



## Technical Note

## Applications of the longline simulator (LLSIM) using US pelagic longline logbook data and Atlantic blue marlin

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## ABSTRACT

Spatiotemporal variability in fishing patterns and species distributions from ocean climatology confound analysis of pelagic longline CPUE. A generalized computer program, LLSIM, was developed to simulate such data to test methods used to quantify abundance trends. The method employs a Monte-Carlo algorithm with a probability of capture computed for each hook on each set based on overlaps of the species- and hook-depth distributions. The method was tested using characteristics of the longline gears and fishing locations of the US pelagic longline fleet and blue marlin latitude-longitude-depth distributions predicted using a species distribution model fitted to 1986–2012 monthly oceanographic data. Catch data were simulated for two hypothetical trends in total abundance. The simulator was capable of performing complex but controlled simulation experiments. Analyses demonstrated the advantage of comparing estimates from alternative standardizations to known true values that are not possible with real data.

## 1. Introduction

There is no clear, superior, objective method for quantifying abundance from longline catch rates, and no accepted best practice. Methodologies to perform accurate analyses using longline data have proven difficult to confirm because the true abundance of the fishery stocks are uncertain (Maunder and Punt, 2004; Maunder et al., 2006). The issue is all the more important because stock assessments of most highly migratory species, including nearly all billfishes worldwide, rely on longline data to quantify stock abundance. Catch rates and catch per unit effort (CPUE) indices are a fundamental requirement of stock assessments, and the standardized indices can be subject to bias introduced by the particular analyst as well as by the data (Maunder et al., 2006). One reason for the lack of best practices for the standardization methodology is that controlled experimentation is impossible. The problem is also growing in complexity because climatic changes are shifting the distributions of species habitats, which can violate stationarity assumptions of common statistical methods (Perry et al., 2005; Caputi et al., 2009). Establishing best scientific methods requires comparing how well alternatives can estimate truth, which is never known in fisheries.

There is no real-world solution to this dilemma. Data simulation is a workable approach but requires the simulations to be based sufficiently

in reality that they capture the important features of real-world variability. Previous studies have utilized simulations to examine differences in standardization approaches (e.g., Carruthers et al., 2011, 2010; Thorson et al., 2016). The longline simulator used in this study differs from these previous studies as it couples independent assessments of spatiotemporal variability in fishing patterns and ocean-climate driven variations in species distribution, allowing for proactive inspection of analytical problems. These previous efforts focused on either incorporating habitat variability into the standardization process (Hinton and Nakano, 1996; Bigelow et al., 2002; Campbell, 2016) or simulating spatiotemporal dynamics (Carruthers et al., 2011).

This research attempts to overcome the dilemma of measuring truth in fish abundance using standardization methods by employing a simulated fish population and a simulated fishery based on a realistic fishing effort pattern. The longline simulator project has three major components; the first involves distributing the fish within the simulated space based on habitat characteristics (the species distribution model) (Goodyear, 2016); the second involves the creation of simulated longline catch and effort data (LLSIM); and the third uses those data to quantify the ability of a method to recreate the true underlying population abundance trend. The project originated as an international effort coordinated by the ICCAT Working Group on Stock Assessment Methods (Anon., 2016).

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The focus this paper is on the second component, the computer model LLSIM, which simulates longline catch-effort data that can be used as a set of knowns for experiments to test alternative methods to analyze such data (Goodyear, 2006a, b). LLSIM requires information about the distributions of species in time and three-dimensional space. This information was obtained through the species distribution model (SDM) for Atlantic blue marlin (*Makaira nigricans*) as discussed in Goodyear (2016). The SDM uses thermal utilization patterns from pop-up satellite tag (PSAT) tagging, published oxygen requirements, and the time-varying distribution of these variables (Goodyear, 2016). The blue marlin distributions obtained from the SDM were paired with realistic longline fishing effort based on the US pelagic longline fishery. The longline simulator was run using a user-defined population of blue marlin, and the resulting longline catch datasets were used to examine the accuracy of CPUE standardizations.

## 2. Methods

The longline simulator is coupled with a simulated distribution of blue marlin that utilizes a habitat suitability model (HSM) (Goodyear, 2016). The species distribution model (SDM) describes the size and extent of the blue marlin habitat by 1° latitude and 1° longitude cells encompassing 46 depth bins. The distribution of blue marlin is reported by month and year in horizontal and vertical components. The distribution is obtained by inputting habitat preference of blue marlin for temperature and depth acquired from PSATs. The construction and validation of the HSM is reported extensively in Goodyear (2016). The resulting SDM used in this study differs only in the source of the environmental data. Data in the original blue marlin SDM varied monthly for an average year, and were obtained from the World Oceans Atlas. The environmental data in this study's SDM varied by month each year from 1986 to 2012, and were obtained from the Community Earth Systems Model (CESM1), which is a global ocean-sea-ice coupled model linked to a biogeochemistry model (Biogeochemical Elemental Cycle) (Lee et al., 2011; Danabasoglu et al., 2012; Long et al., 2013).

The species distribution data required for the longline simulations are defined in two steps. The first defines the average population number alive during the year and month by species (and sex-age grouping if considered). The second step defines the relative densities of the population by latitude, longitude, year, month and depth (these densities are computed so that the sum of the products of the relative density x volume for each latitude, longitude, and depth = 1.0). The products of the two vectors give the actual densities relative to each hook for the simulation.

Blue marlin annual abundance is manually entered into the longline simulator by providing a population file containing numbers of blue marlin per year. This study used both a constant population, set at 500,000 individual blue marlin over 29 years and a declining population, with a 70% reduction over 29 years. Two longline catch datasets, one for each population, were produced by the longline simulator from the methods described below.

### 2.1. Environmental data

Application of the HSM approach to predict the spatial distribution of a species requires quantitative data about the physical environmental variables that are important determinants of its habitat. Temperature and dissolved oxygen concentrations are major factors shaping the pelagic marine environment for blue marlin (Carlisle et al., 2017). Temperature is perhaps the major feature of the pelagic ocean, and is the environmental variable most frequently employed in habitat models. Dissolved oxygen is an important variable to include because at low levels it becomes a critical factor limiting habitat suitability (Prince and Goodyear, 2006). Environmental data were obtained from the CESM1. The model covers the global ocean with a latitudinal and longitudinal resolution of 1.0° and 60 vertical layers with the bottom

level at 5500 m. The vertical depth data bins were matched with the depth data bins in the species distribution model. LLSIM specifies 46 depth bins and the CESM data were truncated at 1969 m to accommodate the depth bins utilized by LLSIM. Depths from 5 m to 150 m are in 10 m bins, bins beyond 150 m in depth become increasingly coarse. The maximum depth for each one-degree latitude and longitude cell is dependent on the bathymetry of the ocean, this information is included in the structure of LLSIM.

### 2.2. US pelagic longline fleet

The effort data used in LLSIM were derived from the US pelagic longline fishery logbooks obtained from the Southeast Fishery Science Center. While the US commercial fishery has been operating since the 1960s, logbook data are only available from 1986. The logbook data contains set-by-set information with the location and timing of the set as well the gear configurations, the target species and the total catch in number of each species. LLSIM partitions the fishing activity into a specification of what is being fished (gear configurations) and where and when each set is deployed (effort), information that is typically included in the reported logbook data.

#### 2.2.1. Gear configurations

The US pelagic longline fleet has historically targeted swordfish, yellowfin tuna and bigeye tuna, with species targeting accomplished through different gear configurations for each target species. These configurations can be partitioned by hook type, numbers of light sticks deployed, bait type and the numbers of hooks between floats (Table 1). Each of the gear variables has four levels, resulting in 256 possible gear configurations. LLSIM has the capacity for 1000 gear configurations, either within one fleet or across several fleets. The available gear combinations that were actually observed in the logbooks yielded 128 discrete gear configurations over the 29-year period. These gear configurations were not constant over the entire time span, differences in targeting and changing regulations dictated which gear was available for each month and year. Each defined gear is represented in a separate input file and is only used by LLSIM if specified by the effort input file. The gear file consists of the essential gear coefficient (k) further discussed in Section 2.3.2, the number of hooks between floats (HBF), the fraction of time the set fishes in daylight, and at each hook position, the average fraction of time the hook spends in each of the 46 depth layers (the depth probability matrix). The daylight fraction had values of 0, 0.25, 0.5, 0.75 or 1. These fractions were calculated from the beginning soak time to the time at the end of haulback from entries in the logbook, considering sunset and sunrise time for the average latitude of the set. Each gear configuration fraction was calculated from the average daylight fraction from all the sets using the specific configurations. An additional descriptor in the gear file denotes the important features of the gear that contribute to the value of the gear coefficient for that gear type (i.e. hook type, light sticks, and bait type).

The initial depths used for the depth probability matrix in the gear files were calculated from the gangion and floatline lengths reported in

**Table 1**

Variables included in gear definitions. Latitude and longitude in one ° cells, HBF = hooks between floats.

| Variable          | Range/Values                    |
|-------------------|---------------------------------|
| Year              | 1986–2015                       |
| Month             | 1–12                            |
| Lat.              | –30 °S to 53 °N                 |
| Long.             | –95 °W to 15 °E                 |
| HBF (4 levels)    | 2–6                             |
| Hook (4 levels)   | Circle, J-hook, combo, unknown  |
| Bait (4 levels)   | Live, dead, artificial, unknown |
| Lights (4 levels) | 0, 1–500, 501–1500, unknown     |

the logbooks. The total depth (gangion plus floatline lengths) for each set within a gear were used to find the probability of a hook being at a certain depth depending on its location between floats (hook location 1,2,3, etc). The average depth across all the sets reported in the logbook for each gear (1–128) were used to populate the hook depth probability matrix. The probabilities of each hook being in each depth layer were found using a Gaussian probability density function using the mean ( $\mu$ ) and standard deviation ( $\sigma$ ) of depths for each gear configuration from the logbook.

Shoaling and sagging are important features of actual fishing depth for longline gear. The catenary approach was not used to account for these effects due to a lack of detailed information in the logbooks, specifically the “sagging rate”, necessary for the calculation (Yoshihara, 1954; Rice et al., 2007). To account for the different depths that hooks occupy based on their position between floats and to account for bias in the reported depths due to currents and drag within the water column, hooks were skewed to a depth 40–60% shallower than the gear average that was reported in the logbooks. Because of gear symmetry and since the maximum HBF configuration in the US data was 6 HBF, the hooks could occur in a maximum of three possible depth situations. These include: 1 with 2 HBF, 2 with 3 and 4 HBF, and 3 with 5 and 6 HBF (Fig.1). 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 proportions in each depth layer were then estimated from the adjusted mean 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. The LLSIM framework is capable of incorporating spatiotemporal variability in shoaling patterns, but models and data to drive that variability have yet to be developed. For now, shoaling is assumed constant for a gear type and is embedded in the depth probability matrix. However, spatiotemporal variability in shoaling could be included in the simulations by using different gears (with different shoaling) in time-space strata where the differences can be quantified.

2.2.2. Distribution of fishing effort

Our intent was to provide a realistic logbook catch and effort data set by modeling real fishing activity as closely as possible without compromising data confidentiality. Sets were removed when less than three vessels fished in the same 1.0° latitude and longitude cell to protect data sources. All set locations were randomly jittered by adding or subtracting 1–5° of latitude and longitude. A large sample of longline

sets was creating from bootstrapping and 297,000 sets were randomly selected, replicating the original amount of usable longline sets, with similar spatiotemporal distributions. These were processed to produce an effort file that defined the year, month, location and gear configuration (1–128) for each set used in the simulation. This approach provided a shareable file of fishing effort for a hypothetical fleet with real-world relevance to the analysis of patterns of fishing for the US longline fishermen.

2.3. Simulations

2.3.1. General protocol

The longline simulator proceeds, hook by hook, for each hook and layer depth for each longline set included in the simulation. The location of each included set and the identity of the corresponding gear configuration are read from a file describing the effort of the US longline fleet. Each gear configuration is defined in a separate gear file, and is assumed to consist of an arbitrary number of “baskets” of longline segments. Each basket is considered to be identical. The gear file contains the overall average essential catchability by species ( $k_{s,g}$ ), the fractions of time fished during hours of darkness and daylight, and the fractions of time spent in each depth layer for each hook position ( $F_{g,h,l}$ ), the hook depth probability matrix. As the datasets used here only contained one species, blue marlin, the  $s$  subscript is equal to 1, however, it is possible to include up to 20 species in the simulations. The number of baskets fished during the set is read from the effort file. Each basket of gear is assigned to be fished either in daylight or darkness based upon the fractions of time fished by the gear in those hours. A probability is calculated for catch on the hook at each species and depth based on the essential gear catchabilities, hook fractions, and species densities ( $D_{s,lat,lon,l,t}$  at the location (latitude, longitude and depth layer) and time fished. These are summed over all depths fished to give a total probability for the hook as:

$$p = \sum_{s=1}^S \sum_{l=1}^L k_{s,g} F_{g,h,l} D_{s,lat,lon,l,t} \tag{1}$$

The effect of soak time is not explicitly modeled but is subsumed into catchability. The computed value of the probability  $p$  is then entered into a Monte Carlo procedure to generate a random number to determine if the hook actually catches a fish. If so, the partial probabilities are used to select the species (if more than one species being simulated), and to track capture depths for studying model performance. The program continues with the next hook in the basket, then the next basket until all of the hooks on the set have been evaluated (Fig. 2) and the simulated catch dataset is output for analysis.

Catch on a hook ( $C_h$ ) is evaluated as a probabilistic event such that:

$$C_h \cong kDN \tag{2}$$

Where  $N$  is the population size, and  $D$  is the average relative density of the species in the cells around the hooks.  $C_h$  has a distribution equivalent to the distribution of  $D$  with a mean proportional to  $kN$ . The

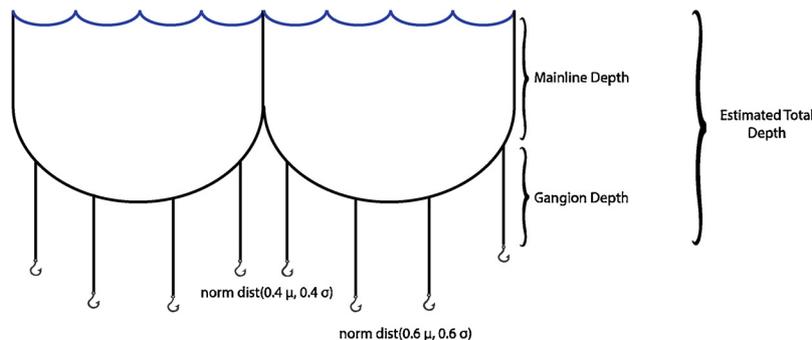


Fig. 1. Schematic of construction of hook depth probability matrix.

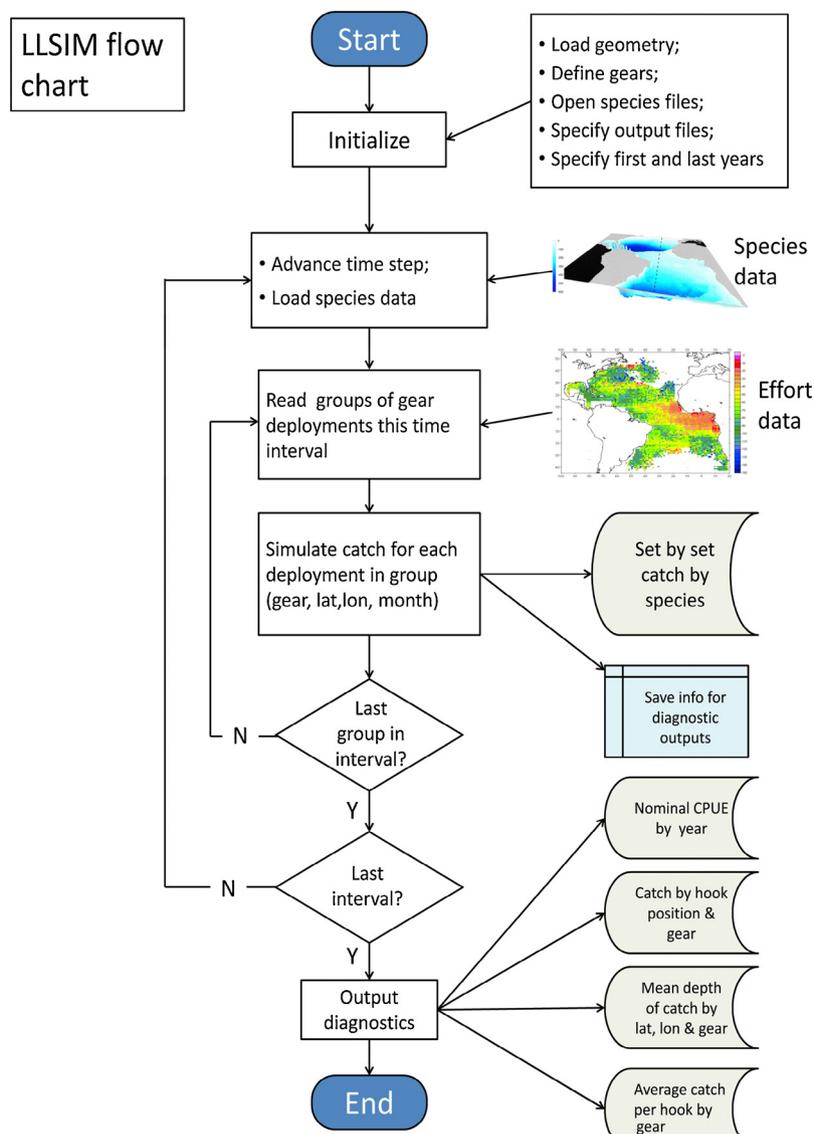


Fig. 2. Flow chart for longline simulator computations (Source: LLSIM User's Manual).

value of  $D$  is defined by the hook depth and species distributions and is not amenable to change. Likewise,  $N$  is defined by the user, in this case, as the constant or declining population values for the time when the simulated set was deployed. Therefore, the gear coefficient  $k$  is the free parameter which contains the scalar that controls the average catch rate.

### 2.3.2. Scaling the catch

LLSIM is intended to simulate sampling of population abundance not fishing mortality. Consequently, the approach employs sampling with replacement in which catches are not removed from the population. One requirement of the simulations is that there should be reasonable agreement in the scale of the catch numbers between simulated and actual data so that simulated data will be relevant to real-world problems. There is a protocol to perform this estimation using average CPUE from a fishery. To obtain initial values of  $k$ , a Poisson GLM was run using the total fish caught in numbers as a function of hooks between floats, hook type, bait type, and number of lightsticks deployed. This results in a gear specific  $k_g$  given the gear configuration. From there, an automated process was employed through a program (RevK). RevK is a separate program intended as a tool to automate the process of adjusting the scalar for model-to-real population units by setting the value of the model's gear essential catchability,  $k$ , to obtain CPUE

simulations of the correct magnitude. The RevK program reads the average CPUE for each gear (and species, if more than one) from output files resulting from a previous run of LLSIM. It also reads the desired magnitude of the CPUE mean for each gear and species from a file containing the true CPUE for each gear configuration. New values of  $k$  are calculated based on the ratios of the simulated desired CPUEs. LLSIM is then run again with the updated gear files with the new  $k$  values. This is an iterative process until the correct magnitude of CPUE is achieved. When the  $k_g$  are estimated using this approach the differences among gears are estimated from the observational data rather than imposed as variables in the simulation. Because of this convention, the values of  $k_g$  reflect the effects of light sticks, bait type and hook type in the CPUE observations for those gears in the fishery itself and were not imposed as a part of the simulation. Detailed information on the program, and specific data input file requirements are discussed in depth in the Longline Simulator User's Manual (Goodyear, 2018).

### 2.4. CPUE standardizations

Two GLM CPUE standardization models were applied to the constant catch population dataset produced by LLSIM. One model contained all the available variables output by LLSIM and the other contained only those variables specific to the time and area of the sets.

**Table 2**  
Final model structure for the two delta lognormal GLMs.

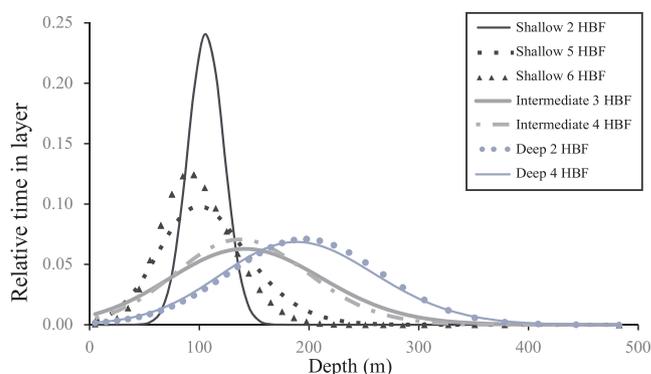
| GLM    | Binomial Model   | Abundance Model   |
|--------|--|---|
| Simple | Pos/total = factor(year) + factor(area) + factor(month)  | lnCPUE = factor(year) + factor(area) + factor(month)  |
| Full   | Pos/total = factor(year) + factor(area) + factor(month) + factor(hbfb) + factor(hook) + factor(bait) + factor(lightsticks) | lnCPUE = factor(year) + factor(area) + factor(month) + factor(hbfb) + factor(hook) + factor(bait) + factor(lightsticks) |

These models were developed using the delta lognormal framework and were run in R with the packages lsmeans and glmmADMB (Lenth, 2016; Fournier et al., 2012). The final model structures for both models are listed in Table 2. The fits of the resulting standardized trends were compared to the known, true population trend using the root mean square error to contrast the reliability of alternative CPUE standardization methods.

### 3. Results and discussion

This study sought to evaluate the feasibility of employing LLSIM to investigate methods for standardizing longline CPUE. An SDM suitable for the purpose was already available for blue marlin (Goodyear, 2016). Corresponding effort data for the US longline fishery adapted here for use in the LLSIM highlight issues about common assumptions used to estimate abundance. The number of hooks between floats is often used to stratify longline data for standardizations using a GLM. Fishing depth is important because of species behavior, but it is also usually unknown or poorly estimated. Historically, higher HBF were believed to be associated with fishing deeper because of increased sagging, and it was used as a proxy for fishing depth (Bigelow et al., 2006). The hook depths used in this study were derived from logbook information that reflected species targeting and the gear profiles did not strongly support this assumption. The average amount of time fished by hooks can be estimated for each depth layer for each hook and gear during a simulation. The results for selected gears during the simulations here illustrate the implications of this assumption (Fig. 3). Some gears with 2 HBF fished deeper than other gears with 4 or 6 HBF. Blue marlin are strongly surface oriented, and catch rates on individual gears are highest for the shallowest hook position for gears in the actual fishery (Goodyear et al., 2008; Yokawa and Uozumi, 2001) and in the simulations. Both observations support pooling data by HBF. Additionally, HBF is usually a significant factor in the GLMs, including here. However, the simulation details reveal that this result can be a spurious consequence of the dominance of a few gears in pooled strata which are actually undermined by other substrata. LLSIM provides the means to test for alternative, potentially more powerful, stratification schemes for actual situations, as well as more academic explorations of the general problem.

The trends in nominal CPUE indices for the two simulated datasets were superficially similar to the nominal CPUE index obtained from the actual US longline logbooks (Fig. 4). The declining nominal trend for the constant population can only have been caused by spatiotemporal patterns in the distribution of fishing effort, including depths fished, that are embedded in the simulations. These are instances of the features hypothesized by Walters (2003) and Bigelow and Maunder (2007) to have undermined Myers and Worm’s (2003) conclusions about a rapid worldwide depletion of predatory fish communities and helped to focus attention on issues related to standardization (Hampton et al.,



**Fig. 3.** Realized fishing depths during the simulation of several gear configurations selected to demonstrate the variability of hook depth.

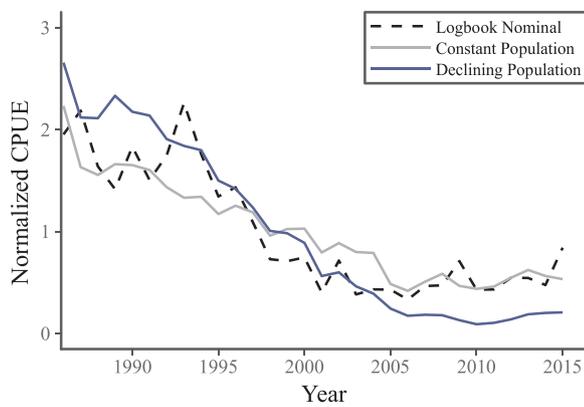


Fig. 4. Normalized nominal CPUE's for US logbook (dashed line), LLSIM catch dataset from a constant population (grey) and LLSIM catch dataset from a declining population (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

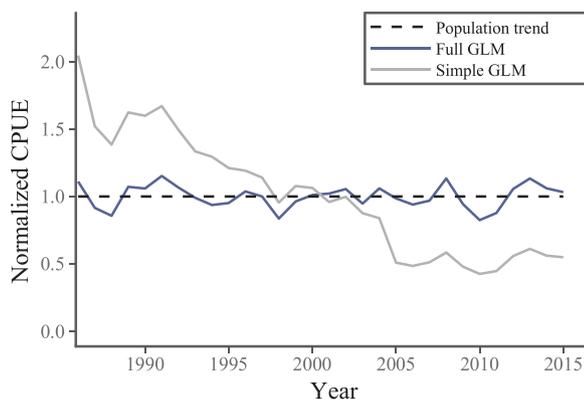


Fig. 5. Standardized CPUE indices obtained from generalized linear model taking into account spatio-temporal shifts and gear configurations (Full GLM – blue) and generalized linear model only containing spatio-temporal information (Simple GLM – grey). Black dashed line represents the underlying population trend. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

2005). Although the three trends in Fig. 4 are superficially similar, closer inspection reveals that the nominal CPUE for the declining population exhibited the largest dynamic range and ended lower. Also, while the decline for the constant population was relatively constant, the values for the actual fishery declined from about 1994 to 2002 and then were about constant thereafter. This difference suggests the actual trends in CPUE in the fishery is unlikely to be explained simply by the temporal patterns of fishing areas and gears used.

The GLM standardizations of the simulated data demonstrated the utility of studying alternative standardized models using simulated data (Fig. 5). The application of the full and simple GLM's exhibited very different outcomes. The results from the simple GLM model showed a monotonic decline in the population, overestimating the true population in the earliest years and underestimating it in the most recent years. In contrast, the full GLM model was able to account for the gear-area effects and eliminate the spurious trend that existed in the nominal and simple GLM results. Uncorrected error remained that may have included residue from inappropriate pooling of HBF. However, the addition of gear specific variables to the simple model, which only contained spatiotemporal information on sets, vastly improved the fit to the true population trend (RMSE improved from 0.44 to 0.08). The inclusion of gear variables is not novel in standardization approaches, but the use of simulated data allows for results to be compared with true values which are never known for “real-world” data.

#### 4. Conclusions

LLSIM is a tool for creating longline datasets for experiments that simulate field data as a precursor for applying a statistical or other method of analysis. The approach outlined here decouples the processes of modeling the population distribution from those associated with the fishery in a way that allows for complex but controlled simulation experiments to be performed. The simulated data are catch by species and gear for each set and at a spatiotemporal resolution of 1° and month and year. This detail allows complex interactions to be included in statistical or other analyses.

LLSIM approaches the CPUE evaluation as a sampling problem and does not internally evaluate mortality or changes in abundance within season or space. Depending on circumstance, such features can be accommodated by coupling LLSIM with an age-structured population simulation. If different age or sex partitions of the population exhibit different spatiotemporal behaviors, they can be accommodated simultaneously as different species cohorts. These cohorts can exhibit their own spatial distributions and temporal abundances consistent with the population simulations. The monthly temporal time step allows within-season abundance to be evaluated monthly. This approach can provide age-sex structured data for analysis. However, depending on the thrust of particular investigations other approaches may be less cumbersome or otherwise more appropriate.

This document describes the basic method for developing datasets from real-world longline fisheries to be used in the simulator and demonstrates their utility. These datasets were applied in another study to identify best practices for longline catch and effort standardizations (Forrestal et al., 2019). Alternatively, simulated datasets can be designed to investigate the robustness of methods applied in connection with specific stock assessments as in Goodyear et al. (2018a,b), or a host of other specific issues. As with real data, findings from simulations are always only as robust as permitted by the design of the experiments. Much can be learned because the nature of the errors is different, and experiments can be shaped to study many different situations.

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#### References

- Anon, 2016. Report of the 2015 meeting of the ICCAT Working Group on Assessment Methods. Collect. Vol. Sci. Pap. ICCAT 78 (8), 2249–2303.
- Bigelow, K., Musyl, M.K., Poisson, F., Kleiber, P., 2006. Pelagic longline gear depth and shoaling. Fish. Res. 77, 173–183.
- Bigelow, K.A., Maunder, M.N., 2007. Does habitat or depth influence catch rates of pelagic species? Can. J. Fish. Aquat. Sci. 64, 1581–1594.
- Bigelow, K.A., Hampton, J., Miyabe, N., 2002. Application of a habitat-based model to estimate effective longline fishing effort and relative abundance of Pacific bigeye tuna (*Thunnus obesus*). Fish. Oceanogr. 11 (3), 143–155.
- Caputi, N., Melville-Smith, R., de Lestang, S., Pearce, A., Feng, M., 2009. The effect of climate change on the western rock lobster (*Panulirus cygnus*) fishery of Western Australia. Can. J. Fish. Aquat. Sci. 67 (1), 85–96.
- Campbell, R.A., 2016. A new spatial framework incorporating uncertain stock and fleet dynamics for estimating fish abundance. Fish. Fish. 17, 56–77.
- Carlisle, A.B., Kochevar, R.E., Arostegui, M.C., Ganong, J.E., Castleton, M., Schratwieser, J., Block, B.A., 2017. Influence of temperature and oxygen on the distribution of blue marlin (*Makaira nigricans*) in the Central Pacific. Fish. Oceanogr. 26, 34–48.
- Carruthers, T.R., Ahrens, R.N.M., McAllister, M.K., Walters, C.J., 2011. Integrating imputation and standardization of catch rate data in the calculation of relative abundance indices. Fish. Res. 109, 157–167.

- Carruthers, T.R., McAllister, M.K., Ahrens, R.N.M., 2010. Simulating spatial dynamics to evaluate methods of deriving abundance indices for tropical tunas. *Can. J. Fish. Aquat. Sci.* 67, 1409–1427.
- Danabasoglu, G., Bates, S.C., Briegleb, B.P., Jayne, S.R., Jochum, M., Large, W.G., Peacock, S., Yeager, S.G., 2012. The CCSM4 ocean component. *J. Clim.* 25, 1361–1389.
- Fournier, D.A., Skaug, H.J., Ancheta, J., Ianelli, J., Magnusson, A., Maunder, M., Nielsen, A., Sibert, J., 2012. AD Model Builder: using automatic differentiation for statistical inference of highly parameterized complex nonlinear models. *Optim. Methods Softw.* 27, 233–249.
- Forrestal, F.C., Schirripa, M., Goodyear, C.P., Arrizabalaga, H., Babcock, E.A., Coelho, R., Ingram, W., Lauretta, M., Ortiz, M., Sharma, R., Walter, J., 2019. Testing robustness of CPUE standardization and inclusion of environmental variables with simulated longline catch datasets. *Fish. Res.* 210, 1–13.
- Goodyear, C.P., 2006a. Performance diagnostics for the longline CPUE simulator. *Collect. Vol. Sci. Pap. ICCAT* 59 (2), 615–626.
- Goodyear, C.P., 2006b. Simulated Japanese longline CPUE for blue marlin and white marlin. *Collect. Vol. Sci. Pap. ICCAT* 59 (1), 211–223.
- Goodyear, C.P., Luo, J., Prince, E.D., Hoolihan, J.P., Snodgrass, D., Orbesen, E.S., Serafy, J.E., 2008. Vertical habitat use of Atlantic blue marlin (*Makaira nigricans*): insights into interaction with pelagic longline gear. *Mar. Ecol. Prog. Ser.* 365, 233–245.
- Goodyear, C.P., 2016. Modeling the time-varying density distribution of highly migratory species: Atlantic blue marlin as an example. *Fish. Res.* 183, 469–481.
- 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>.
- Goodyear, C.P., Forrestal, F., Schirripa, M., Lauretta, M., 2018a. Standardizing US Blue Marlin Longline CPUE Using Habitat Covariates. SCRS/2018/017. .
- Goodyear, C.P., Schirripa, M., Forrestal, F., Lauretta, M., 2018b. Habitat Covariates for Standardizing Longline CPUE: An Example with Blue Marlin. SCRS/2018/018. .
- Hampton, J., Sibert, J.R., Kleiber, P., Maunder, M.N., Harley, S.J., 2005. Decline of Pacific tuna populations exaggerated. *Nature* 434 (April), E1–E2 2015.
- Hinton, M.G., Nakano, H., 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. IATTC* 21, 171–200.
- Lee, S.-K., Park, W., van Sebille, E., Baringer, M.O., Wang, C., Enfield, D.B., Yeager, S.G., Kirtman, B.P., 2011. What caused the significant increase in Atlantic Ocean heat content since the mid-20th century? *Geophys. Res. Lett.* 38, L17607.
- Lenth, R.V., 2016. Least-squares means: the R package lsmeans. *J. Stat. Softw.* 69 (1), 1–33.
- Long, M.C., Lindsay, K., Peacock, S., Moore, J.K., Doney, S.C., 2013. Twentieth-century oceanic carbon uptake and storage in CESM1 (BGC). *J. Clim.* 26, 6775–6800.
- 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.
- Myers, R.A., Worm, B., 2003. Rapid worldwide depletion of predatory fish communities. *Nature* 423, 280–283.
- Perry, A.L., Low, P.J., Ellis, J.R., Reynolds, J.D., 2005. Climate change and distribution shifts in marine fishes. *Science* 308 (5730), 1912–1915.
- Prince, E.D., Goodyear, C.P., 2006. Hypoxia-based habitat compression of tropical pelagic fishes. *Fish. Oceanogr.* 15, 451–464.
- 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.
- Thorson, J.T., Fonner, R., Haltuch, M.A., Ono, K., Winker, H., 2016. Accounting for spatiotemporal variation and fisher targeting when estimating abundance from multispecies fishery data. *Can. J. Fish. Aquat. Sci.* 73, 1–14.
- Walters, C.J., 2003. Folly and fantasy in the analysis of spatial catch rate data. *Can. J. Fish. Aquat. Sci.* 60, 1433–1436.
- Yokawa, K.Y., Uozumi, Y., 2001. Analysis of operation pattern of Japanese longliners in the tropical Atlantic and their blue marlin catch. *Collect. Vol. Sci. Pap. ICCAT* 53, 318–336.
- Yoshihara, T., 1954. Distribution of fishes caught by the long line IV. On the relationship between  $k$  and  $\phi$  with a table and diagram. *Bull. Japan. Soc. Sci. Fish.* 19 (10), 1012–1014.