SCRS/2015/031 Collect. Vol. Sci. Pap. ICCAT, 72(8): 2313-2317 (2016)

PROPOSED STUDY DESIGN FOR BEST PRACTICES WHEN INCLUDING ENVIRONMENTAL INFORMATION INTO ICCAT INDICES OF ABUNDANCE

Michael J. Schirripa[1] and C. Phillip Goodyear[2]

SUMMARY

It is now a generally accepted fact that variation in the plant's climate and its effects on the worlds ocean is increasing. Given this increased variation, the relatively narrow tolerance levels for temperature and highly migratory nature of the tuna and tuna like species under the management of ICCAT, methods of accounting for responses of tuna to their changing environment are timely and necessary. Most important is how these factors manifest themselves in indices of abundance; in the case of ICCAT, indices of catch-per-unit effort (CPUE). The study design proposed here will use a longline simulator as an operating model to generate data sets in which the true stock abundance and environmental are known with certainty. These data sets will then be analyzed with two comparative methods: (1) using the environmental data as a covariate in the standardization of CPUE via a generalized linear model, and (2) use of the data within the stock assessment model explicitly to modulate catchability. The criteria used to evaluate each method will include goodness of fit, degree of uncertainty, and model parsimony.

RÉSUMÉ

C'est désormais un fait généralement accepté que la variation climatique de la planète et ses effets sur les océans du monde sont en augmentation. Compte tenu de cette variation accrue, des niveaux de tolérance relativement étroits de la température et du caractère hautement migratoire des thonidés et des espèces apparentées relevant de la gestion de l'ICCAT, il est opportun et nécessaire de disposer de méthodes qui expliquent les réponses des thonidés face au changement de leur environnement. Il est plus important encore de comprendre comment ces facteurs se manifestent dans les indices d'abondance ; dans le cas de l'ICCAT, dans les indices de capture par unité d'effort (CPUE). Le plan d'étude proposé dans le présent document utilisera un simulateur palangrier comme modèle opérationnel pour générer des jeux de données dans lequel la véritable abondance du stock et l'environnement sont connus avec certitude. Ces jeux de données seront ensuite analysés avec deux méthodes comparatives : (1) en utilisant les données environnementales comme covariables dans la standardisation de la CPUE par un modèle linéaire généralisé ; et (2) en utilisant explicitement les données du modèle d'évaluation des stocks pour moduler la capturabilité. Les critères utilisés pour évaluer chaque méthode incluront la qualité de l'ajustement, le degré d'incertitude et la parcimonie de modèle.

RESUMEN

Actualmente, es un hecho generalmente aceptado que la variación climática del planeta y su efecto en los océanos está aumentando. Teniendo en cuenta esta creciente variación, los relativamente pequeños niveles de tolerancia para la temperatura y el carácter altamente migratorio de los túnidos y especies afines que recaen bajo el mandato de ICCAT, sería oportuno y necesario disponer de métodos para representar las respuestas de los túnidos a su entorno cambiante. Lo más importante es cómo se manifiestan estos factores en los índices de abundancia y, en el caso de ICCAT, en los índices de captura por unidad de esfuerzo (CPUE). El diseño de estudio propuesto utilizará un simulador de palangre como modelo operativo para generar conjuntos de datos en los que se conozca con certeza la verdadera abundancia del stock y el medio ambiente. Estos conjuntos de datos se analizarán con dos métodos comparativos: (1) usando los datos medioambientales como una covariable en la estandarización de la CPUE mediante un modelo lineal generalizado y (2) usando los datos dentro del modelo de evaluación de stock explícitamente para modular la capturabilidad. Los

[1] NOAA Fisheries, Southeast Fisheries Center, Sustainable Fisheries Division, 75 Virginia Beach Drive, Miami, FL, 33149-1099, USA. Email: Michael.Schirripa@noaa.gov
[2] Independent Scientist, 1214 N Lakeshore Drive, Niceville, FL, USA. phil_goodyear@msn.com

criterios utilizados para evaluar cada método incluirán la bondad del ajuste, el grado de incertidumbre y la parsimonia del modelo.

KEYWORDS

Catch/effort, environmental factors, climatic data

Introduction

It is now a generally accepted fact that variation in the plant's climate and its effects on the worlds ocean is increasing. For marine fish, specifically those of the highly migratory nature, this increased climate variation has led to changes in distribution, migratory patterns, and susceptibility to various fishing gears. Many of these changes have created situations where there is no historic analog to the current climatic and biological conditions. These changes become especially problematic when they manifest themselves through the fishery dependent indices of abundance (such as catch-per-unit-effort) used to assess the status of the stocks, such as is done routinely by ICCAT.

One of the key aspects of CPUE interpretation is the catchability factor, usually denoted by *q*. The q parameter denotes the extent in which the population at large is available to the gear from which the CPUE is derived. CPUE is function of both stock abundance and the *q* of the fishing gear, however these two factors are many often times convoluted. For example, the population size of the stock could remain relatively stable year-to-year, but changes other time dependent functions, (e.g. species distribution, gear configuration, species targeting) can result in changes in *q* that will in turn result in variations in the estimated CPUE, despite the constant stock size. In this way, time varying *q* is especially troublesome.

The SCRS has already recommended that work be undertaken to determine how best to incorporate environmental variables into the stock assessment process. The objective of this writing is to propose the overall approach and methodology of a study to address this request, the results of which will be used to arrive at "best practices" recommendations. While the study will be designed around catchability of (swordfish?), the results should be able to provide much more universal guidance on the handling and use of environmental data.

Material and methods

Simulation methods – Previously, the ICCAT Methods Working Group recommended the use of simulated data sets with known values of underlying population trends to test the robustness of CPUE standardization methods (Anon. 2004). A longline CPUE data simulator (LLSIM) was developed to meet this requirement to simulate known data for testing a variety of hypotheses (Goodyear 2006). The core element of the simulation is the catch on a single hook of a longline set. Each hook has a depth probability distribution and attributes of latitude, longitude, year, month, time of day, and position along the longline. Each of these attributes is associated with the individual longline set. The catch is a probabilistic event and is simulated for each hook of each set. Several species and species groups can be simulated simultaneously, permitting the inclusion of species competition. The catch on the hook is based on the local species densities and their relative catchabilities. Species densities may vary by latitude, longitude, year, month, and depth and are externally specified. The simulator has been applied to evaluate several aspects of longline data related to effects of environmental attributes and the implications of shifts in species targeting by the fisheries (Goodyear and Bigelow 2010, Goodyear and Bigelow 2012, Schirripa and Goodyear 2012).

Spatial detail – The X-Y spatial structure of the simulator is from 45S to 55N latitude and 95W to 20E longitude, exclusive of major land masses (**Figure 1**). This area is broken down into 6224 cells; each cell is 1 degree of latitude by 1 degree of longitude. All spatial distributions of input and output variables reference an array of cell identities. Each longitude-latitude cell is also divided into 46 depth strata. The number and depth of the depth strata are arbitrary, but the number of depth layers cannot easily be increased because of array size limitations. The depths of each layer can be readily adjusted.

Longline sets – The longline effort for each simulation is defined by the gear specifications in two files. The first defines each gear in terms of the number of hooks per basket and the proportion of time fished in each depth layer below the surface. The second file specifies the number and locations of sets of each gear in each longitude-latitude cell for each month and year of the simulation. The gears fished and their distribution in time and space are externally derived and consequently may be specified randomly or from some design consideration. We propose that this study use a suite of gears that best represent the data sets used to construct the abundance indices used in the stock assessment model fits. This may require random assignments of sets from larger spatial resolutions to the 1° x 1° resolution of the simulator.

Species – The program is designed to simulate longline catch of 1 to 6 species at a time. Each species may be partitioned into 4 sex-age groupings as needed to reflect dissimilar distributions and behaviors of different life history assemblages of the species populations. Where appropriate, one or more of the "species" could also be an aggregate of "other species" to account for competition for hooks. Species data required for 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 gives the actual densities relative to each hook for the simulation. We propose that this study use several possible vectors for population abundances. One of these should replicate the best case result from the most recent assessment. Others should include arbitrary upward, downward, constant, and fluctuating population trends. At least one trend should include separate treatment of juvenile and adult swordfish. Inclusion of a species that exhibits important competition for baits may also be useful.

Inclusion of environment – Environmental variability is included by through its effect on population density by latitude, longitude, month, year and depth. Where not needed, as in the isolation of species targeting issues, the relative density can be assumed constant (e.g., see Schirripa and Goodyear, 2010). Other previous applications have use the yearly-averaged monthly distributions of CPUE, with vertical distributions predicted from monthly-average delta T assumptions by latitude and longitude, or have used environmental temperatures from the World Ocean Atlas monthly mean temperature data (Goodyear 2006, Goodyear and Bigelow 2010, Goodyear and Bigelow 2012, Ishii and Kimoto 2009).

In the proposed study, the environmental effect must be specified in latitude, longitude, month, year and, depending on assumptions about the gears to be included, also depth. Day length is one obvious variable to consider that has a predictable seasonal pattern but lacks annual variability. Temperature and dissolved oxygen vary both by month and year. Other measured environmental features may also predictably alter species distributions. We propose that the temporal species distributions should be modeled based on day length and/or year-month environmental temperature data at a minimum. It is important that the year effects be included can be used to replicate the trends in Atlantic Multidecadal Oscillation. Alternatives for possible null assumptions need more thought.

Output –The principal output is the simulated catch by species for each set. It gives the year, month, longitude, latitude, gear id, hooks per basket, total hooks fished, total baskets fished, and the number of individuals caught by species on each simulated set. The year, month, latitude, and longitude can be used to pair with environmental data, and the resulting combined data can be pooled for analysis using any pooling scheme that might be applied to the "real" datasets. These may include pooling various combinations of geographical areas, time, fleets, and/or hooks between floats.

Analysis Methods

The GLM Method. The first method is to include the environmental information as a covariate into the CPUE standardization process, generally accomplished through a general linear model. For instance, observations of sea surface temperature are included in the model statement in an attempt to discern if there is a significant effect from that parameter. This method works well if there sufficient CPUE observations spanning a wide enough range of sea surface temperatures. While this method may help reduce any *bias* in the mean CPUE estimates as a result of uneven sample of sea surface temperatures, it does not necessarily provide a more *accurate* index of abundance.

The Parameter Method. The second method of including environmental data into the assessment process is to allow the q parameter to be estimated within the assessment model, and to allow annual deviations in this parameter as dictated directly by the deviations in the environmental data as follows:

$$q_t = q_{base} * \exp(\beta * ENV_t)$$

where q_t is the catchability at time step t, q_{base} is the estimated mean q value, ENV_t is the environmental data at time step t, and β is an estimated parameter depicting the sensitivity of *q* to ENV. While this method allows *q* to vary directly at each time step, it does so in a manner that assumes no observation error in the environmental data.

The Data Method. The third method we will explore is a hybrid of the first method. By setting up annual deviations in *q*, as outlined in the first method, but treating the predicted deviations from the environmental data as informed Bayesian priors (complete with estimated annual error), we treat the environmental time series more like true data with observation error rather than annual fixed values that are followed without regard to the rest of the observational data. The negative log likelihood is penalized for deviating from the priors and so the remaining data sources are able to conflict with, or corroborate, the environmental data on equal terms.

Evaluation of Results

The results of this study will be evaluated from quantitative, as well as qualitative observations. We will not necessarily attempt to provide guidance as to whether or not environmental data *should* be used in any particular assessment, but rather *how* it should be used once the decision to include it has been made.

With regard to the GLM method, we will compare the unstandardized CPUE time series to the standardized by first looking for a significant "environmental effect" within the ANOVA process. If one exists, then a visual examination of the two trends will be used to determine if a meaningful difference exists.

With regard to the parameter method, we will examine the value and standard deviation of the estimated β parameter to determine if it has a value different from zero (denoting a significant value). However, since 95% confidence (i.e. 1.96 standard deviations) is a purely arbitrary significance level, we will also consider whether or not the log likelihood is reduced by at least 2 units given the addition of each new β parameter introduced into the model. This is essentially equivalent to applying the Akaike Information Criteria (AIC) which seeks to find the balance between model fit and model parsimony. A Bayesian Information Criteria will also be examined for further examination of model parsimony.

With regard to the data method, the inclusion of additional data is not as straight forward as the addition of model parameters. However, in the case of simulation testing, such as this, the determination of whether or not to include additional data is much more straight forward as we will have the actual, true population (and q) trajectories to compare against. In fact, all three methods will be compared to the actual known population trends in an effort to discern which is the most appropriate, based on accuracy.

Literature cited

Anon. 2004. Report of the 2003 meeting of the ICCAT Working Group on Assessment Methods. Collect. Vol. Sci. Pap. ICCAT, 56(1): 75-105.

Ishii, M. and Kimoto, M. 2009, Reevaluation of historical ocean heat content variations with time-varying xbt and mbt depth bias corrections. Journal of Oceanography: 65: 287-299.

Goodyear, C. P. 2006. Simulated Japanese Longline CPUE for Blue and White Marlin. Collect. Vol. Sci. Pap. ICCAT, 59(1): 211-223.

Goodyear, C. P. and K. A. Bigelow. 2010 Preliminary explorations of Cpue standardization of the U.S. longline observer sailfish data using STATHBS. Collect. Vol. Sci. Pap. ICCAT, 65(5): 1713-1724.

Goodyear, C. P. and K. A. Bigelow. 2012. Preliminary analyses of simulated longline atlantic blue marlin CPUE with HBS and generalized linear models. Collect. Vol. Sci. Pap. ICCAT, 68(4): 1510-1523.

Schirripa, M. J., and C. P. Goodyear. 2010. CPUE standardizations of species targeting in longline fisheries: initial investigations of the utility of simulated data for method verification

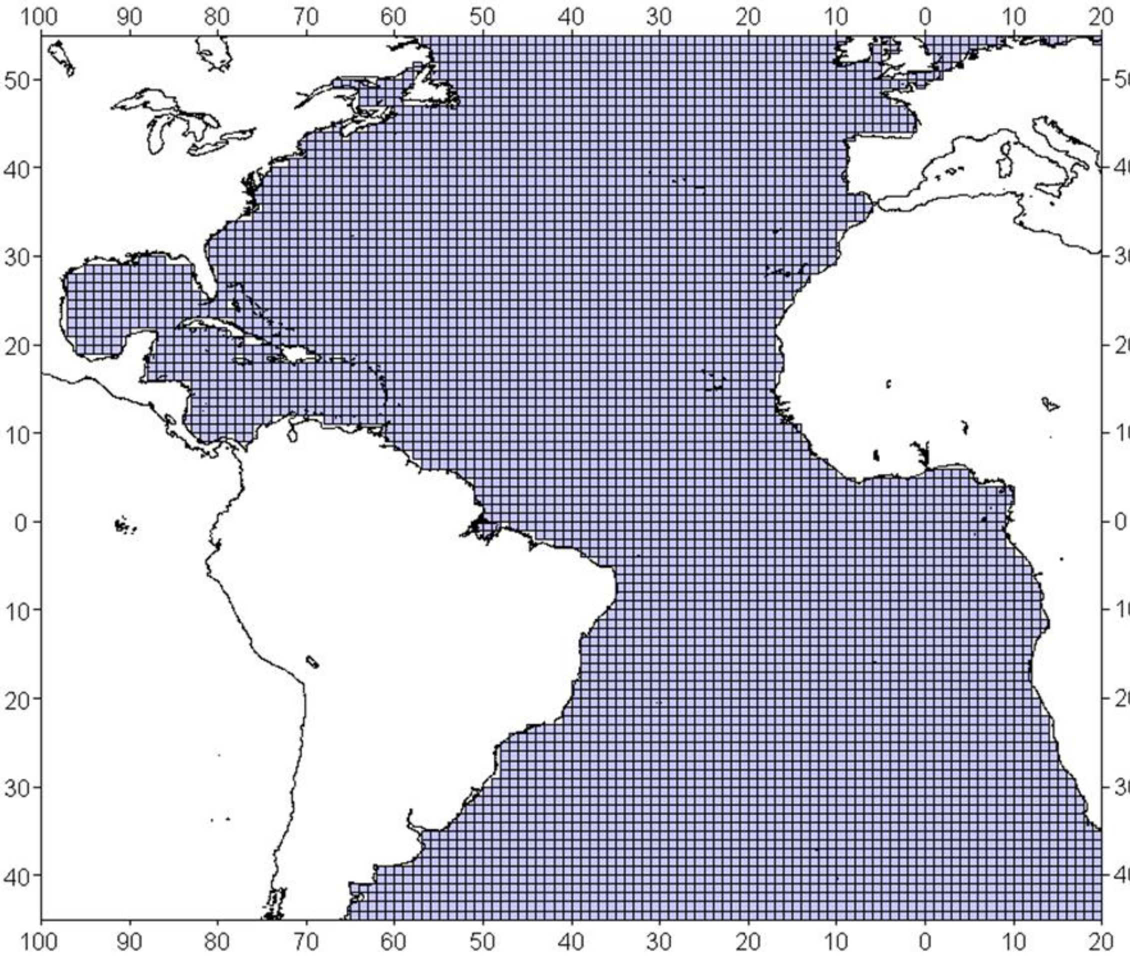

Figure 1. Spatial scale of the simulator.