HBF IS AN UNRELIABLE INDEX OF FISHING DEPTH FOR US LONGLINES

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SUMMARY

Statistical models for estimating abundance trends for pelagic species are often fitted to CPUE data using the number of hooks between floats (HBF) as a covariate. This convention was originally based on observations indicating depths fished increased with HBF. The validity of this assumption was examined using the 1986-2015 hook-depth distributions for128 longline configurations from US logbooks estimated in a previous study. Time at depth and mean depth fished varied greatly for gears with the same number of HBF. Additionally, large annual variations were observed in the proportions of sets configured to fish at different depths and in the average depths fished by gears with the same number of HBF. A significant negative correlation predicted its appearance as a covariate in statistical models; however, the original basis for stratifying CPUE data by HBF was invalid for the US fishery. Fishing depth decreased with HBF in contrast to the traditional belief that it should increase. Expectations that HBF will be a surrogate for fishing depth should be accepted with skepticism until confirmed by analysis.

KEYWORDS
CPUE, Longline Data, Stock Assessment, Statistics, Population Modeling

1. Introduction

Stock assessments often rely on models fitted to indices of abundance to evaluate the status of target species and set sustainable harvest levels. For highly migratory species, the indices are often based on statistical models that utilize catch per unit effort (CPUE) based on presumptions about similarities in catchabilities of various longline gears. The number of hooks between floats (HBF) is a common metric used as a covariate in that process (e.g., Anon 2017, 2018). This metric was initially developed based the species targeting in the early Japanese fishery (Suzuki et. al. 1977, Hinton and Nakano 1986). These authors documented an increase in the number of hooks per basket of gear (HPB) as the fishery shifted to target deep-water species. Also, HBF has been routinely collected as part of catch-effort statistics whenever longline data have been recorded. The near ubiquitous availability of this variable encourages its use whenever catch data are analyzed. [Note: HBF and HPB are equivalent because a basket of gear contains the hooks on a section of gear between floats.]

Suzuki et. al. (1977) noted that species preferring deeper, cooler water were more frequently encountered in the harvest of gears with more HBF. This observation supported the notion that the longline hooks on these gears were sagging more deeply in the water column. The underlying theory was that the temperature stratification of the water column caused deeper hooks to encounter species that preferred cooler temperatures. Hinton and Nakano (1986) presented a method to incorporate these features when standardizing longline CPUE to estimate trends in species abundance. They used a catenary curve to compute the hook depths but adjusted the values upward to account for a difference between observed and predicted depths. Both hook and fish distributions are important in this paradigm. Based on this work, Goodyear (1993) assumed catenary dynamics for fishing depths for simulations of longline

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catches of Blue Marlin (*Makaria nigricans*) by gears with differing HBF. However, subsequent studies using time at depth recorders attached to longline hooks found little agreement between catenary-predicted and actual depths fished (Bigelow et al. 2006; Rice et al. 2007). The current version of the longline simulator (LLSIM) requires users to provide the probability distributions of the species in three-dimensional space by month computed from behavioral and environmental information. These time-depth distributions are matched with probability distributions for time at depth for each hook position between floats for each longline set for each gear (Goodyear 2018, Forrestal et.al 2019b). There is a large literature dealing with the incorporation of environmental and catch information in the construction of longline CPUE indices that involves depths fished and species distributions that is beyond the scope of this note (e.g., see Maunder and Punt 2004; Maunder et al. 2006). HBF continues to be a common covariate in ICCAT CPUE standardization analyses often without explanation of a mode of action. The LLSIM protocol provides data to examine assumptions about HBF and fishing depths. Here we explore the reliability of the assumption that fishing depth increases at higher HPB using the gear configurations and effort estimated for the 1986-2015 US Atlantic longline fishery.

2. Method

2.1. Data

In an earlier study Forrestal et al. (2019a) assembled a gear-effort matrix from US longline logbooks to describe that fishery. These data covered the period 1986-2015 with 128 discrete gear types and were first used in a blind study of the performance of standardization methods (Forrestal et al. 2019b). In these studies, each “gear” was one of the unique longline configurations identified in the US longline logbooks. These data were adopted for this study unchanged. The mean depths fished for each of the gears in that study were calculated as the sum of gangion and floatline lengths reported in the logbooks adjusted to account for hook position (**Figures 1** and **2**). The maximum confirmed HBF configuration in the US logbook data was 6 HBF. Because of gear symmetry, the hooks could occur in three possible depth situations due to their location on the mainline. These include: a single depth in gears with 2 HBF, two different depths in gears with 3 and 4 HBF, and three different depths in gears with 5 and 6 HBF.

Where hooks had a single depth distribution (2 HBF), the mean depth was set at 60% of the reported mean depth (mean depth from logbook*0.60). For other configurations, the mean depths for the deepest hooks were set to 60% of the mean reported depths. Means for the intermediate hooks were set to 50% and means for the shallowest hooks were set to 40% of the reported mean depths. For example, in a 5 HBF gear, hooks 1 and 5 were set to 40%, hooks 2 and 4 were set to 50% and hook 3 was set to 60% of the reported depth. This range is consistent with observations of the differences between actual hook depths versus those estimated based on the gear configuration (Bigelow et al., 2006; Rice et al., 2007). The probabilities of each hook being in each depth layer were found using a Gaussian probability density function using the mean (μ) and standard deviation (σ) of depths for each gear configuration from the logbook. The proportions in each depth layer were then estimated from the mean adjusted for the hook positions using the normal distribution and the standard deviation. This process resulted in a probability distribution for each hook in each layer from the surface to the deepest layer considered (2km).

In addition to fishing depths, Forrestal et al. (2019b) also estimated the distribution of sets for each gear in each 1-degree latitude-longitude cell for each year. To avoid privacy issues the Forrestal study applied Monte Carlo methods to create a data set describing a synthetic fishery that closely resembled the US longline fishing. Notably, jittering was added to the location of where each set was deployed (latitude and longitude), but not which gear was used for a set. Thus, the numbers of sets by each gear type each month and year were the same as in the actual fishery. The data file contained about 280 thousand sets for the period 1986-2015. The simulated catches from these sets were used for the analyses reported in Forrestal et al. (2019a and 2019b). We also use them here to investigate partitioning the US longline fishing effort using HBF as a covariate.

2.2. Analyses

We evaluated several issues important to the interpretation of this dataset: 1) In the US Atlantic longline fishery - did the depths fished by gears increase with increasing values of HBF in conformity with the ideas proposed by Suzuki et al. (1977) and Hinton and Nakano (1966)? 2) Are temporal variations in the level of effort at different depths sufficient to make this issue important in analyses of abundance from CPUE data? 3) Do the temporal patterns in HBF mirror the patterns in fishing effort at different depths? 4) Are the results artifacts of the inclusion of minor gears that were small parts of the total effort?

2.2.1. Depths fished by gears with the same HBF. The probability distributions for time fished in successively deep layers for the gears were evaluated by inspection. Temporal stability was evaluated by first sorting the gears by median depth fished by the hooks. The gears were then assigned to shallow, intermediate, or deep categories depending on their position in the cumulative distribution equally divided into thirds. the resulting proportions of sets by depth category were inspected by year to see if fishing depths had been consistent through time.

2.2.2. Temporal patterns in fishing depths. The same three depth categories were applied to see if there was evidence of annual variability, and to see if there were seasonal patterns in proportions of sets by gears in the shallow, intermediate and the deepest layers. Variability in depths fished would be expected to affect catch rates in ways that need to be considered during statistical procedures to estimate abundance trends from CPUE data.

2.2.3. Mean hook depths by year for gears with the same HBF. To see if the ensemble of gears in the fishery that shared the same HBF might actually resemble the annual pattern of actual hook depths, we computed the mean hook depths for all longline sets pooled by the same HBF each year. The same data would also show if the depths fished by gears sharing the same HBF were stable with time. Differing annual trends in depths fished by gears sharing the same HBF could cause depth-related changes in CPUE of a depth-stratified species that may be impossible to remove via statistical analyses using HBF as the only covariate to represent depth effects.

2.2.4. Variability of CPUE for gears with the same HBF. A scattergram of the mean CPUE (catch per thousand hooks) and HBF for each gear was constructed for the simulated catch for the entire simulation where the population was constant. These data were examined for unexpected patterns or possible outliers.

2.2.5. Testing for the effects of minor gears. Each of the 128 gears contributes equally in some of the analyses here. However, in in a CPUE standardization, not all gears are represented by the same number of observations. The importance of data from a particular gear depends largely on its relative contribution to the total number of observations by all gears with the same HBF. This feature was evaluated by inspecting scattergrams of median depth fished by HBF where gears fishing successively fewer total numbers of hooks were removed. Median depth fished was also regressed against HBF to see if the elimination of minor gears would restore the positive correlation between depth and HBF originally used to justify using it as a covariate.

3. Results

3.1. Depths fished by gears with the same HBF

The probability distributions for time fished by hooks in successively deep layers were highly variable for gears with the same HBF (**Figure 3**). This finding does not support the notion that the mean depth fished increased with HBF or that gears with like HBF would have similar catchabilities for species with different depth distributions (**Figure 3**).

3.2. Temporal patterns in fishing depths

The monthly proportions of sets by gears that fish in shallow, intermediate and the deepest layers were examined to evaluate importance of including fishing depth in analyses. The results show that there were very large variations in the proportions of sets that fished in the three depth zones by year (**Figure 4**). There were also monthly variations in the yearly average proportions of sets in the depth zones suggesting seasonal shifts in the depths targeted by fishermen (**Figure 5**). These could be to either follow seasonal patterns of a species or to change species targeted. Taken together, these results suggest that CPUE standardizations using catch data from this fishery would require a complex model with some kind of stratification to minimize the effects of the gear and species depth distributions that would otherwise bias the nominal CPUE.

3.3. Mean hook depths by year for sets with the same HBF

The mean hook depths fished by gears with the same HBF were not stable with time (**Figure 6**). The mean depths fished by 2 HBF gears showed the greatest amount of year-to-year variation, but other HBF configurations were also variable. These differences are presumably the results of gear-design preferences by diverse groups of fishermen as they adapt to spatial or temporal changes in depth preferences of the targeted species, when they change target species, or when technological advancements are being introduced to the fishery. The variation in depths fished in these data are inconsistent with the pattens in **Figure 4** making it unlikely that HBF would correctly represent the pattern in depths fished by chance.

3.4. Variability of CPUE for gears by HBF.

The scattergram of the mean CPUE (catch per thousand hooks) by gears partitioned by HBF for the entire time series of the simulation with a constant population reported in Forrestal et al. (2019a) is shown in **Figure 7**. The bin with 6 HBF had the least variability and 5 HBF had the greatest variability. Data from one 2- HBF gear and one 5-HBF gear were noticeably higher than their neighbors with CPUE values of approximately 15 and 19 per thousand hooks, but it is unclear whether either could be considered an outlier. Data from neither gear could be sufficient to appreciably alter the results presented here. The scatter in **Figure 7** is consistent with average CPUE being a multifactor outcome of the fishing operation.

3.5. Testing for the effects of minor gears.

Figures 8-11 explore the reliability of assuming that HBF predicts fishing depth and the degree to which the inclusion of lesser-used configurations may bias the results. Although there was considerable variation in median depth fished by hooks by gear, there was a statistically significant decrease with increasing HBF in the US fishery. This finding is in contrast to the results of earlier studies that provided the initial support for the conclusion that HBF increased the depth fished (Suzuki et. al. 1977; Hinton and Nakano 1986). Also, the overall pattern of declining average fishing depths with increasing HBF seen here persisted when the analysis was successively limited to those gears that increasingly predominated the fishery (Figures **8-11**). While this trend persisted throughout, the overall pattern was that less than 25% of the variation in median fishing depths was the consequence of HBF.

4. Discussion

Reliance on HBF as a covariant in longline cpue analyses traces its roots back to the discovery that gear configurations with higher HBF caught species that lived deeper in the water column (Suzuki et. al. 1977). The discovery of a negative correlation between fishing depth and HBF in the US longline logbook data (Figures 8-11) undermines that relation. Part of the explanation may lay with the dynamic range of HBF in the US fishery which ranged from only 2 to 6 hooks compared to 4 to 15 hooks in the early Japanese fishery that served as the precedent. The importance of this discovery may extend back to first time the early Japanese data were extrapolated to other situations where HBF was used as a covariate, and may include many ICCAT-related analyses based on pelagic longline CPUE data. This is important because changes in fishing depth configurations may bias in the estimation of stock abundance that could obfuscate analyses by adding trends in the pooled data when no real trend exists. Alternatively, it could mask the appearance of a trend when one actually exists, or otherwise reshape patterns in the pooled data that ultimately degrade or corrupt results. Analysts may not have personal experience with the various fisheries that provided the catch and effort data necessary for stock assessment analyses. This fosters reliance on previous assessments for guidance. However, prior results do not necessarily justify subsequent assumptions. Particularly if the reasons for assumptions and results were never fully understood.

HBF needs to be correlated with catchability (q) to be useful as a numeric variable. As a categorical variable it can simply identify gears that share the same catchability. In the case of the US data evaluated here, there was a significant negative correlation between depth and HBF, so it could be responsible for some of the variability in catch rates. This may one reason why HBF was found useful during the simulation studies reported in Forrestal et al (2019a). Alternatively, the preponderance of some gears may have smothered the influence of different gears that shared the same number of HBF when the analyses were performed. Either way, given the large gear to gear variability reflected in the scatter in Figures 7-11, other mixtures of the gears could have produced time series without a significant correlation or other agreement between catchability and HBF. More insidiously, the mix of gears with the same HBF could switch from a positive to a negative correlation with q (via depth) during the time series. This could allow HBF to explain part of the variance in fitted models, but to be inappropriate for the most recent years where accuracy is most important.

Expectations that HBF will be a surrogate for fishing depth should be accepted with skepticism if the trend has been unconfirmed for a time series of longline catch data. Notwithstanding whatever predictability may have existed between HBF and *q* with gears employed in the early Japanese fishery, this note shows that the diversity of configurations in the recent US fishery makes extrapolation of those relations to other situations highly questionable. They should be questioned in other CPC's logbook data. These findings suggest that the bases for using HBF as a covariate should be revisited with each assessment.

Acknowledgements

Goodyear's contribution was supported by The Billfish Foundation, Fort Lauderdale FL, USA.

References

Anon. 2017. Report of the 2017 ICCAT Atlantic Swordfish stock assessment session. Collect. Vol. Sci. Pap. ICCAT, 74(3): 841-967

Anon. 2018. Report of the 2018 ICCAT Blue Marlin Stock assessment meeting. Collect. Vol. Sci. Pap. ICCAT, 75(5):813-888.

Bigelow, K., M. K. Musyl, F. Poisson, and P. Kleiber. 2006. Pelagic longline gear depth and shoaling. Fisheries Research 77:173–183.

Forrestal, F.C., Schirripa, M., Goodyear, C.P., Arrizabalaga, H, Babcock, E., Coelho, R., Ingram., Lauretta, M., Ortiz, M., Sharma, R. and Walter, J. 2019a. Testing robustness of CPUE standardization and inclusion of environmental variables with simulated longline catch datasets. Fisheries Research 210: 1-13. https://doi.org/10.1016/j.fishres.2018.09.025

Forrestal, F.C., Goodyear, C.P., Schirripa, M. 2019b. Applications of the longline simulator (LLSIM) using US pelagic longline logbook data and Atlantic Blue Marlin. Fisheries Research 211: 331–337.

Goodyear, C.P. 1993. Tests of the robustness of habitat-standardized abundance indices using simulated blue marlin catch-effort data. Mar. Freshw. Res. 54,369–381.

Goodyear, C. P. 2003. Tests of the robustness of habitat standardized abundance indices using simulated blue marlin catch-effort data. Marine and Freshwater Research 54:369–381.

Goodyear, C.P., 2018. Simulating Longline Catch with LLSIM: A User's Guide (Version 2). May 2018. https://doi.org/10.13140/RG.2.2.11577.83040.

Hinton, M.G., and H. Nakano. 1996. Standardizing catch and effort statistics using physiological, ecological, or behavioral constraints and environmental data, with an application to blue marlin (Makaira nigricans) catch and effort data from the Japanese longline fisheries in the Pacific. Bull. I-ATTC 21(4):171-200.

Maunder, M.N., Hinton, M.G., Bigelow, K.A., Langley, A.D., 2006. Developing indices of abundance using habitat data in a statistical framework. Bull. Mar. Sci. 79 (3), 545–559.

Maunder, M.N., Punt, A.E., 2004. Standardizing catch and effort data: a review of recent approaches. Fish. Res. 70, 141–159.

Rice, P.H., Goodyear, C.P., Prince, E.D., Snodgrass, D., Serafy, J.E., 2007. Use of catenary geometry to estimate hook depth during near-surface pelagic longline fishing: theory versus practice. North Am. J. Fish. Manag. 27, 1148–1161.

Suzuki, Z., Y. Warashina and M. Kishida. 1977. The comparison of catches by regular and deep tuna longline gears in the western and central equatorial Pacific. Bull. Far Seas Fish. Res. Lab., 15:51-89.

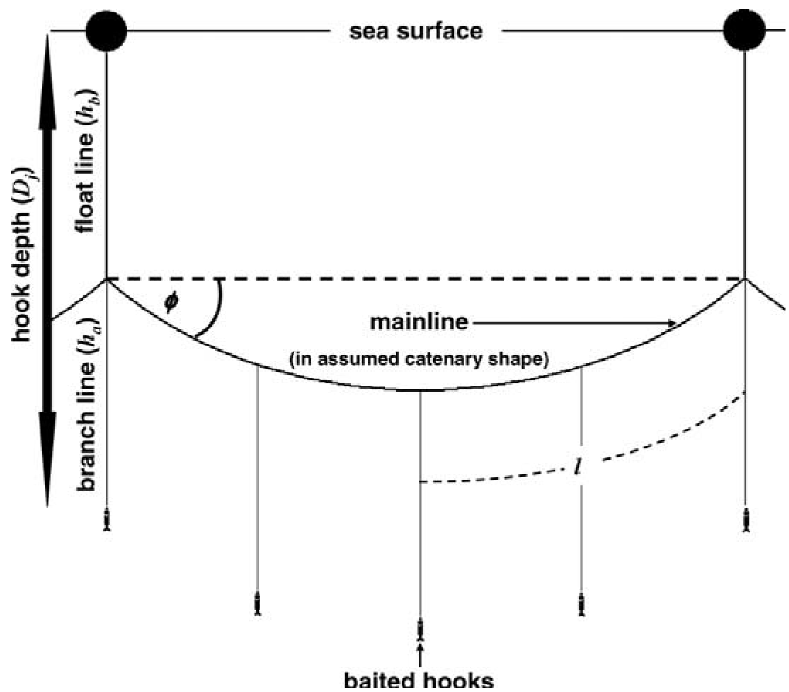

Figure 1. Elements of longline that affect the time at depth distributions of fished hooks [From Rice et al (2007)]. A principal feature that is not depicted is a weight that may be attached to the bottom of the float line to accelerate sinking of the mainline to the intended fishing depth.

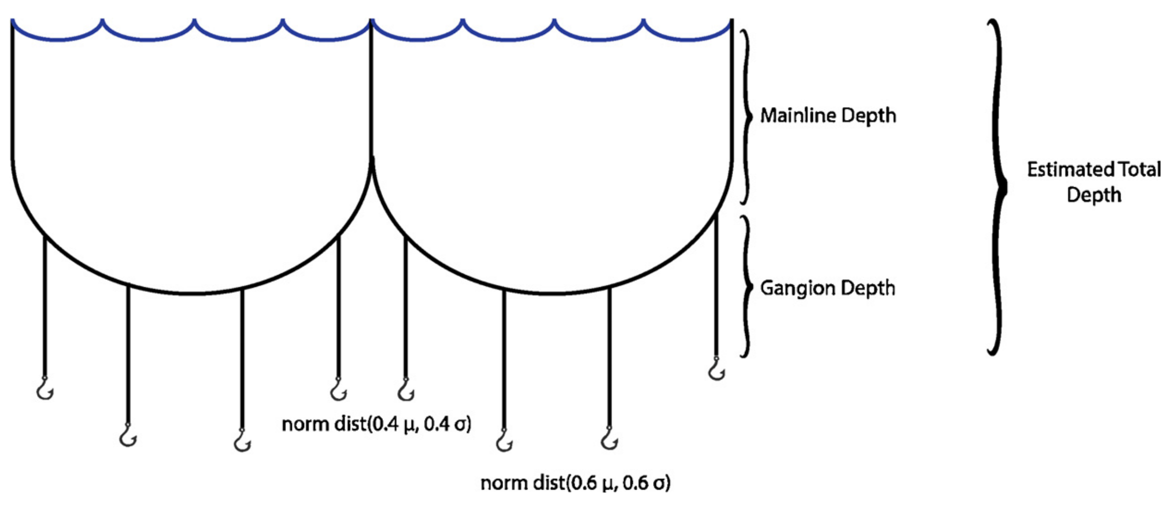

Figure 2. Longline features used to estimate the time at depth distributions of fished hooks in Forrestal et al (2019b) that are used for this study.

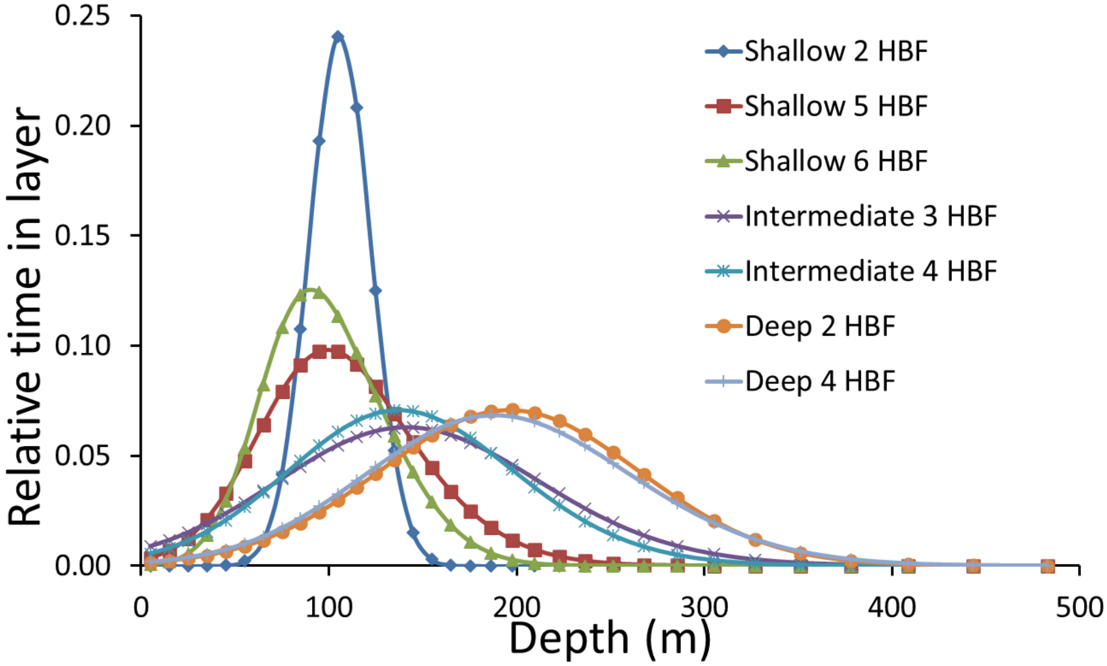

Figure 3. Computed time at depth distributions for longlines with different configurations selected to illustrate unpredictability of fishing depth by HBF.

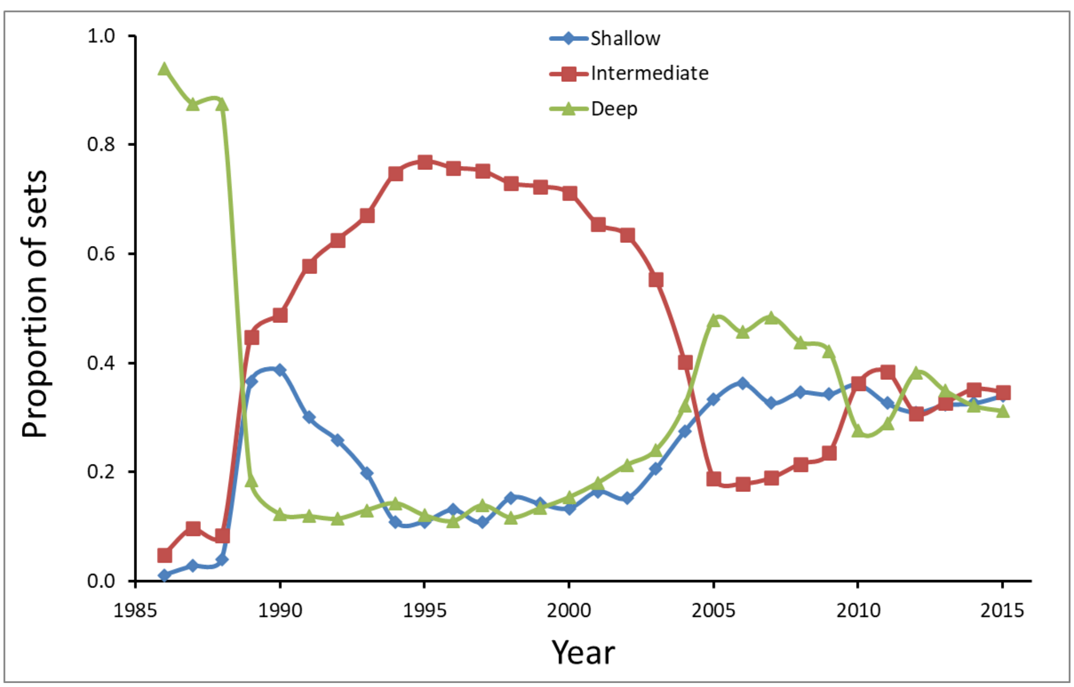

Figure 4. Proportion of longline sets made by gears fishing in shallow, intermediate or deep configurations each year. The depth categories were assigned by sorting the mean depths into shallow, intermediate and deepest thirds of the distribution of mean depths fished by all gears.

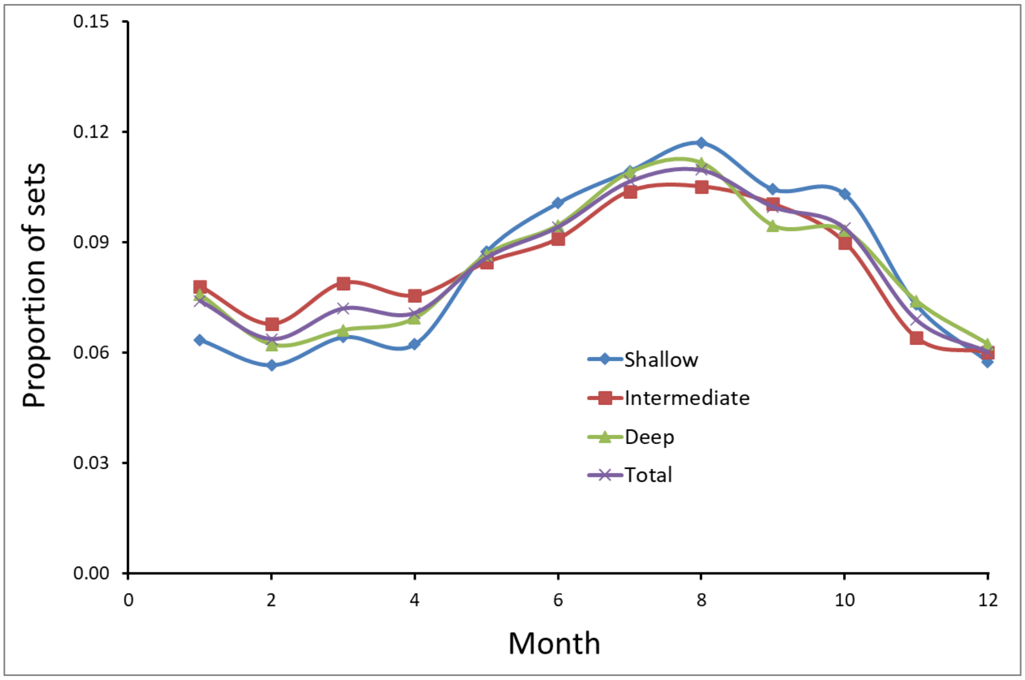

Figure 5. Proportions of sets by depth fished for each month of the year summed over years. The order of fishing depths varies by month which may be indicative of targeting.

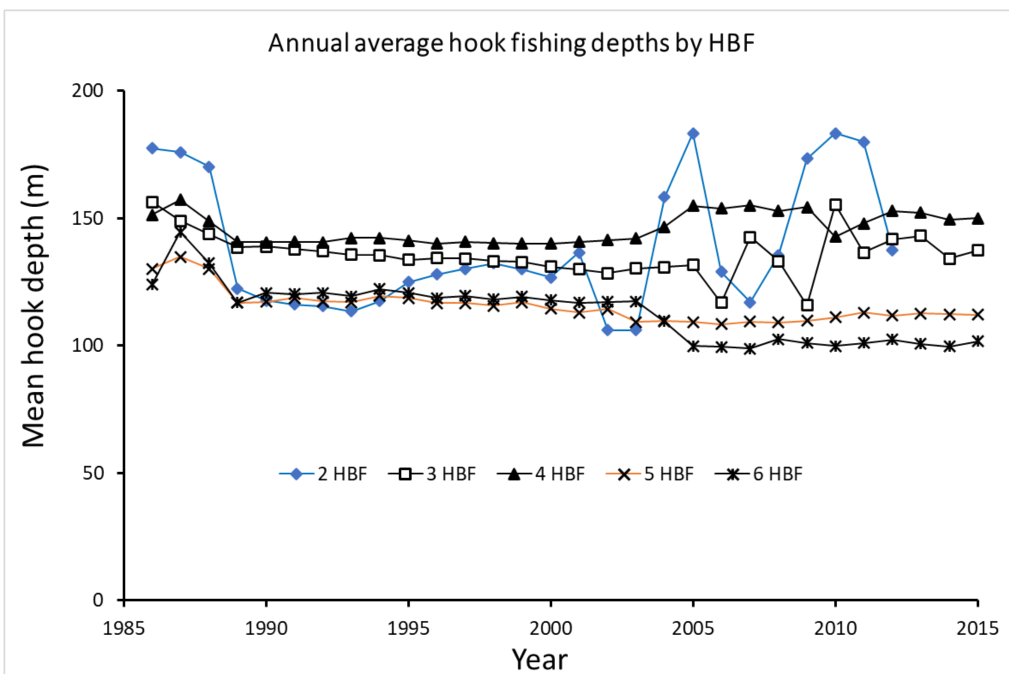

Figure 6. Mean depths fished by gears with the same number of HBF by year. These data show that gears with the same HBF were inconsistently targeting depths by year and longer periods.

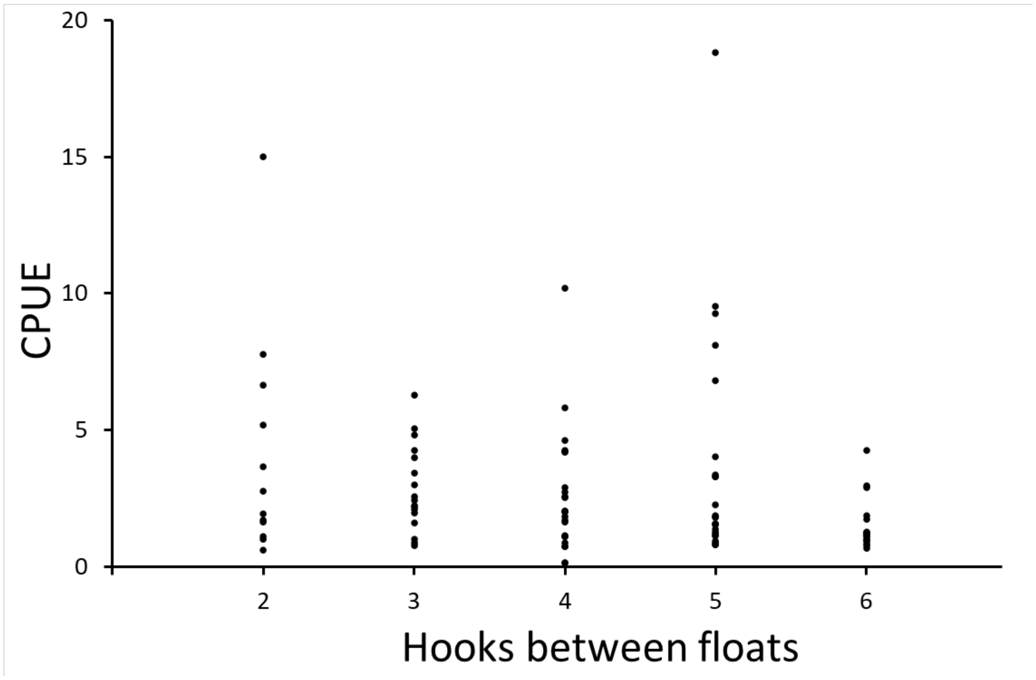

Figure 7. Scattergram of CPUE (number of Blue Marlin caught per thousand hooks) in the data simulations with the constant population assumption in Forrestal et al (2019a). Each data point is the mean CPUE for all sets of one of the 128 gear configurations pooled over years. These data illustrate the great variability in CPUE among longlines with the same number of HBF.

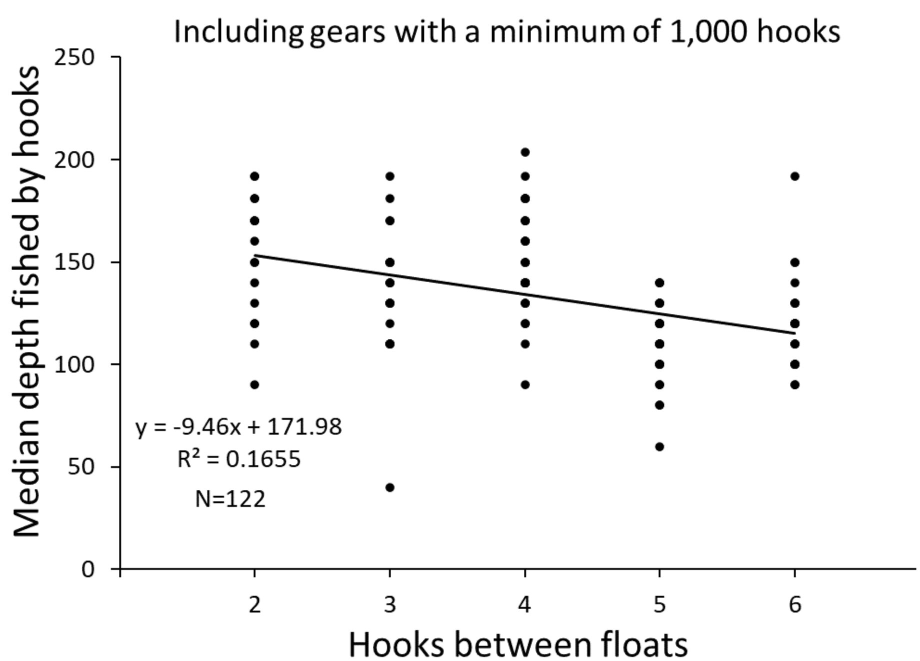

Figure 8. Scattergram of median depth fished by longlines with different HBF. The data were trimmed to only include gears that fished a minimum of 1000 hooks. The data illustrate the high degree of variability of depth fished but also a significant decline in depth fished with increasing HBF

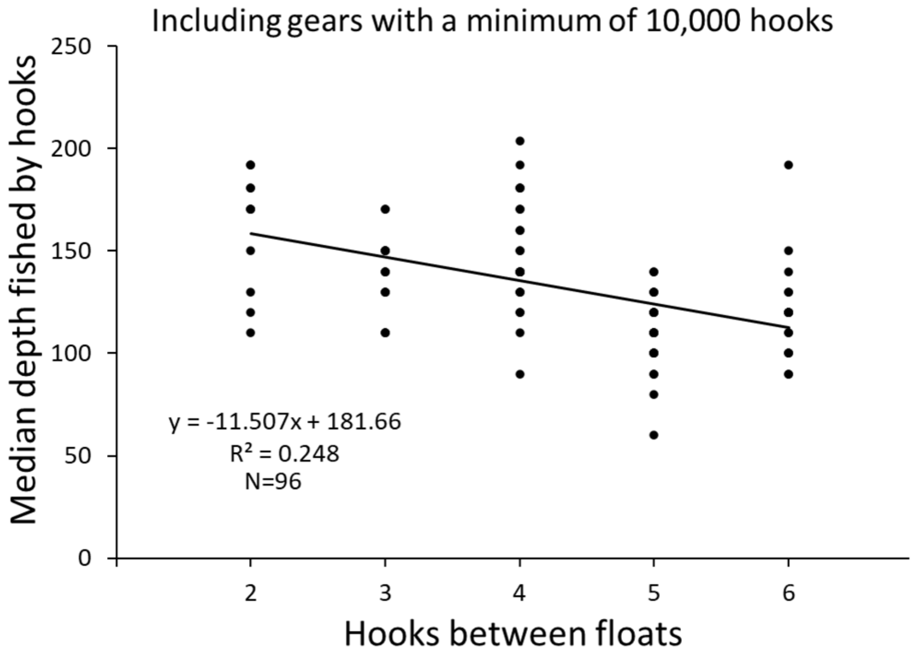

Figure 9. Scattergram of median depth fished by longlines with different HBF. The data were trimmed to only include gears that fished a minimum of 10,000 hooks. The data illustrate the high degree of variability of depth fished but also a significant decline in depth fished with increasing HBF

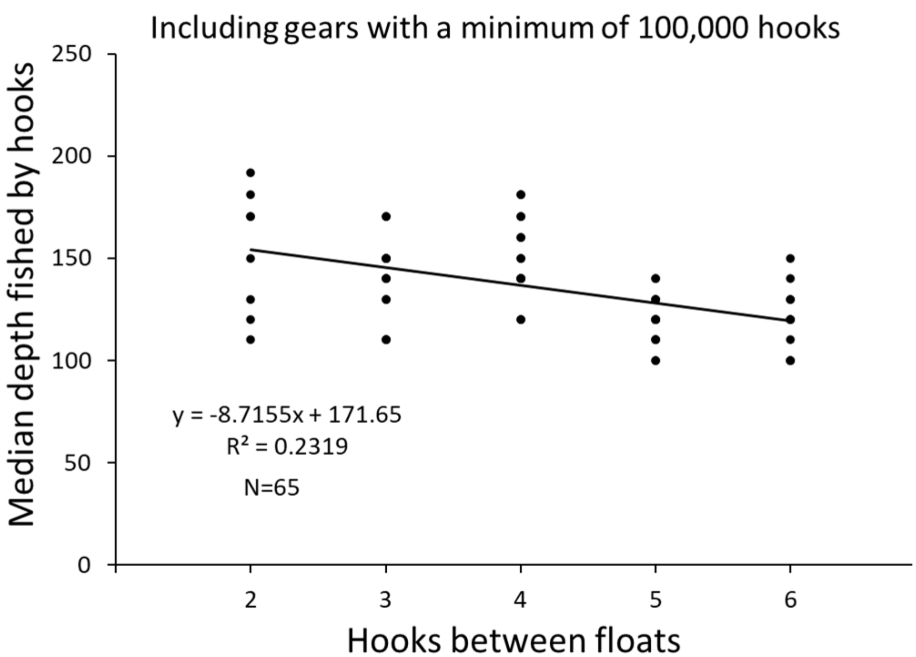

Figure 10. Scattergram of median depth fished by longlines with different HBF. The data were trimmed to only include gears that fished a minimum of 100,000 hooks. The data illustrate the high degree of variability of depth fished but also a significant decline in depth fished with increasing HBF

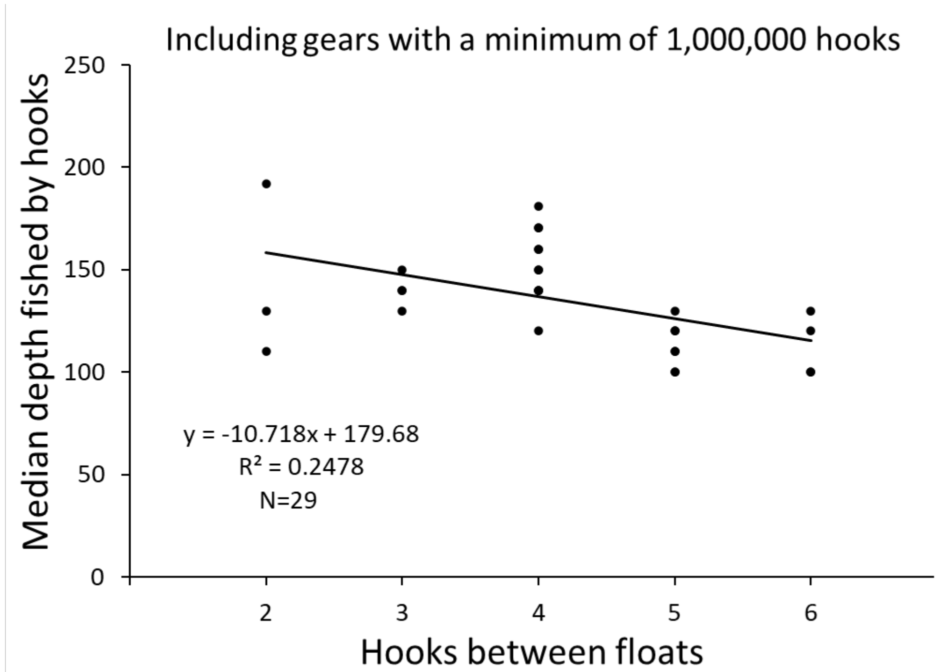

Figure 11. Scattergram of median depth fished by longlines with different HBF. The data were trimmed to only include gears that fished a minimum of 1,000,000 hooks. The data illustrate the high degree of variability of depth fished but also a significant decline in depth fished with increasing HBF