negatively associated with salinity for *C. crysos* and *E. alletteratus*. Water temperature followed a predictable seasonal pattern, while salinity, which influenced some species' presence, varied greatly among years. Although the variance in model results was large, our study provides a tool for monitoring the presence of migratory species and an understanding of variables that influence their presence.

KEYWORDS: Coastal pelagic fishes, predictive modeling, human-made patch reefs, fisheries oceanography, generalized linear models

INTRODUCTION

Understanding how specific environmental variables affect the presence of coastal pelagic fishes can improve the ecological understanding of and ability to sample these species. Ideally, the presence of coastal pelagic migratory species (CPS) could be forecast based upon hydrographic and biological information prior to their arrival at any coastal location. Unfortunately, very little information exists about the presence of CPS, with the exception of recreational species that recently have been tracked by satellite "pop-up" data recorders. Horizontal and vertical movement responses to temperature and salinity (i.e. behavioral/habitat preferences) exist for some large species, such as billfish (Braun et al. 2015, Goodyear 2016, Loefer et al. 2007), dolphin (Farrell et al. 2014, Kleisner et al. 2010), a few scombrid species (Kleisner et al. 2010), and pelagic sharks (Hammerschlag et al. 2011, Loefer et al. 2005, Musyl et al. 2011). Yet, information on some species of less recreational importance or less available to tagging projects remains elusive. Historical limitations to port sampling of landings, especially with catches reflecting seasonal occurrence at some unknown distance from port, has made oceanographic correlations impossible to determine. Presently, the large number of acoustic arrays being deployed and monitored in the oceans should greatly enhance our understanding of marine fish movements (Block et al. 2016).

This study represents an initial description of some of the environmental conditions that were associated with the ephemeral presence of several coastal and migratory fishes common along the Southeastern coast of the United States. Our objectives were to:

- i) Describe a relationship between the presence of several CPS and some measurable hydrographic factors and a biological factor,
- ii) Describe the range in the temperatures and salinities of bottom waters through annual cycles (2000 - 2008), and
- iii) Demonstrate the usefulness of long-term series of brief video data sets in offshore fisheries research, especially when associated with simultaneous oceanographic measurements/data sets.

These fisheries oceanographic results from a specific position (Eulerian approach) may contribute to more detailed future studies which could lead to improved predictions of species presence based upon environmental parameters.

METHODS

We constructed a circular human-made reef (HMR) of approximately 177 m², made up of 13 concrete pyramids (Fish Haven/Artificial Reefs, Inc.), at a mid-shelf location 72 km off Georgia, USA in May, 1999. The site location was on sandy bottom, at a depth of approximately 25 m, and was not disclosed to the public. Six cameras recorded 10 s black and white videos hourly during daylight from a position on the central unit, which commanded about 360° view, including six reef clusters. See Barans et al. (2005) for detailed camera, visual data, and transmission specifications and Seim (2003) for the oceanographic program description.

We analyzed video data files collected from 1999 to 2008 for the presence of CPS. These files were previously analyzed for resident species (Barans et al. 2005, 2014). Similar to the resident fish study, we only included video files that had “good” or “fair” visibility and <50% biogenic fouling in the analysis (Table 1). Additionally, only species identifications with a reviewer confidence of “positive” or “confident” were analyzed. Replicate video data files for cameras 1 - 6 were pooled by each of four time of day increments for each day (< 10:00, 10:00 - 13:00, 13:00 - 16:00, > 16:00 local standard time [LST]; often representing > 18 video datasets). Species were considered present if observed in any of the videos. By pooling data, multiple sightings of the same individual were reduced to one value of presence or absence, maximizing the probability of species detection during that part of the day and providing the most conservative indication of occurrence. This “pooling” of data from ≤ 6 cameras resulted in the differences in number of observations reported in our study (Table 1) and Table 1 from Barans et al. (2014). Data were compartmentalized into seasons to capture the unique differences in multiple factors among seasons (January - March, April - June, Jul - September, October - December). Seasons with < 25 observation periods, either because of insufficient numbers of video data files and/or incomplete environmental data, were excluded from analyses. Envi-

Table 1. Total number of observations (camera data pooled) in each year and season used to determine predictors of presence of pelagic fish species at a human-made patch reef off Georgia, USA, 1999 - 2008. Any season with < 25 observations (underlined) was omitted from analysis.

Year	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec	Total
1999	0	0	<u>21</u>	<u>17</u>	38
2000	78	243	59	34	414
2001	0	0	0	0	0
2002	0	0	<u>9</u>	234	243
2003	0	0	0	0	0
2004	35	37	61	233	366
2005	138	199	100	0	437
2006	0	0	<u>15</u>	85	100
2007	139	256	368	261	1,024
2008	270	198	298	0	766
Total	660	933	931	864	3,388

ronmental data for each observation period consisted of mean bottom water temperature (°C) and salinity (Practical Salinity Units, PSU), which were computed from six-minute observations recorded < 1 km away by data loggers (Seim 2003).

Temporal and environmental factors that might influence the probability of presence of eight groups of CPS (*Caranx crysos*, *Carcharinus* sp., *Decapterus* sp., *Euthynnus alletteratus*, *Mola mola*, *Seriola dumerili*, *S. rivoli-ana*, and *Sphyrnaena barracuda*) were analyzed. Where possible, fish presence/absence was analyzed at the species level. However, carcharinid sharks were combined to the genus level because of small sample numbers of individual species [*C. brevipinna* (n = 3), *C. limbatus* (n = 14), *C. plumbeus* (n = 36), *C. taurus* (n = 3), and *Carcharinus* sp. (n = 28)]. Additionally, *Decapterus* sp. was only identified to the genus level from video footage (Table 2).

The potential predictors of pelagic fish presence were time of day, mean bottom water temperature (°C), mean bottom water salinity (PSU), and presence of prey fish (i.e., *Decapterus* sp.) at the HMR. All predictor variables were calculated as in Barans et al. (2014). Year was eliminated as a predictor variable because of the unequal number of observations among years and seasons, likely leading to differences in detection probabilities among years (Table 1). There were also concerns about model over-specification because of small sample sizes when year was included as a predictor variable. In addition, temperature was correlated with both season ($r = 0.52$; Figure 1) and Julian Day ($r = 0.51$); therefore, only temperature was used as a predictor.

The presence/absence data for the eight groups of pelagic fishes were analyzed with generalized linear models (GLMs) with a logit link (logistic regression). The candidate set of models for each species included 1–4 predictor variables for probability of presence (P), in all combinations. Akaike’s information criterion with the small sample size adjustment (AIC_c; Akaike 1973, Hurvich and Tsai 1989) was used to evaluate the fit of each of the candidate models. Akaike weights (w_i , range = 0–1) were calculated to assess the relative fit of each of the candidate models, with the best fitting model having the greatest w_i (Burnham and Anderson 2002). The confidence set of models for each pelagic fish group contained all models whose Akaike weight was within 10% of the greatest weight (Thompson and Lee 2000). To account for model selection uncertainty, model-averaged estimates of the model coefficients were calculated from the confidence set of models (Burnham and Anderson 2002). Odds ratios were calculated for all model-averaged estimates of model parameter coefficients to aid in interpretation. All analyses were performed in program R (R Core Team 2015). AIC_c and model-averaged estimates were calculated with the package MuMIn (Bartón 2015).

RESULTS

Mid-shelf water temperatures generally followed predictable seasonal patterns (Figure 1), while salinity values were more variable (Figure 2). Throughout the nine-year study period, mean bottom water temperature during the observation periods had a range of 13.6 - 28.4°C, and

mean bottom water salinity ranged from 32.7 to 36.3 PSU (median = 35.6 PSU).

There was a total of 3,388 observation periods in the nine-year time series, with the fewest observations occurring between January and March. Pelagic fish groups were present in as few as 2% of observation periods (*Carcharinus* sp. and *M. mola*) and as many as 31% of observation periods (*Decapterus* sp.; Table 2). Most groups were observed least between January and March, except for *E. alletteratus* and *M. mola*, which were observed most often during this season (Table 2).

Decapterus sp. was present in 31% of observation periods. The most plausible model for predicting probabili-

ty of presence of *Decapterus* sp. included salinity and temperature (Table 3). This model was 4.2 times more likely than the next best approximating model, the global model (time, salinity, temperature, *Decapterus* sp. presence). These two models (salinity and temperature and the global model) made up the confidence set of models. Based on the model-averaged coefficients, probability of *Decapterus* sp. presence was most influenced by salinity. Probability of presence of *Decapterus* sp. increased 1.99 - 3.14 times with each 1.0 PSU increase in salinity (Table 4). Temperature also positively affected *Decapterus* sp. presence (1.09 - 1.14 times more likely to occur with each 1.0 °C increase in temperature; Figure 3). The maximum

Table 2. Seasonal observations and proportion of total observation periods (4/day) with presence of each group of pelagic fish at a human-made patch reef off the coast of Georgia, USA, 2000–2008. Seasonal maximums underlined.

Species	Jan-Mar	Apr-Jun	Jul-Sep	Oct-Dec	Total	Proportion present
<i>Caranx crysos</i>	1	27	<u>287</u>	27	342	0.10
<i>Carcharinus</i> sp.	7	22	27	<u>28</u>	84	0.02
<i>Decapterus</i> sp.	149	183	<u>428</u>	277	1,037	0.31
<i>Euthynnus alletteratus</i>	<u>55</u>	4	3	24	86	0.03
<i>Mola mola</i>	<u>49</u>	19	0	3	71	0.02
<i>Seriola dumerili</i>	7	34	<u>139</u>	76	256	0.08
<i>Seriola rivoliana</i>	3	17	<u>93</u>	17	130	0.04
<i>Sphyraena barracuda</i>	7	83	163	<u>187</u>	440	0.13

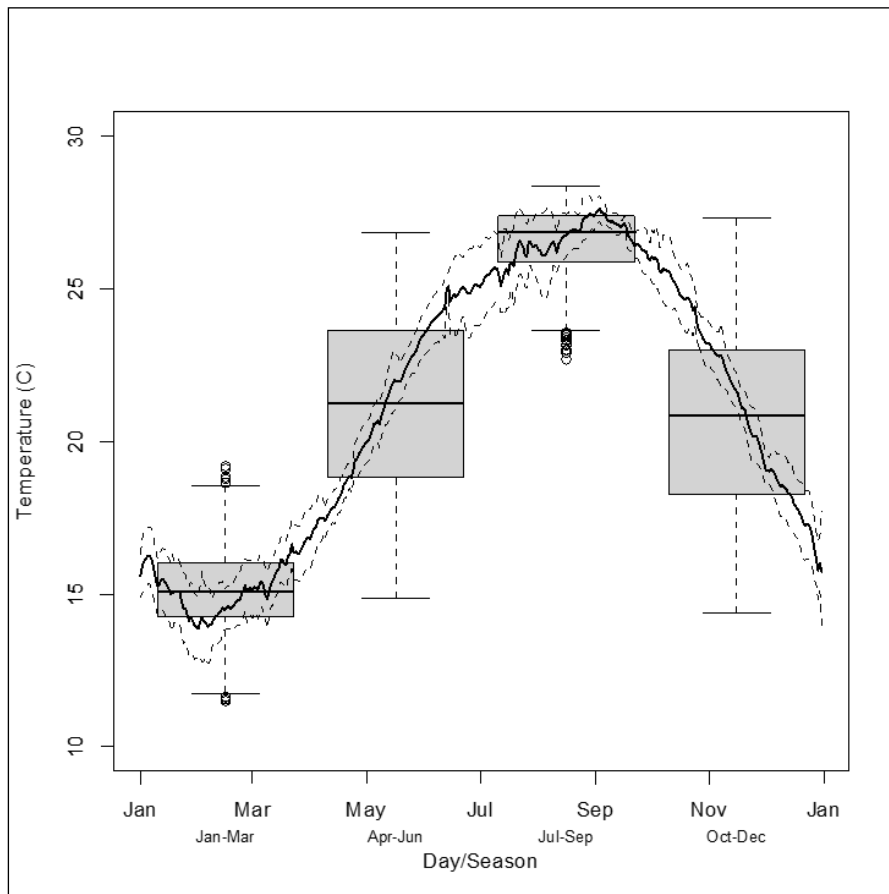


Figure 1. Mean bottom water temperatures by season (boxplots) and date (solid line) at a human-made patch reef off the coast of Georgia, USA, 1999–2008. Dashed lines represent the 95% confidence interval of daily temperatures.

predicted probability of presence of *Decapterus* sp. was $P = 0.56$ (95% CI = 0.40 - 0.71) at the greatest observed salinity (36.3 PSU) and temperature (28.4°C).

S. barracuda was present in 13% of observation periods (Table 2). The model containing temperature as the sole predictor was the most plausible model predicting *S. barracuda* presence ($w_i = 0.28$), though the confidence set included seven models overall (Table 3). This species was 1.17 - 1.26 times more likely to be present with each 1°C increase in temperature (Table 4; Figure 3), with no other informative predictor variables for *S. barracuda* (the coefficients of the other predictor values spanned zero). The greatest predicted probability of presence of *S. barracuda* was $p = 0.31$ (0.14 - 0.56) when estimated at the greatest observed temperature (28.4°C), with no effect of salinity, time of day, or *Decapterus* sp. presence.

The most plausible model predicting presence of *C. crysos*, which was observed 10% of the time (Table 2), included temperature, salinity, and *Decapterus* sp. presence as predictor variables ($w_i = 0.69$; Table 3). This model was 2.4 times more likely than the next most plausible model, the global model. These two models comprised the confidence set of models (Table 3). In the composite model, temperature and *Decapterus* sp. presence were predicted to have a strong positive effect on probability of presence, whereas salinity had a negative effect on probability of

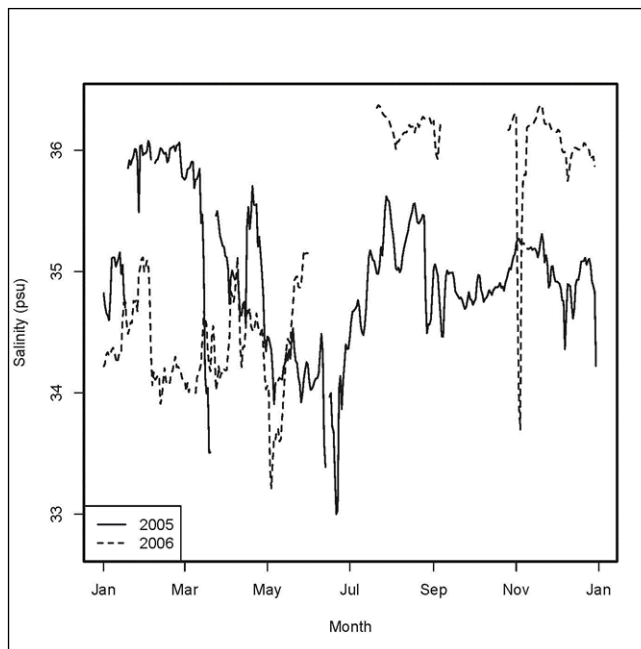


Figure 2. Daily salinity (PSU) of bottom water at a human-made patch reef off Georgia, USA, showing the wide differences between years 2005 and 2006.

Table 3. Log likelihood (LogL), AICc, Δ AICc, and Akaike weights (w_i) of only the confidence set of models describing the probability of presence of each pelagic fish group on a human-made patch reef off the coast of Georgia, USA, 2000–2008. Temp = temperature, Time = time of day.

Candidate model	LogL	AIC _c	Δ AIC _c	w_i
<i>Caranx crysos</i>				
Temp, Salinity, <i>Decapterus</i> presence	-669.16	1346.33	0.00	0.69
Time, Salinity, <i>Decapterus</i> presence, Temp	-667.01	1348.05	1.72	0.29
<i>Carcharinus</i> sp.				
Temp, <i>Decapterus</i> presence	-253.86	513.72	0.00	0.43
Temp	-255.75	515.51	1.79	0.18
Temp, Salinity, <i>Decapterus</i> presence	-253.82	515.66	1.94	0.16
Time, Temp	-253.70	517.42	3.69	0.07
Salinity, Temp	-255.75	517.51	3.79	0.06
Time, Salinity, <i>Decapterus</i> presence, Temp	-251.86	517.76	4.03	0.06
<i>Decapterus</i> sp.				
Salinity, Temp	-1482.72	2971.45	0.00	0.81
Time, Salinity, Temp	-1481.15	2974.33	2.88	0.19
<i>Euthynnus alletteratus</i>				
Time, Salinity, <i>Decapterus</i> presence, Temp	-192.31	398.66	0.00	0.98
<i>Mola mola</i>				
Temp, <i>Decapterus</i> presence	-237.93	481.87	0.00	0.61
Temp, Salinity, <i>Decapterus</i> presence	-237.66	483.33	1.46	0.30
<i>Seriola dumerili</i>				
Temp, Salinity, <i>Decapterus</i> presence	-601.96	1211.93	0.00	0.47
Time, Salinity, <i>Decapterus</i> presence, Temp	-599.28	1212.60	0.67	0.33
Temp, <i>Decapterus</i> presence	-603.81	1213.62	1.69	0.20
<i>Seriola rivoliana</i>				
Temp, Salinity, <i>Decapterus</i> presence	-357.19	722.40	0.00	0.59
Time, Salinity, <i>Decapterus</i> presence, Temp	-354.72	723.48	1.07	0.35
<i>Sphyraena barracuda</i>				
Temp	-1000.98	2005.97	0.00	0.28
Salinity, Temp	-1000.03	2006.07	0.10	0.26
Temp, Salinity, <i>Decapterus</i> presence	-999.48	2006.98	1.01	0.17
Temp, <i>Decapterus</i> presence	-1000.65	2007.30	1.34	0.14
Time, Temp	-999.51	2009.04	3.07	0.06
Time, Salinity, Temp	-998.54	2009.11	3.14	0.06
Time, Salinity, <i>Decapterus</i> presence, Temp	-997.95	2009.93	3.96	0.04

presence. *C. crysos* was predicted to be 1.79 - 2.13 times more likely to occur with every 1°C increase in temperature (Figure 3), and to be 2.02 - 3.53 times more likely to occur when *Decapterus* sp. is present (Table 4). *C. crysos* was predicted to be 1.27 - 2.81 times less likely to occur with each 1 PSU increase in salinity. The maximum predicted probability of presence of *C. crysos* was $p = 0.94$ (0.59 - 1.00) at the greatest observed temperature (28.4°C), lowest observed salinity (32.7 PSU), and when *Decapterus* sp. was present.

S. dumerili was present in 8% of the observation periods (Table 2). The most plausible model of *S. dumerili* presence included temperature, salinity, and *Decapterus* sp. presence ($w_i = 0.47$). This model was 1.4 times more likely than the next most plausible model (global model, $w_i = 0.33$; Table 3). Along with these two models, the confidence set also included the model with temperature and *Decapterus* sp. presence as predictors. Presence of *S. dumerili* was 1.28 - 1.45 times more likely with each 1 °C increase in temperature (Table 4; Figure 3). Additionally, *S. dumerili* was 2.34 - 4.41 times more likely to be present when *Decapterus* sp. was present. The maximum predicted probability of presence of *S. dumerili* was $p = 0.61$ (0.20 - 0.91) at the greatest observed temperature (28.4°C), lowest observed salinity (32.7 PSU), and with *Decapterus* sp. present.

The confidence set of models predicting presence of *S. rivoliana*, which was present in 4% of the observation periods (Table 2), included the global model and the model of salinity, temperature, and *Decapterus* sp. presence (Table 3). The probability of presence of *S. rivoliana* was predicted to increase with every one-unit increase in temperature (1.59 - 2.14 times more likely; Figure 3) and salinity (1.51 - 6.44 times more likely). *S. rivoliana* was 1.18 - 2.63 times more likely to be present when *Decapterus* sp. was present. The greatest probability of presence of *S. rivoliana* was $p = 0.47$ (0.01 - 0.98) at the maximum observed temperature (28.4°C) and salinity (36.3 PSU), with *Decapterus* sp. present.

E. alletteratus was observed in 3% of the observation periods (Table 2). The global model (time, salinity, temperature, *Decapterus* sp. presence) was the only plausible model predicting *E. alletteratus* presence ($w_i = 0.98$; Table 3). This model was 55.8 times more likely than the model with the next greatest Akaike weight ($w_i = 0.017$). The probability of presence of *E. alletteratus* was predicted to decrease with every one-unit increase in temperature (1.25–1.55 times less likely; Figure 3) and salinity (1.17–3.02 times less likely; Table 4). *E. alletteratus* was predicted to be 3.06 - 12.08 times more likely to be present when *Decapterus* sp. was present. In addition, this species was predicted to be present less often before 10:00 LST. The maximum probability of presence of *E. alletteratus* $p = 0.77$; 0.43–0.93) was at the minimum observed temperature (13.6°C) and salinity (32.7 PSU), with *Decapterus* sp. present, and at 13:00 - 16:00 LST.

Members of *Carcharinus* sp. were present in 2% of the observation periods (Table 2). The most plausible model predicting the presence of *Carcharinus* sp. included temperature and *Decapterus* sp. presence as predictor variables ($w_i = 0.43$; Table 3). This model was 2.4 times more likely

than the next most plausible model (temperature only). The confidence set of models included temperature and *Decapterus* sp. presence; temperature; temperature, salinity, and *Decapterus* sp. presence; time and temperature; salinity and temperature; and the global model. Temperature had a positive effect on *Carcharinus* sp. presence, with probability of presence predicted to be 1.04 - 1.23 times greater with each 1 °C increase in temperature (Table 4; Figure 3). All other predictor variables had a large confidence interval that spanned zero, indicating that these variables carried little predictive power. The maximum predicted probability of presence of *Carcharinus* sp. was $p = 0.05$ (0.01 - 0.34) at the greatest observed temperature (28.4°C), with a slight positive influence of the presence of *Decapterus* sp.

M. mola was present in only 2% of the observation periods (Table 2). The logistic model containing temperature and *Decapterus* sp. presence was the most plausible model for predicting presence of *M. mola* (Table 3). This model was 2.1 times more likely than the next plausible model, which included salinity, temperature, and *Decapterus* sp. presence. These two models comprised the confidence set of models. The coefficient for temperature in the composite model indicated that *M. mola* would be 1.31 - 1.60 times less likely to be present for each 1°C increase in bottom water temperature and was 1.43 - 5.51 times more likely to be present when *Decapterus* sp. was also present (Table 4; Figure 3). The maximum probability of presence of *M. mola* was $p = 0.29$ (0.10 - 0.61) at the minimum observed temperature (13.6°C), maximum observed salinity (36.3 PSU), and when *Decapterus* sp. was present.

The presence of prey fish (*Decapterus* sp.) increased the probability of presence of each of the CPS evaluated, except for *S. barracuda*. The greatest difference occurred for *E. alletteratus*, for which $p = 0.77$ when *Decapterus* sp. was present, but $p = 0.35$ when *Decapterus* sp. was absent and temperature, salinity, and time of day were optimal for this species. Under otherwise optimal conditions, the probability of presence decreased from $p = 0.94$ to $p = 0.86$ for *C. crysos*, from $p = 0.29$ to $p = 0.13$ for *M. mola*, from $p = 0.61$ to $p = 0.33$ for *S. dumerili*, and from $p = 0.47$ to $p = 0.34$ for *S. rivoliana*. In all cases, the 95% CI of these predictions with and without *Decapterus* sp. present overlapped, demonstrating that the statistical power for these comparisons is still somewhat low.

DISCUSSION

We were able to use video footage and GLMs to predict the probability of presence of each of the coastal pelagic species observed at our camera array, and to calculate coefficients for the factors that influenced that probability of presence. Water temperature was a significant predictor of presence for all species, though the magnitude of the coefficient for this variable differed among species. For all species but *Decapterus* sp., probability of presence was zero at the least optimal observed temperature. This indicates that even when the magnitude of the temperature coefficient was small, it was still quite influential. Salinity also influenced the probability of presence of many species, like *C. crysos*, *Decapterus* sp., and *E. alletteratus*. Two of the driving forces of the Southeastern oceanic conditions are river runoff (Blanton and Atkinson 1983) and

Table 4. Estimates, standard errors, 95% confidence interval (CI), odds ratio estimates, and odds ratio 95% CI of model-averaged estimates of the coefficients for the composite logistic regression models predicting the presence of each group of pelagic fish at a human-made patch reef off the coast of Georgia, USA, 2000 - 2008. LST = Local standard time. Estimates of the coefficients for time are defined as compared to the time period of 10:00 - 13:00 LST.

	Estimate	Standard Error	95% CI		Odds ratio	Odds Ratio 95% CI	
			Lower	Upper		Lower	Upper
<i>Caranx crysos</i>							
Intercept	3.663	7.042	-10.140	17.465	38.963	0.000	3.85*10 ⁷
Temperature	0.671	0.044	0.583	0.758	1.955	1.792	2.133
Salinity	-0.638	0.202	-1.034	-0.242	0.528	0.356	0.785
<i>Decapterus</i> presence	0.983	0.142	0.705	1.261	2.672	2.023	3.528
<10:00 LST	0.015	0.107	-0.195	0.224	1.015	0.823	1.251
13:00-16:00 LST	0.026	0.112	-0.193	0.246	1.027	0.824	1.279
>16:00 LST	-0.086	0.173	-0.425	0.252	0.917	0.654	1.287
<i>Carcharinus</i> sp.							
Intercept	-6.298	6.429	-18.899	6.302	0.002	0.000	545.679
Temperature	0.124	0.041	0.044	0.205	1.132	1.044	1.227
Salinity	-0.018	0.185	-0.380	0.344	0.982	0.684	1.410
<i>Decapterus</i> presence	0.388	0.358	-0.314	1.090	1.474	0.731	2.973
<10:00 LST	0.025	0.151	-0.271	0.320	1.025	0.763	1.377
13:00-16:00 LST	0.035	0.163	-0.284	0.355	1.036	0.753	1.426
>16:00 LST	-0.071	0.250	-0.562	0.420	0.932	0.570	1.522
<i>Decapterus</i> sp.							
Intercept	-36.012	4.066	-43.981	-28.043	0.000	0.000	0.000
Temperature	0.106	0.012	0.083	0.130	1.112	1.086	1.138
Salinity	0.916	0.116	0.689	1.144	2.499	1.991	3.138
<10:00 LST	-0.022	0.071	-0.162	0.117	0.978	0.851	1.125
13:00-16:00 LST	0.006	0.056	-0.103	0.115	1.006	0.902	1.122
>16:00 LST	-0.032	0.087	-0.202	0.138	0.969	0.817	1.148
<i>Euthynnus alletteratus</i>							
Intercept	24.343	8.532	7.620	41.066	3.73*10 ¹⁰	2037.968	6.83*10 ¹⁷
Temperature	-0.334	0.055	-0.441	-0.226	0.716	0.643	0.798
Salinity	-0.628	0.243	-1.104	-0.153	0.533	0.332	0.858
<i>Decapterus</i> presence	1.805	0.350	1.118	2.491	6.077	3.059	12.075
<10:00 LST	-1.976	0.755	-3.455	-0.496	0.139	0.032	0.609
13:00-16:00 LST	0.122	0.353	-0.569	0.813	1.129	0.566	2.254
>16:00 LST	-0.200	0.413	-1.008	0.609	0.819	0.365	1.839
<i>Mola mola</i>							
Intercept	0.905	6.137	-11.122	12.933	2.473	0.000	4.14*10 ⁹
Temperature	-0.372	0.050	-0.471	-0.273	0.689	0.625	0.761
Salinity	0.061	0.172	-0.276	0.398	1.063	0.759	1.489
<i>Decapterus</i> presence	1.034	0.344	0.360	1.707	2.811	1.434	5.513
<i>Seriola dumerili</i>							
Intercept	1.023	8.353	-15.349	17.396	2.782	0.000	3.59*10 ⁷
Temperature	0.307	0.033	0.243	0.371	1.359	1.275	1.449
Salinity	-0.320	0.243	-0.796	0.156	0.726	0.451	1.169
<i>Decapterus</i> presence	1.167	0.161	0.851	1.483	3.213	2.342	4.407
<10:00 LST	-0.035	0.132	-0.294	0.224	0.965	0.745	1.250
13:00-16:00 LST	0.014	0.122	-0.224	0.252	1.014	0.799	1.287
>16:00 LST	-0.149	0.251	-0.640	0.342	0.861	0.527	1.407
<i>Seriola rivoliana</i>							
Intercept	-59.266	13.427	-85.582	-32.950	0.000	0.000	0.000
Temperature	0.611	0.077	0.461	0.761	1.842	1.586	2.141
Salinity	1.136	0.371	0.410	1.863	3.115	1.506	6.440
<i>Decapterus</i> presence	0.565	0.204	0.166	0.965	1.760	1.180	2.625
<10:00 LST	-0.166	0.278	-0.711	0.379	0.847	0.491	1.461
13:00-16:00 LST	-0.018	0.163	-0.338	0.301	0.982	0.713	1.352
>16:00 LST	-0.187	0.304	-0.783	0.409	0.829	0.457	1.505
<i>Sphyraena barracuda</i>							
Intercept	-10.103	5.035	-19.972	-0.234	0.000	0.000	0.792
Temperature	0.191	0.018	0.155	0.227	1.211	1.168	1.255
Salinity	0.107	0.145	-0.178	0.392	1.112	0.837	1.479
<i>Decapterus</i> presence	-0.042	0.096	-0.231	0.146	0.958	0.794	1.157
<10:00 LST	0.005	0.064	-0.120	0.131	1.005	0.886	1.140
13:00-16:00 LST	0.013	0.070	-0.124	0.150	1.013	0.884	1.161
>16:00 LST	-0.030	0.097	-0.219	0.160	0.971	0.803	1.173

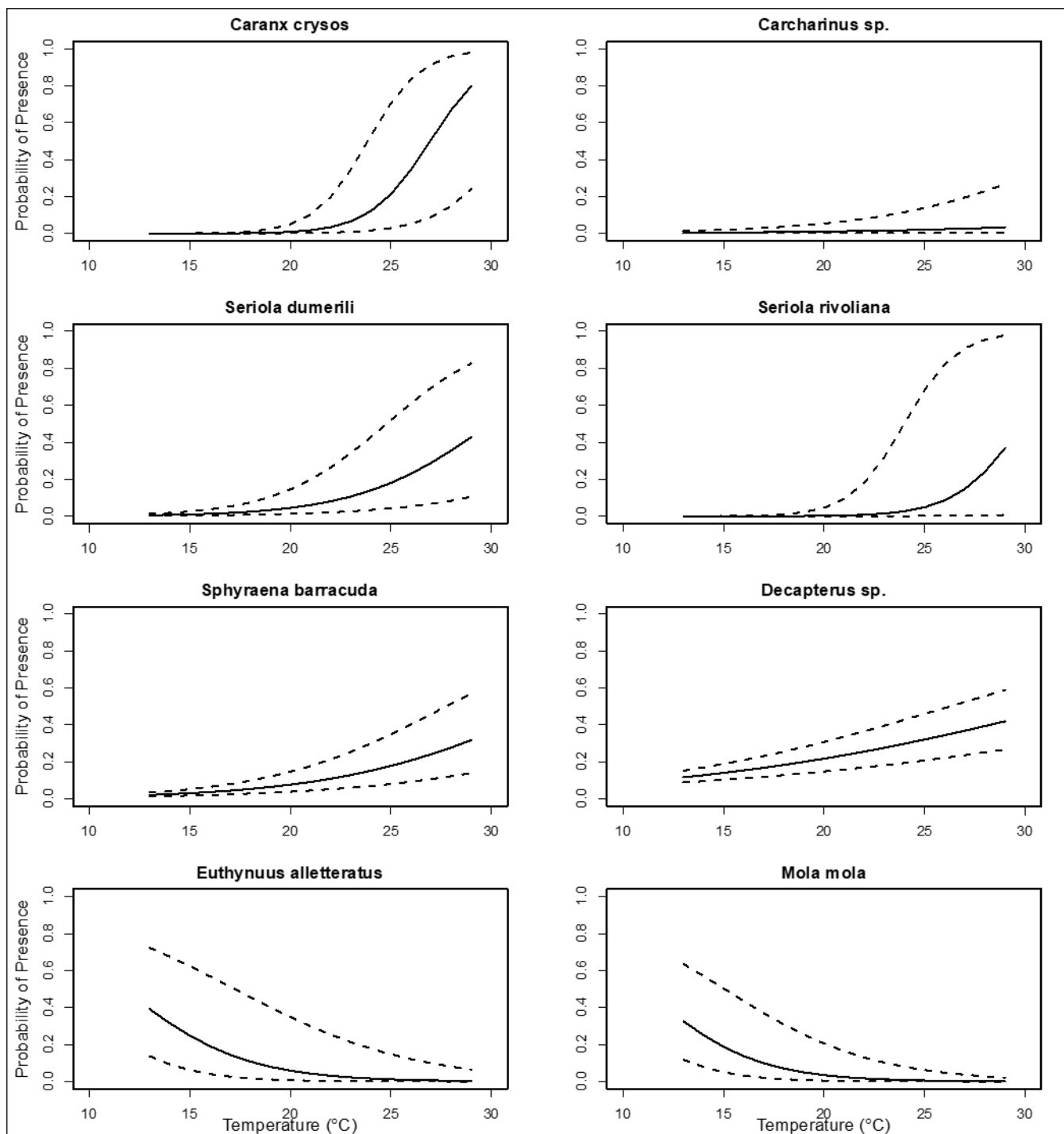


Figure 3. The probability of presence of each coastal pelagic species over the range of observed temperatures (°C) when salinity is held constant at the median salinity (35.6 PSU), *Decapterus* sp. is present, and time is 10:00–13:00 LST (local standard time). Dashed lines represent the probability of presence calculated with the 95% confidence intervals of the estimated coefficient of temperature.

cross shelf intrusion of the Gulf Stream (Blanton et al. 1981). Seasonal changes in mid-shelf water temperatures follow relatively predictable annual cycles, while salinities of bottom waters can vary widely (e.g., Figures 1 and 2). The seasonal temperature cycle provides a more reliable pattern of change that correlated with season and would be reinforced by photoperiod. Salinity likely played a larger role in short-term fluctuations of presence of CPS (as opposed to seasonal migration cues), as salinity was quite variable, but did not vary according to season.

The probability of presence of most predator species at our human-made patch reef increased with the presence of prey fish, *Decapterus* sp., with the exception of *S. barracuda*. For example, *S. dumerili* was four times more likely to be present when *Decapterus* sp. were present. Similarly, increased presence of another predator species, Atlantic Bluefin Tuna (*Thunnus thynnus*), also was positively influenced by the presence of a forage species (Atlantic Herring, *Clupea harengus*) in the Gulf of Maine (Schick and Lutcavage 2009). We also expected that probability of presence for most visual predators would be greater during midday periods (i.e., 10:00 - 13:00 LST) when light penetration at depth is greatest. Bluefish (*Pomatomus saltatrix*) have been found to swim faster (peaking at midday) and in more organized schools during day than at night (Stehlik 2009). Somewhat surprisingly, time of day only had a statistically significant effect on *E. alletteratus*, with a decreased probability of presence at < 10:00 LST.

Unlike the predators in our study, *Decapterus* sp. was present most often (31%) and in all seasons, and salinity played a larger role in probability of presence for this species than did temperature. Our greatest predicted probability of *Decapterus* sp. presence was at temperatures and salinities that were similar to previous observations. *Decapterus* sp. along the coast of the Southeastern USA were widely distributed during summer and fall and in deep waters (28 - 110 m) in winter and spring (Hales 1987). Within the Colombian Caribbean Sea, *Decapterus* sp. were associated with water temperatures > 25 °C and salinities > 36.6 PSU (Paramo et al. 2003).

The fall seasonal appearance of *S. barracuda* at our study site was more related to water temperatures than that found for most other CPS, although even at the greatest observed temperature, *S. barracuda* were still predicted to be somewhat rare ($p = 0.30$, 95% CI = 0.13 - 0.55). DeSylva (1963) suggested that *S. barracuda* preferred waters of 74°F (23.3 °C) and that individuals off southern Florida do not migrate, while those north of central Florida do. The high site fidelity of *S. barracuda* off St. Croix, US Virgin Islands (Becker 2016), may support this, while the fact that *S. barracuda* in the Bahamas disappeared from the study site (60% of the time), especially in summer (O'Toole 2011), supported the suggestion that some "northern" *S. barracuda* migrate. We suspect that the individuals observed at our human-made patch reef migrated from this more northern area, though tagging studies would be necessary to confirm this.

The increased probability of presence of most CPS with increasing water temperatures, which coincided with

the summer season (July - September) suggests that all but *E. alletteratus* and *M. mola* are seasonal migrants that have tropical affinities. Our relatively small data set for both species could indicate local interruptions of larger seasonal north/south movements suggested for *E. alletteratus* by Manooch et al. (1985) and observed for *M. mola* (Sims et al. 2009). *M. mola* may make foraging stops in long distance movements to exploit patches of food found along the way (Sims et al. 2009). *M. mola* also preferred daytime temperatures of 8 - 20°C at depths > 50 m and nighttime temperatures of 12 - 22°C at depths < 50 m off California (Thys et al. 2015), which may explain why their probability of presence was greater at lower temperatures. Small single species schools of *E. alletteratus* were observed swimming very rapidly and usually repeatedly through the near bottom fish assemblages, seemingly in a wide range of temperatures 18 - 30°C, and may have been attracted to schools of *Decapterus* sp., a common food item (Garcia and Posada 2013).

Both jack species (*S. dumerili* and *S. rivoliana*) were almost always observed in small numbers in our video footage, in addition to their somewhat low maximum predicted probabilities of presence ($P_{S.dumerili} = 0.60$, $P_{S.rivoliana} = 0.43$). *S. dumerili* were often seen in small numbers among *C. crysos* in feeding swarms, but they were rarely observed as the dominant species. *S. rivoliana* rarely were observed at the site. The observed *S. rivoliana* individuals may represent displaced residents that do not regularly migrate, since they were year-round residents at a shallow seamount in the Azores (Fontes et al. 2014).

At our study site, sharks (*Carcharinus* sp.), most commonly sandbar sharks (*Carcharinus plumbeus*), were often associated with a multi-species group of pelagic predators attacking forage species. This feeding behavior, in which associated forage species are forced out of the water column down to the near-bottom, has been previously observed (Auster et al. 2013). Carcharid sharks in our study appeared to co-occur temporally with the other CPS associated with high water temperatures. Conrath and Musick (2008) found that juvenile *C. plumbeus* in bays and lagoons of Virginia, USA, occupied waters of 19.9 °C in winter and 24.0 °C in summer.

Although water temperature was an important factor contributing to the presence of many CPS, model results suggested a limited relationship between species presence and that one factor. In most species, multiple factors influenced the probability of presence, and likely there are more biotic and abiotic factors that should be included in future analyses, with some of these factors potentially interacting in non-linear ways to affect species presence. For example, we found that *M. mola* were predicted to be present more often with *Decapterus* sp., despite feeding feed primarily on jelly fish (Thys et al 2015). Likely there are other factors that we did not include in our models that might have contributed to the presence of *M. mola*. Complicating factors may remain immeasurable, at least for a time, including behavioral responses to natural biological clocks (both seasonal and daily), any differences between increasing (spring) and decreasing (fall) thermal conditions, and complex interactions between species as predators or prey. In addition, climate change could alter species' migration

phenology in the future, as water temperatures increase or no longer correlate in the same manner with photoperiod (Bradshaw and Holzapfel 2008). Sampling of pelagic species, commonly associated with mid-water habitats, with a benthic camera limits the observation times to those infrequent periods during which the species appears near bottom, possibly to prey on species like *Decapterus* sp. or species more closely associated with the shelter of the reef habitat (Auster et al. 2013).

Our models resulted in very large confidence intervals for many of the analyzed species. Many factors may contribute simultaneously to the variance associated with a species level of prediction of fish presence. Examples from previous studies include: differences in preferred temperatures between fed and unfed and/or pregnant and not pregnant Atlantic stingrays (Wallman and Bennett 2006), body size in Pacific salmon (Morita et al. 2010), as well as individual differences in movement patterns of *S. barracuda* (Becker et al. 2014). In addition, the small sample sizes in this study likely influenced these large confidence intervals, indicating the preliminary nature of our estimates of predictable relationships between presence of pelagic species and dynamic environmental factors. The data from this study represented an eight-year period (2000 - 2008), yet the frequency of pelagic species present (near the bottom) may have been too low for anything but early results from our analyses. Resulting equations of this study should be helpful in predicting presence of these eight species/groups. While acknowledging that our small data sets resulted in large variances, we considered our efforts to predict pelagic fish presence by correlations with dynamic environmental factors an early effort.

Despite some problems associated with visual sampling, undisturbed assemblages and untagged individuals can be observed. We feel that the long time series of visual data of this study demonstrates the usefulness of underwater stationary cameras and should allow better predictive information through correlations between species presence and complementary environmental factors, especially as reliability of both cameras and measurement systems improve.

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