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A REVIEW OF METHODS FOR ASSESSING THE IMPACT OF FISHERIES ON SEA TURTLES

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SUMMARY

There are growing concerns on the impacts of marine fisheries in vulnerable bycatch species, such as sea turtles. The International Commission for the Conservation of Atlantic Tunas (ICCAT) is preparing an assessment on the impacts of ICCAT fisheries on sea turtle populations, with the assessments scheduled to start in 2013, and the data preparation starting in 2012. Integrated in this process, this document was prepared to compile, describe and revise some currently available methodological approaches to analyse the interactions and impacts of fisheries on sea turtle populations. The following analysis are addressed: modelling (standardizing) bycatch rates, analysing and modelling mortality rates, studies on the effects of hook styles and bait types, and methods for conducting Ecological Risk Assessment (ERA). The issue of data overdispersion and zero-inflation, common on bycatch of pelagic longline fisheries is addressed, and some possible modelling alternatives are presented. Summary tables with a compilation of data useful for conducting an ERA on sea turtles impacted by ICCAT fisheries are provided.

RÉSUMÉ

Les impacts des pêcheries marines sur les espèces accessoires vulnérables, comme les tortues marines, suscitent de plus en plus de préoccupations. La Commission internationale pour la conservation des thonidés de l'Atlantique (ICCAT) prépare une évaluation sur les impacts des pêcheries de l'ICCAT sur les populations de tortues marines, les évaluations devant démarrer en 2013 et la préparation des données ayant débuté en 2012. Dans le cadre de ce processus, ce document a été élaboré pour compiler, décrire et réviser certaines approches méthodologiques actuellement disponibles afin d'analyser les interactions et les impacts des pêcheries sur les populations de tortues marines. Les analyses suivantes ont été abordées : modélisation (standardisation) des taux de prise accessoire, analyse et modélisation des taux de mortalité, études sur les effets des styles d'hameçons et des types d'appâts et méthodes visant à réaliser l'évaluation des risques écologiques (ERA). Le document présente la question relative à la surdispersion et à l'inflation des zéros dans les données, phénomène courant dans les prises accessoires des pêcheries pélagiques palangrières,ainsi que quelques alternatives possibles de modélisation. Il fournit des tableaux récapitulatifs contenant une compilation des données utiles pour réaliser une ERA sur les tortues marines affectées par les pêcheries relevant de l'ICCAT.

RESUMEN

Existe actualmente una inquietud creciente sobre el impacto de las pesquerías marinas en especies vulnerables de captura fortuita, como las tortugas marinas. La Comisión Internacional para la Conservación del Atún (ICCAT) está preparando una evaluación del impacto de las pesquerías de ICCAT en las poblaciones de tortugas marinas, con una evaluación programada para 2013, y la preparación de datos en 2012. Integrado en este proceso, este documento se preparó para recopilar, describir y revisar algunos enfoques metodológicos actualmente disponibles para analizar las interacciones e impactos de las pesquerías en las poblaciones de tortugas marinas. Se abordaron los siguientes análisis: modelación (estandarización) de tasas de captura fortuita, análisis y modelación de tasas de mortalidad, estudios de los efectos de los tipos de anzuelos y tipos de cebos y métodos para

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realizar evaluaciones de riesgo ecológico (ERA). Se abordó el problema de la sobredispersión y de los ceros aumentados en los datos, fenómeno común en la captura fortuita de las pesquerías de palangre pelágico, y se presentaron algunas posibles alternativas de modelación. Se proporcionan tablas con una compilación de datos útiles para realizar una ERA sobre tortugas marinas afectadas por las pesquerías de ICCAT.

KEYWORDS

Bycatch, CPUE standardization, data analysis, Ecological Risk Assessment, ICCAT, GLM and GAM models, hook-bait effects, mixed models, mortality rates, zero-inflation.

1. Introduction

There have been growing concerns on the impacts of commercial fisheries on vulnerable bycatch populations, including the sea turtles. The International Commission for the Conservation of Atlantic Tunas (ICCAT) is currently working on evaluating the interactions and impacts of tuna fisheries in sea turtle populations in the Atlantic Ocean. Population assessments are schedule for 2013, with data preparation and analysis of available methodologies starting in 2012. This process started with the compilation of the available information on the interactions with sea turtle populations that is presented by Coelho et al. (2013) in another ICCAT SCRS paper, and the compilation and discussion of possible methodologies for assessing the impacts, which are presented now in this document.

The aims of this paper are therefore to present and discuss some possible methodological approaches that can be used to infer on the impacts of fisheries in sea turtle populations. This paper reviews some of those methods, but it should be noted that different fisheries and fleets may have different specificities not necessarily covered in this document. We focus especially in what we believe are the more relevant and appropriate methods when addressing issues of relatively rare and generally data-poor bycatch species, such as the sea turtles bycaught in ICCAT fisheries.

2. Modeling sea turtle catch rates

Many stock assessment methods use information from relative indexes of abundance of the species of concern over time. Ideally, the data should be based on fishery-independent datasets, collected for example during scientific surveys using statistically adequate protocols (e.g. random sampling within predetermined *strata* such as area, season, year, etc). This type of data is very difficult to obtain and costly, as sampling collection occurs in the high seas. Therefore, and particularly when dealing with bycatch species (e.g. sharks, sea turtles, marine mammals sea birds) the only data available is usually based on fishery-dependent datasets (either fishery observer or logbook data), collected by commercial fishing vessels while operating during their normal fishing operations.

One commonly collected type of fishery-dependent data is catch and effort information from the fishery, usually presented as catch-per-unit-of-effort (CPUE). In pelagic longline fisheries, CPUEs are commonly presented either in number (e.g. N/1000 hooks) or biomass (e.g. Kg/1000 hooks). This data has the characteristic of not having been randomly collected (it is not independent), and therefore the direct CPUEs calculated from the “raw” data are usually referred to as “nominal” or “non-standardized” CPUEs. For transforming this data into a relative index of abundance, it is first necessary to adjust the data for the impacts of other factors other than the changing abundances of the catch rates over time, and this process is usually referred to as “CPUE standardization”. By doing this, it is possible to build a time series of the species CPUEs over time that in theory only reflects the changes in the species abundance, and where other effects, inherent to the fishery-dependence itself, have been removed.

Most of the currently used methods for standardizing CPUEs are done by fitting statistical models to the data. There are several modeling options available, the choice depending on the data itself and the underlying assumptions of each method. The sections below summarize some of these methods, and address a number of the issues and assumptions that each method implies. One particularly important issue that needs to be addressed when modeling CPUEs of relatively rare bycatch species (such as the sea turtles), is the fact that many fishing sets have zero catches, which results in a CPUE of zero for that particular fishing set. Maunder and Punt (2004) revised recent approaches used for catch and effort data standardization. While their work was not specific for sea turtles, it is applied for most bycatch species in general, as it has a strong focus on zero-inflated datasets.

2.1 Response variable

As mentioned before, when modelling sea turtle CPUEs, the response variable is usually presented as N of Kg per 1000 hooks. This is commonly used for longline fisheries, but the effort can be as any other measure of effort appropriate for each specific fishery (e.g. Km of net for net fisheries, hours of fishing or area covered for trawl fisheries, etc). In either case, those nominal CPUEs will result in a continuous variable. However, it is possible to address the issue of catch rates using different forms of response variables, particularly when addressing relatively rare bycatch species. The commonly used forms of the response variable in these models can be summarized as:

1) *Continuous variable*: This is possibly the most common case, where the response variable (nominal CPUE) is calculated as the catch in biomass (Kg) or number (N) per effort (e.g. Kg/1000 hooks; N/1000 hooks).

2) *Discrete variable (counts):* In such cases the response variable used in the models is the catch in numbers (e.g. N turtles per set), and the effort (N hooks) can be used as an offset variable to the models.

3) *Binary variable:* Given that sea turtle (as well as some other bycatch species) captures are relatively rare events, it is conceivable to use a simplified approach, in which the response variable is coded as a binomial variable. In such approach, the interpretation of this response variable would be, for example: 0 = fishing set with zero catches of the species of concern; 1 = fishing set with "at least" the capture of 1 specimen of the species of concern.

Depending on the type of the response variable, the models used are different, particularly the type of error distribution that can be assumed. If the response variable is the discrete counts then the most used options are Poisson and negative binomial (NB) distributions. Given that the response variable is often zero-inflated, then possible alternative approaches are Zero-Inflated Poisson (ZIP) and Zero-Inflated Negative Binomial (ZINB) models. When the response variable is continuous, the most commonly used approaches are the delta method, or some recent applications with tweedie exponential errors. In the simplified binomial approach, the models used are binomial, usually with a logit link function (logistic models).

2.2 Explanatory variables

Explanatory variables used for modelling CPUEs can potentially be any variable that is significant in terms of explaining part of the CPUEs variability. Traditional linear models can only use continuous explanatory variables, while analysis of variance (ANOVA) will only use categorical variables. When using generalized models such as Generalized Linear Models (GLM) or Generalized Additive Models (GAM), a combination of continuous and categorical explanatory variables can be used. Many studies will usually test for significance (and possibly include), the following potential explanatory variables:

1) Vessel, with each vessel corresponding the one vessel monitored in the fleet;
2) Year, used as a categorical variable, with each year corresponding to one year of the time series;
3) Month or season;
4) Location variables, usually either the study area divided into smaller areas (categorical variable), or the latitude and longitude of the study area.

Those are possibly the minimum explanatory variables typically used in CPUE standardization, but other variables that can also be tested for significance and used in the models include:

5) Temperature, usually the Sea Surface Temperature (SST);
6) Soaking time, typically the period of time between setting and retrieving the fishing gear;
7) Gangion size, the size of the monofilament gangion (section of the fishing gear fixed to the main line);
8) Branch line material, typically monofilament, multifilament, or wire for longline fisheries;

9) Hook style, categorical variable corresponding to the type of hook (e.g. circle, J-style or tuna hooks);

10) Bait type, categorical variable corresponding to the type of bait (e.g. hooks baited with squid vs. fish);

11) Some measure of *vessel size* (e.g. tonnage, length, or other).

These are just some examples of possible explanatory variables that can be used (tested) in the models. However, and for each specific case, the researchers that are familiar with the data and the fishery may ponder testing any other variables that they may consider relevant to the analysis. The essential idea is that any variable that can account for explaining part of the CPUE variability can and should be used (or tested) in the models. One important point to consider is that in these models with the objective of standardizing CPUE time series there is the need to keep the year variable in the models, even if the year effect is not significant.

Common approaches to test the significance of adding additional variables are likelihood ratio tests for comparing nested models, assuming that if significant differences in nested models are detected, then the most complete model (with an added variable) should be used. On the contrary, if no significant differences are detected in two nested models, then the simplified model should be used. Another approach is to use information criteria analysis, such as the Akaike Information Criteria (AIC) or the Bayesian Information Criteria (BIC) to measure the gain in information penalized by the increase in model complexity when additional variables are added. In theory such information criteria will result in the most parsimonious model.

Finally, it is also important to account for possible significant interactions between the explanatory variables in the models. Most modelling approaches will consider only the significant first degree interactions between pairs of variables, as higher degree interactions usually render the models too complex and difficult to interpret.

2.3 Models

2.3.1 Generalized Linear Models (GLM)

GLMs are possibly the most commonly used methods for standardizing catch and effort data (Maunder and Punt 2004). GLMs are a class of statistical models that generalize the classical linear model. One advantage of GLMs is that the explanatory variables may be continuous or categorical (or a mixture of the two types). Another important aspect (and limitation) is that these models are based on a linear predictor (based on a linear combination of the explanatory variables), and as such, the concepts of classical linear regression in terms of the estimation of the parameters in a linear predictor still applies. Important references on GLM modelling include the books by McCullagh and Nelder (1989), Dobson (2002) and Agresti (2002). Books with examples of applications of GLMs (and other models), and examples on how to program and run the models in R (R Development Core Team 2011), include the books by Faraway (2006) and Zuur et al. (2009).

In the classical linear model formulation, models have a Gaussian error distribution, and the link between the systematic component (linear predictor produced by the explanatory variables) and the random component is the identity function [$f(x)=x$]. The extensions that McCullagh and Nelder (1989) introduced with GLMs were that: 1) the data are not necessarily assumed to come from a Gaussian distribution and can come from any of the exponential family, and 2) the link function between the linear predictor and the random component may be any monotonic differentiable function. GLMs are therefore defined by the distribution of the response variable, and by the link function, i.e., on how the linear combination of the explanatory variables relate to the expected value of the response variable. The usual procedure for applying a GLM is: 1) establish the type of the response variable (as specified before in this paper); 2) select a distribution appropriate for the response variable, depending on the characteristics of the data (e.g. binomial for catch/no-catch data, Poisson or negative binomial for counts, Gaussian or gamma for continuous data, etc); and 3) use a link function appropriate to the distribution and the data, to link the systematic and random components.

One important assumption (and possibly limitation) within GLMs is that the relationship between the expected value of the response variable (after applying the link function) and the explanatory variables, must be linear. This assumption of linearity only applies to the continuous explanatory variables. If there are continuous variables in the model whose relationship with the response variable is non-linear, they can be included in the GLM models by: 1) using an appropriate link function as discussed before; 2) possibly by adding interaction terms between variables; 3) by transforming the explanatory variables, for example by raising to various powers or using fractional polynomials; and 4) by categorizing the continuous variable into several categories and treating it as a categorical explanatory variable. Mauder and Punt (2004) alert that raising covariates to high order powers should be used with care and only if absolutely necessary and, if needed, recommend the approach of discretizing and treating the variables as categorical.

An example of a study using this type of categorization of continuous variables was used by Pons et al. (2010) while standardizing catch rates for *C. caretta* in the SW Atlantic. In their study, Pons et al. (2010) had some continuous explanatory variables (e.g. SST and vessel characteristics) that were initially evaluated for linearity with non-parametric smoothing functions (splines). When the relationship of these variables with the dependent catch rate (in this case the log CPUE) was non-linear, the variables were split into categories before inclusion in the GLM model. This solved the problem of the non-linear relationship between the response variable and the linear predictor, and the model that was formulated verified this GLM modelling assumption.

2.3.2 Generalized Additive Models (GAM)

GAMs are semi-parametric extensions of GLMs that further extend the linear model by replacing the linear predictor with an additive predictor using smooth functions. As mentioned before, one of the assumptions and limitations of GLMs is that the response variable needs to be linear (after applying a link function) with the set of continuous explanatory variables. The previous section of this paper mentioned some alternatives that can be used when such relationships are non-linear (e.g. categorization, transformation), but in situations where there are highly non-linear and non-monotonic relationships, GAMs may be more appropriate. Guisan et al (2002) mentioned that due to this fact, GAMs are sometimes referred to as data-driven rather than model-driven models, because in GAMs the data determines the nature of the relationships between the response and explanatory variables, rather than assuming some form of a parametric relationship as is done with GLMs. Important references for these models are the book by Hastie and Tibshirani (1990), and the revision paper by Guisan et al. (2002), as well as other papers with examples of applications published in a special edition of Ecological Modelling (vol. 157, 2002).

An example of a GAM modelling approach for assessing interactions between sea turtles and fisheries was used by Murray (2011) for the U.S. dredge scallop fishery. The fishery in question is not an ICCAT fishery, but the approach can be applied for any fishery of interest, including ICCAT fisheries. The author used a GAM model with a Poisson distribution to model the expected turtle interaction rate in the fishery. Nine initial explanatory variables were selected based on the *a priori* knowledge of the fishery, specifically SST, depth, latitude, chlorophyll, use of a chain mat, time of day when the turtle was captured (categorized in six 4hr periods), number of hauls made on a trip, tons of scallops landed, and frame width of the dredge. Explanatory variable selection was carried out by a forward stepwise selection, and the final explanatory variables considered significant were the SST (non-linear smoothed variable), depth (non-linear smoothed variable), and use of a chain mat (categorical), with those variables cumulatively explaining 21% of the variation.

Another example of an application was recently presented by Winter et al (2011), that focused on another bycatch group also characterized by low catch rates, specifically sea birds captured in the U.S. Atlantic pelagic longline fishery. Even thought the species group focused was not the sea turtles, the analytical problems found for sea birds (low catch rates and high proportions of zeros) are similar to the case of sea turtles. In terms of models, the authors compared modeling approaches with GLMs, GAMs and GLMs for spatio-temporally autocorrelated observations. They used the delta method approach to deal with the zero observations, and that technique is also discussed in more detail below in this paper. In this example applied to sea bird bycatch, the final conclusions in terms of modeling approaches were that the GLMs gave the most consistent predictions of the total annual captures, and the authors recommended their use in future studies.

2.3.3 Mixed models (GLMM and GAMM)

While in GLMs and GAMs the parameters of the explanatory variables are considered as fixed constants, in mixed models some of the parameters are treated as random. Therefore, the Generalized Linear Mixed Models (GLMMs) and Generalized Additive Mixed Models (GAMM) extend the GLM and GAM approaches respectively, by allowing some of the parameters to be treated as random variables, allowing for the introduction of variability in the models. An important reference on mixed models is the book by McCulloch and Searle (2001), and a good revision with examples of applications was recently published by Zuur et al. (2009). This last book provides examples of applications and scripts to run these types of models in R.

In general, random effects in these types of studies seem to have been introduced mainly to deal with interactions between year and other categorical variables (e.g. area, season). An example of this is the study by Rodríguez-Marín et al. (2003) that used a GLMM to standardize bluefin tuna (*Thunnus thynnus*) CPUEs in the baitboat fishery off the Bay of Biscay. The final model selected included the explanatory variables year, age, month, number of crew, number of bait tanks, and the interaction year*month as a random component.

Another example of mixed models for CPUE standardization is the work by Chang (2003) that presented a document to ICCAT with white marlin catches from the Taiwanese fleet operating in the Atlantic Ocean. The author used GLMs and GLMMs under a lognormal model approach, using the main factors of year, quarter, area, and target. The first degree interactions considered were quarter*area, quarter*target and area*target for the GLM model, and year*area + year*quarter as random interactions in the GLMM. The response variable in these models was logCPUE calculated in biomass (Kg/1000 hooks), and the author dealt with the zeros in the response variable by transforming the CPUE into logCPUE + 10% mean (see sections below in this document for more details on this method).

In their study to standardize billfishes CPUEs for the Venezuelan pelagic longline fishery, Ortiz and Arocha (2004) also treated significant interactions that included the factor year as random. In this study the authors used a delta method approach to deal with the zero catches (discussed below in this paper), and started by selecting the set of fixed factors and interactions that were significant for each model (with each error distribution considered). Then, with the variable selection process completed, they treated all the interactions that included the factor year as random, and this allowed for the introduction of variability associated with year interactions. This process converted the original GLM into a GLMM. The significance of the random interactions was evaluated with likelihood ratio tests (comparing nested models), with the Akaike Information Criteria (AIC), and with the Schwarz's Bayesian information Criterion (BIC).

Another example with these types of mixed models is the recent study by Burgess et al. (2010) that presented a document to ICCAT reporting the bycatch of non-target species by the Maltese longline fleet targeting bluefin tuna. That fleet captures a series of bycatch species, including the loggerhead sea turtle (*C. caretta*), and the authors used GLMMs to model the bycatch rates both in number and weight of these bycatch species. The fixed explanatory variables used were wind speed, wind direction, temperature, lunar phase, date, latitude and longitude. In this case, the variables that were fitted as random were the observer and vessel factors, to account for variation associated with individual vessels and observers in the study.

2.4 Dealing with zero catches

Datasets of bycatch species CPUEs commonly have some (often many) fishing sets with zero catches. Those represent the fishing sets that existed (have an associated effort), but resulted in zero catches for the species of concern. This poses a mathematical problem in terms of modelling: for example, one possible way of commonly modelling catch rates is to use a log link in a GLM with some continuous distribution (e.g. Gaussian, gamma). However, in such cases, the fishing sets with zero catches (CPUE = 0) pose a particular problem, as the log of zero is undefined, and adjustments need to be made for accommodating those observations.

One possible solution that is sometimes used is to add a small constant (δ) to the calculated catch rates for all observations, in a way that the response variable CPUE is replaced by an adjusted CPUE (CPUE + δ). As mentioned by Campbell (2004), the value of δ is somewhat arbitrary, and that constitutes a problem, as the author of each particular study needs to decide what value should be added to the CPUE without biasing the results. One common practice in the past seems to have been using the value of 1 (e.g. one of the possibilities tested by Punt et al. (2000) when standardizing CPUEs of a coastal shark in Australia). Xiao (1997) adverts that very small values (e.g. 10^{-100}) should be avoided because of the properties of the log function as it approaches zero. Campbell (2004) recommends that setting δ to 10% of the overall mean catch rate in the analysis seems to minimize the bias for this type of adjustments.

However, the approach mentioned before may be more adequate when the number of zero observations is small, and several authors (e.g. Campbell 2004) advert that when many fishing operations result in zero catches, other alternative strategies such as the delta method (Lo et al. 1992) or models for counts that can incorporate observations of zeros (e.g. Poisson distribution) may be more appropriate. Maunder and Punt (2004) summarize the three classes of methods that can handle zero observations, specified as: 1) statistical distributions that allow for zero observations, 2) methods that inflate the expected numbers of zeros and, 3) the delta method that uses two separate models to predict the proportions of positive catches, and then model the catch rates when the set is positive. Usually, when modelling bycatch species (including the case of sea turtles), the number/proportion of observations with zero catches tends to be high, and therefore these alternative methods may be more appropriate than adding a constant. The following sections of this paper address some of these possible alternative methods.

2.4.1 Models for count data

The discrete response variable in these types of studies is often the catch in numbers (counts) of specimens per fishing set or trip. This approach could in theory also be applied to the catch in biomass (weight) by rounding the data to the nearest integer, but in such cases the use of a continuous distribution seems to be more appropriate (Maunder and Punt 2004). In those cases, when the objective of the study is to model the catches as a discrete variable (counts), it is possible to use a discrete statistical distribution that explicitly allows for zero counts, and models the integer values of the response variable. The most widely used distribution for modelling count data is possibly the Poisson distribution, traditionally known as the distribution used for modelling rare events (**Figure 1**). This distribution assumes that the variance is equal to the mean [$\mathrm{var}(Y) = \mu$], which may be a limitation in modelling CPUEs of bycatch species, frequently overdispersed.

Bycatch data is often overdispersed, which means that the variance is usually larger than the mean, and in such cases the Poisson distribution is not appropriate to model the data. The dispersion parameter of a Poisson model can be calculated with the Pearson residuals (Agresti 2002): when this parameter is close to 1 then the dataset is probably not overdispersed, while a value higher than 1 probably reflects an overdispersed dataset. Zuur et al. (2009) advise that in general a dispersion parameter larger than 1.5 means that some action needs to be taken to correct for it, while values between 1 and 1.5 can usually be considered as not overdispersed. There are several alternative possibilities to model overdispersed count data, but perhaps the most commonly approach is to use the negative binomial (NB) distribution that allows for the variance to be larger than the mean, with a quadratic relationship between the mean and the variance ($\mathrm{var}(Y) = \mu + \mu^{2/k}$, where k is an estimated parameter) (Maunder and Punt 2004). **Figure 2** presents some examples of shapes (probability mass functions) of the negative binomial distribution.

An application with these types of models was used by Pradhan and Leung (2006), for modelling interactions between sea turtles with pelagic longline fisheries in Hawaii. The data used was the NMFS Observer data from the Honolulu Laboratory, and while the original observer dataset was discriminated at the “fishing set” level, the authors aggregated the data to the “fishing trip” level, suggesting that most of the covariates (e.g. season, lightstick colour used, bait type, history of previous interactions, etc) remained constant between the different sets within a given trip. The aggregated data used in the analysis consisted of 923 trips carried out between 1994 and 2003, with 771 referring to tuna targeted trips and 152 to swordfish targeted trips. The analysis was separated by the type of trip, as tuna-targeted versus swordfish-targeted trips employ different technologies that result in substantially different degrees of turtle interactions. The response variable in the model was the count of sea turtles captured during each fishing trip, with this value varying from zero to several. In this study, it was interesting to note that in terms of modelling approaches, the Poisson model was found to be more appropriate for the tuna-targeted trips (reflecting absence of overdispersion), while the negative binomial model was adopted for the swordfish targeted trips due to overdispersion in the data. The major conclusions of the study were that there were about 6% and 55% chances that at least one sea turtle per trip was encountered in tuna and swordfish targeted fishing trips, respectively, meaning that more sea turtle interactions are associated with the swordfish fishery.

Another example of these models applied to sea turtles is the work by Petersen et al. (2009) for the South African pelagic longline fleet. The authors used a GLM with a Poisson distribution and log link function. The explanatory variables investigated were year, season, area, vessel name, target species (i.e. tunas or swordfish), moon phase (eight phases), branch-line length, bathymetry, bait type (fish, squid or combination) and Beaufort scale (eight levels). In this case, the response variable was the catch in numbers, and the effort (number of hooks per set) was used as an offset variable.

Other authors have used this approach as a possibility to model their data in a comparative way to other approaches. For example, Punt et al. (2000) used, among other possibilities, Poisson and negative binomial error distributions in GLMs to standardize CPUE data (rounded to the nearest integer) for the school shark, *Galeorhinus galeus* in Australia. Besides those modeling possibilities, other alternatives tested were 1) adding a constant to the catch rates followed by log transforming the data and then consider a Gaussian or gamma distribution (as discussed before in this paper) and, 2) a delta method approach that is discussed in more detail below. This specific paper was focused on a coastal shark species in Australia (non-ICCAT), but the type of comparative strategy used (comparing several possible modeling approaches) seems to be very useful and is highly recommended, as different situations/datasets (different species, fisheries, fleets, etc) may require different types of models.

2.4.2 Zero inflated models for count data (ZIP and ZINB)

The proportion of zeros that can be explained by a Poisson or a negative binomial distribution is related to the distribution of the other (non zero) values, meaning that for each given distribution of non-zero observations there is a fixed proportion of zeros that can be accounted for (**Figures 1 and 2**). In some cases it may happen that the proportion of zeros in a dataset is higher than expected by the distribution, and that constitutes a zero-inflated dataset. Two commonly used zero-inflated distributions for count data are the zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB).

Zuur et al. (2009) presented an important revision of zero-inflation models for count data, with several examples of case studies and applications. The authors also present a discussion on the sources of the excessive zeros, that are summarized as: 1) structural or true zeros, that are an intrinsic part of the structure of the data (i.e. the sea turtle does not interact with the longline gear because of a series of combinations intrinsic to the data itself, for example season of the year, sea turtle size, etc), and 2) false zeros that can occur for any other reason. There is also an additional source of zeros, the “bad zeros”, that using the example by Zuur et al. (2009) would be the ones obtained, for example, by sampling elephants in the sea. Those are simple to identify and the straightforward solution is to remove them. The problems occur mainly because the other sources of zeros (true and false) cannot usually be separated by the researcher, and have to be dealt with.

Zero inflated models are in practice a mixture of two distributions, the first a component that models zeros versus non-zeros (binomial), and the second a distribution that includes both zeros and positive values (e.g. Poisson or negative binomial). The processes causing the zero values may either be the same or different than the processes leading to the positive values, which means that the explanatory variables used in each model may be the same, or different. Like in the Poisson *vs.* negative binomial examples provided before, in the cases of zero-inflation it is also common to choose between ZIP and ZINB, with this referring mainly to the count component of the models. The ZIP model addresses the issue of the zero-inflation but not an eventual overdispersion in the count component of the model, which means that if the count component of a dataset is overdispersed then the chosen model should be the ZINB. ZIP and ZIBN models are nested, so it is possible to compare them using a likelihood ratio test. In terms of model interpretation, the outputs of the zero-inflated models result in a two model component. The logistic model explains the presence of false/excess zeros versus the rest of the data, and can be used to predict when false/excess zeros are more or less likely to occur. The second component explains the count data, including part of the true zeros that were observed.

An example of an application of zero-inflated models was used by Cambiè (2011) to model interactions of sea turtles with trammel nets in Sardinia, Italy. This study focused small-scale artisanal (non-ICCAT) fisheries but the application could also be used in ICCAT fisheries. The data was based on fishers interviews, where the boat owners voluntarily agreed to provide information on captures and sightings of sea turtles during their regular fishing operations, including latitude and longitude of each turtle, weight of the turtle, date (month and year) and other specifications on the fishing gear. The data analysed referred to the period 1992-2001. A ZIP model was used to estimate the abundance of sea turtles bycatch per vessel using trammel nets during the 1992-2001 period. The ZIP model was able to accommodate the excess of zeros caused by the absence of sea turtle bycatch, and for the count model a dispersion parameter of 1.06 (close to 1) was calculated, meaning that after removing the excessive zeros, the count data was not overdispersed.

2.4.3 Delta method

The delta modelling technique has been more commonly applied to standardize CPUE time series (usually using a continuous response variable) of species that have zero catches in some of the fishing sets. The method involves fitting two “sub-models” to the data as described by Lo et al. (1992). Typically, the dataset is separated into two components: The first component consists of binomial data, usually coded as 1= positive set, i.e., set with the capture of at least one specimen of the species of interest, and 0 = set with zero catches of the species of interest. The second components are the catch rates for the positive sets. Two separate sub-models are then applied, one to calculate the expectation of a positive set occurring, and the second to calculate the catch rate expectation conditional to the set being positive. Usually, the first model follows a binomial error distribution with a logit link function, while the second model usually follows a Gaussian error distribution after log-transforming the response variable. However, different link functions and/or distributions can be considered and tested in each particular case. For the first component, and given the binary nature of the data, the distribution has to be binomial, but instead of using a logit link function it is also possible to test, for example, a probit link. For the second component, instead of using a lognormal distribution it is possible to test other distributions, for example a gamma. **Figure 3** represents the probability density function of the lognormal distribution with several different means and standard deviations.

After fitting the models, and in the cases that this approach is used mainly for CPUE standardization, the final objective is to create a relative index of abundance that reflects the yearly variability in the species abundance along the time series considered. Usually, this is calculated as the least squares means (LS means) of the factor year for the selected models. For this reason, and in these types of models, there is the need to keep the variable year as an explanatory variable even in eventual cases of models where the year is not significant (Maunder and Punt 2004). The standardized CPUEs for the delta method models are then calculated as the product of the expected probability of a set being positive (first component) and the expected catch rate conditional for positive sets (second component) (Lo et al. 1992).

An example of an application using this technique was carried out by Ortiz and Arocha (2004) to standardize CPUEs of billfishes captured in the Venezuelan pelagic longline fishery. Even though this example refers to billfishes and not sea turtles, the application was for a dataset with a large proportion of zeros, which is probably similar to the case of sea turtles. Specifically, Ortiz and Arocha (2004) analysed data from 3,494 longline sets (carried out between 1991 and 2001), and depending on the species only 22-28% of the sets were positive. The authors compared different possibilities of distributions particularly for their second model (modelling the catch rates conditional to a set being positive), and compared lognormal, gamma, and Poisson distributions. The results of their study indicated that the delta-lognormal model, using a binomial error distribution for the probability of a positive catch, and then a lognormal error for the positive catch rates, was the best approach for the characteristics of that dataset analysed.

Another example of applications with the delta method are the annual NOAA/NMFS Reports on marine mammals and sea turtle bycatches from the pelagic longline fisheries (Johnson et al. 1999; Yeung 1999, 2001; Garrison 2003, 2005; Garrison and Richards 2004; Fairfield-Walsh and Garrison 2006, 2007, 2008; Garrison et al. 2009; Garrison and Stokes 2010), using data from the pelagic longline fishery observer program and the mandatory fishery logbook reporting program. The bycatch rates (catches per hook) are quantified and modelled with the delta-method based upon the observer data by year, fishing area, and quarter. The estimated bycatch rates are then multiplied by the total fishing effort (number of hooks) reported by the logbook program for estimating the total number of interactions of each species with the fishery.

Also with an application for sea turtles, Pons et al (2010) standardized catch rates of *C. caretta* caught by the Uruguayan and Brazilian pelagic longline fleets in the SW Atlantic. The proportion of zero observations in their fishery observer dataset was moderate (annually positive sets ranged between 20–60%), and so the authors opted for a delta lognormal model. Like in previous examples, two sub-models were fitted: the first was a binomial model with a logit link function to calculate the expectation of a fishing set capturing at least one sea turtle (i.e. expectation of a set being positive), and the second was a lognormal model (Gaussian distribution after log transformation) for calculating the expectation of the sea turtle catch rates conditional to a set being positive. The explanatory variables considered were: year (categorical: 1998-2007), quarter (categorical: 1: Jan-Mar; 2: Apr-Jun; 3: Jul-Sep; 4: Oct-Dec), SST (categorical: 1: < 20◦C; 2: 20-25 ◦C; 3: > 25 ◦C); area (categorical: 3 areas); vessel length (categorical: 1: < 24 m; 2: >= 24 m), fishing gear (categorical: 1: monofilament; 2: multifilament). The authors started with a preliminary analysis on the continuous explanatory variables (SST and vessel size) that were initially verified with non-parametric smoothing functions (splines). Given that their relationship with the log transformed catch rates were non-linear, the variables were categorized. Overall, their approach seemed to perform well under those conditions with a moderate proportion of zero observations in the fishery.

2.4.4 Tweedie models

Besides the delta-method approach that seems to be more commonly used, another possible approach are tweedie models. As mentioned before, one difficulty with modeling catch rates is that the CPUEs are continuous but have some cases with exact zeros (when no catches are recorded) and most statistical models will have difficulty with this mixture of discrete and continuous distributions. The tweedie distribution is part of the exponential family of distributions, and is defined by a mean (μ) and a variance ($\varphi\mu^p$), in which φ is the dispersion parameter and p is an index parameter. Particular cases occur when p=0 (Normal, with mean = μ and variance = $\varphi\mu$); p=1 and φ=1 (Poisson, with mean = variance = μ); and p=2 (gamma, with mean = μ and variance = $\varphi\mu^2$). When the index parameter (p) takes values between 1 and 2, the distribution is continuous for positive real numbers but, unlike the Gaussian, gamma or lognormal, has an added discrete mass of zeros. **Figure 4** represents examples of the probability density functions of the tweedie distribution, with various index parameters (p) and dispersion parameters (φ).

To the best of our knowledge, not many fisheries studies have applied this type of models. An example is the study by Candy (2004) for the Patagonian toothfish (*Dissostichus eleginoides*) fishery (CCAMLR fishery in the Antarctic region), with the author testing the utilization of tweedie distributions in both GLM and GLMM approaches. The final conclusions of that paper were that the best approach to model the catch rates of that species in that particular fishery was to use a mixed model (GLMM) with random vessel effects, and a tweedie error distribution with an index parameter of 1.3.

Using data from the Japanese pelagic longline fishery, Shono (2008) compared several modeling approaches for modeling yellowfin tuna (*Thunnus albacares*) catches in the Indian Ocean and silky shark (*Carcharhinus falciformis*) catches in the North Pacific, in both cases aiming for CPUE time series standardization. The shark dataset consisted of a high proportion of zeros (>80%), while in the tuna example the zeros were approximately 10%. On both datasets, the author compared and tested four modeling approaches: 1) model the log CPUE by standard linear regression after first adding a small constant to all CPUE values; 2) model catches using a Poisson or negative binomial GLM and with effort as an offset; 3) model CPUEs with the delta lognormal approach using a binomial logit model to estimate the zero catch and a lognormal model for the positive catch rates and 4) model CPUEs with a tweedie GLM. The tweedie model performed better with both datasets, but in the case of the tuna (approximately 10% zeros) the differences between the tweedie model and adding a small constant were small, with the author recommending the utilization of the method that adds a small constant from the practical viewpoint. In the example with the shark species (approximately 80% of zeros) the tweedie model performed better and was followed in second by the delta lognormal method. For such cases with much more zeros, which will most likely be the case of most bycatch species, including the sea turtles, Shono (2008) recommended therefore the utilization of the tweedie model or, alternatively, the delta method for practical reasons. For this example with a high proportion of zeros, the model of adding a small constant performed very poorly and is not recommended by the author.

More recently, Coelho et al. (2012a) used a tweedie GLM to test the effects of several hook and bait combinations on swordfish catches in the pelagic longline fishery (Portuguese fleet) operating in the Atlantic equatorial area. In this dataset the percentage of zeros was moderate, representing slightly over 20% of the fishing sets. The index parameter of the particular tweedie distribution was estimated with a profile likelihood function and calculated to be 1.36, resulting in a distribution that accounted for approximately 19% of zeros. The model seemed to perform well in that particular dataset and under those conditions.

As far as the authors are aware of, tweedie models have not yet been applied to modelling sea turtle catch rates. However, these models seem to perform well under substantially different situations, ranging from extreme cases with >80% of zeros, to moderate cases with 10-20% zeros. They should be a possible alternative, and it is recommended that they are compared to the other methods more commonly used.

3. Modeling sea turtle mortality rates

3.1 Response variable

For modelling sea turtle mortality rates, the response variable is usually binomial, and one possible notation is: 1 = the event occurred, in this case the turtle died in the fishing process; 0 = the event did not occur, in this case the turtle was captured and released alive. Choosing the "event of interest" for each particular study is up for the researchers to decide, and as long as the definitions are clearly stated in the methods it does not make a difference to the results.

3.2 Explanatory variables

Like in the examples provided previously in the section addressing CPUE modelling, the explanatory variables in a binomial model for calculating the mortality rates can be any combination of discrete and continuous variables. Besides the examples of possible explanatory variables already provided before, some additional covariates that might be significant and important to test when addressing mortality issues are:

1) Specimen size, as it is conceivable that the odds of dying from the fishing process may vary depending on the specimen size;

2) Capture time, measured as the time the specimens spent in the fishing gear after being captured. This may be used as a more precise alternative to the soaking time, as it can potentially and more accurately predict

the mortality rates. The assumption in this case is that there is an expectation of increased mortality as the time the specimens spent in the fishing gear increases. For longline studies, in order to obtain these values there is the need to deploy hook-timers in the longline, as done by Morgan and Carlson (2010) while assessing the mortality rates of coastal sharks captured in the U.S. bottom longline fishery.

Like mentioned before in the section on modelling CPUEs, the researchers conducting the analysis may ponder to test any other explanatory variables that they may considered relevant for explaining mortality rates. Like in the previous case, common approaches to tests the significance of additional variables are likelihood ratio tests (for comparing nested models), and using information criteria such as AIC and BIC.

3.3 Models and examples

Important references on binomial models are the books by Hosmer and Lemeshow (2000) and Agresti (2002). For interpreting the outcomes of a binomial model, it might be more simple and interesting to calculate the odd-ratios of each level of each variable, with reference to the baseline level of the variables. For example, if such a model is used to compare the mortality rates with different hook types (e.g. J-style vs. circle hook) it might be simpler for interpretation of the results to consider the hook commonly used by the fleet as the baseline level of the variable, and the alternative hook as the level for which a model parameter, and a comparative odds-ratio, is calculated. If the binomial model is using a logit link function, then the odds-ratios are calculated as the exponential values of the model parameters. For the continuous variables, it might be easier in terms of interpretation to calculate the odds-ratios for a certain increase of the explanatory variable. For example, Coelho et al. (2012b) calculated binomial GLM models for explaining part of the hooking mortality as a function of specimen size (for pelagic sharks), and for parameter interpretation the odds-ratios of the expected changes in mortality were calculated for an increase of 10 cm in specimen fork length.

In terms of binomial GLM assumptions, and for the continuous explanatory variables, the same assumption in terms of the linearity in the relationship between the expected value of the response variable and the explanatory variables still applies, as already discussed for the CPUE modelling section of this paper. This means that if the continuous variables in the model have non-linear relationships with the response variable, then those need to be addressed either with transformations or categorizations. For the categorical variables, binomial GLMs assume that all levels of the categorical variables have sufficient information in the binomial response to allow contrasts in the data and achieve model convergence. These assumptions are similar to the contingency tables and chi-square tests assumptions, in which the contingency tables should not have cells with zero values (counts) or more than 20% of the cells with predicted values lower than 5.

For estimating sea turtle mortality in trammel nets is Sardinia Italy, Cambiè (2011) used observer data on the immediate sea turtle mortality and binomial GLM models. Even though the fishery in question is not an ICCAT fishery, the methodology could be applied to the case of sea turtles captured in ICCAT fisheries. In such case, the event of "interest" (coded as 1 for the response variable) was considered to be the sea turtle surviving the incidental capture by the trammel net, and the explanatory variables used were turtle weight (kg), depth of the gear (m) and the sea surface temperature (SST, ºC). In this case, model goodness-of-fit was determined using the Hosmer-Lemeshow test (Hosmer and Lemeshow 2000) and model discrimination capacity was evaluated with the Area under the Curve (AUC) of a Receiver Operating Characteristic (ROC) curve. This allows the estimation of model adequacy, determined by the values of model sensitivity (capacity to correctly detect the occurrence of an event) and model specificity (capacity to correctly exclude cases where the event did not occur).

Another possible approach is to test for differences in the hooking locations, as those may result in different catch rates and/or mortality rates. One possible approach is to use contingency tables and chi-square analysis to test, for example, if different hook-bait combinations will result in different proportions of dead *vs.* alive turtles. Examples of studies that have used such approach are Sales et al. (2010) and Santos et al. (2012). If the resulting contingency tables ore of the 2*2 type (e.g. testing the proportions of 2 conditions (dead vs. alive) in function of 2 hook styles (circle vs. J-style), then it is advisable to use the Yates continuity correction.

Most of the mortality studies address mainly the issue of the immediate (short-term) mortality usually measured at time of fishing gear retrieval (at-haulback). The status of the turtles (alive or dead) is recorded at that time, and the analysis is then carried out based on those data. However, it is possible to conceive that some of the turtles that are released alive (therefore considered alive for this short-term mortality analysis) may have severe trauma or injuries resulting from the fishing operations and/or dehooking, which may result in medium- to long-term mortality. For addressing that issue, there is the need to remotely follow the sea turtles post-release movement patterns for at least a few days, in order to determine if after being released the specimens survive and return to their normal behavioural patterns. Perhaps the easiest way, even though expensive, to conduct such types of telemetry studies is by using satellite telemetry. With satellite telemetry tags, the specimens are tagged and released, and once the transmitters are activated the archival data is transmitted by satellite. The advantages of such systems are that there is no need to physically recover the tags, as the archived data is transmitted by satellite, or to physically accompany the turtles, as would be the case if using, for example, active acoustic telemetry. Bjorndal et al. (1999) strongly recommend the continued use of satellite transmitters that can provide information on the dive profiles, and eventually assess behavioural differences between normal and hooked turtles. This allows not only the estimation of the effective post-release mortality, but also to determine eventual behavioural changes that may occur due to the fishing and releasing process.

However, and before applying such tags to estimate post-release survival, careful considerations in terms of experimental design need to be considered. One particular important aspect is that specimen selection needs to be randomized (possibly considering *strata*), as any kind of specimen selections towards either the healthier or the more injured specimens will introduce significant bias in the study. Another consideration is that if such experiments are being conducted from scientific vessels (or commercial vessels hired for the study) there is the need to guarantee that the experimental fishing conditions mimic the commercial fisheries conditions (e.g. number of hooks, fishing gear soaking time, handling of the specimens by the crew, etc) as closely as possible, so that extrapolations become possible. An important revision on the use of satellite telemetry on sea turtles is the revision paper by Godley et al. (2008). The authors revise and describe the advances in the use of satellite telemetry mainly with regards to movement patterns and habitat use, but other issues, such as estimating post-release survival are also addressed and reviewed.

An example of a study that seems to have been very well designed and conducted is the study by Campana et al. (2009) for the blue shark. Similar studies can be adapted to any other marine species that are captured and released from both the commercial, as well as from recreational fisheries. In their study, Campana et al. (2009) randomly selected a sample of 40 blue sharks (both healthy and injured) that were tagged with satellite pop-up archival tags after being captured by Canadian longline vessels targeting swordfish in the NW Atlantic. One shark which was dead upon fishing gear retrieval was also tagged and returned to the sea, in order to confirm the tag characteristics of a shark that died after release. In this case the tags were programmed to record depth, temperature and light intensity at 1 min intervals and for a period of 2 to 6 months, which was assumed as a long enough recording period to include any mortality due to capture and handling trauma, as well as more extended mortality due to factors such as internal damage or cessation of feeding associated with swallowed hooks. Any non-transmitting tags were excluded from the analysis and it was not assumed the specimen had died, as tags may not transmit due to malfunction, predation, etc. The tags were also programmed to release from the specimen if a constant depth was maintained for a period of 4 days, which in the case of the blue sharks would be indicative of a dead specimen. The probability of survival after discarding was modelled with survival analysis, both with Kaplan-Meier survival curves, was well as with parametric approaches using exponential, weibull, and lognormal distributions. The results of this study allowed estimating that the surviving sharks exhibited a depth holding recovery behaviour for a period of 2-7 days after release, that all healthy sharks survived, and that 33% of those that were badly injured or gut hooked died.

4. Studies on the effects of hook style and bait type on sea turtle catches

Several recent studies have addressed the issue of using alternative hook styles and bait types to minimize the catch rates of sea turtles. These studies usually consider one hook style and bait type as the standard used by the fishing industry (for each particular fleet and fishery) and assess the effects of using alternative hooks and/or baits on the catch rates.

A conference on circle hooks (International Circle Hook Symposium) was held in May 2011 in Miami, FL, USA, devoted entirely to the effects of using alternative circle hooks on the catch rates of targeted and by-catch species. Many papers that were presented during that conference referred to the effects of such gear modifications both for the sea turtle bycatch rates, as well as on other target and bycatch species from a number of fisheries.

4.1 Response variable

In terms of modelling, the response variable of these types of studies is usually the bycatch rate per unit of effort (CPUE) that is the same variable already discussed before on the section on CPUE standardization. Like in that case, this variable is often a continuous variable with an added mass of zeros, as there are many fishing sets with zero sea turtle catches.

Likewise, it is also possible to use the response variable as the catches (counts). If the effort remained constant during all fishing sets of the experiment then there is no need to add a variable for effort, but if changes occurred then it is possible to add the effort as an offset variable.

4.2 Explanatory variables

In these types of studies the explanatory variables are usually the hook style and bait type, as those are the two variables that are being tested. Many of these studies have been carried out under scientific conditions, meaning that the complications of an entirely fisheries-dependant dataset are not so evident. For example, in these types of experiences it is relatively common practice to use commercial vessels hired to carry out the experiments using the hook and bait specifications requested by the scientists, and where other fishing gear characteristics are previously standardized and remain constant during the experiments.

One common approach in terms of experimental design to these studies (where the effects of bait and hook are being tested) is to alternate the hook styles along the longline (e.g. Bolten et al. 2002; Bolten and Bjorndal 2003, 2004, 2005) or longline sections (e.g. Watson et al. 2005, Santos et al. 2012), as these strategies seem to minimize potential confounding effects specific to each set, for example location, water temperature, turtle density, soaking time and other factors. If the hooks are changed by each longline section, another common way to introduce randomization into the experiment is to alter the order of the sections, for example by changing the first section in the water every set, and then following a fixed continuous scheme as used by Santos et al. (2012).

Hook styles vary greatly. Common hook styles tested in those experiments are J-style, circle hooks and tuna hooks. However, and within those general categories, there are different sizes, shapes, hooks with or without lateral offsets, and different offset degrees. Due to this large variability, it is recommended that the researchers conducting those experiments clearly describe in detail the hooks being tested, and consider always adding tables with the detailed measurements, as well as photographs of the hooks, so that the readers can have a clear idea of what is being tested.

Another variable commonly tested in those studies are the bait types. If different baits are being tested in such an experiment (where different hooks are also being compared), Watson et al. (2005) recommend using only one type of bait per fishing set to reduce potential confounding effects to the experience. However, other authors have configured the longline in sections, with each hook-bait combination placed on each section (e.g. García-Cortés et al. 2009), and in this case the position of each hook-bait combination on the longline was rotated. Bait types commonly used and tested in such experiments are usually comparing fish with squid baits, or some combination of both.

4.3 Models and examples

In those experiments, the explanatory variables tested (bait and hook types) are categorical, and as such an Analysis of Variance (ANOVA) could conceivable be used to compare the effects of the variables. However, in this type of experiments, with relatively rare species, it is to be expected that the data will not follow the ANOVA assumptions, specifically normality of the data and homogeneity of the variances, and as such, alternative hypothesis tests and models have to be considered.

One possible approach is to use non-parametric hypotheses tests to compare the median observed catch rate values. For example, it is possible to apply Mann-Whitney tests to compare median catch rate values between two hook types, with this test being commonly considered as the non-parametric equivalent to a parametric t-student test. If the variable being analyzed has more than 2 levels (e.g. three of more hook styles), it is then possible to use non-parametric Kruskal-Wallis tests, commonly considered the non-parametric equivalent to a parametric ANOVA.

However, and besides those possible hypothesis tests, it might be more informative to use statistical models to analyse the effects of hooks and baits. Ultimately, the problems of these types of models and analysis will be similar to the problems of standardizing CPUEs, but in this case the explanatory variables considered will often be only the bait and hook effects, while for CPUE standardization other variables are also considered and tested. The reason for that is that often those experiments are carried out in more controlled environments (often commercial vessels chartered to carry out the experiments according to the study design), meaning that the other operational factors are maintained the most standardized possible during the experiments. Additionally, the main objective of CPUE standardization is usually to follow the year effect in the catch rates to construct annual indices of abundance, while in these studies the main objective is to compare the effects of the variables hook and bait in the sea turtle catch rates.

A number of projects and studies have been carried out for comparing the effects of hooks and baits on sea turtle catches. Most studies seem to agree that the use of circle hooks (instead of J-style) and fish bait (instead of squid) are efficient in significantly reducing the incidental bycatches of sea turtles, even though there are some studies with conflicting results. Additionally, and in some cases, the gear modifications may either increase the catches of other bycatch groups (e.g. sharks) or reduce the catches of the targeted species (e.g. swordfish) which may pose socio-economic implications to the fishery. The efficiency of such gear modifications for the sea turtles seems therefore to be taxa, fishery and even fleet specific, and as such it is recommended that such bycatch mitigation measures (gear modifications) should be tested in rigorous experiments before being implemented (Read 2007). Some examples of studies that used different methodological approaches are described below.

Read (2007) reviewed the efficacy of circle hooks by reviewing the results of five projects conducted in the northwestern Atlantic, Azores, Gulf of Mexico, and Ecuador. The author analyzed both the experimental design as well as the methodology used by each study. Overall, three of the five experiments demonstrated a significant reduction in sea turtle capture rates, and four out of five demonstrated a reduction in mortality. However, in one case, circle hooks reduced the catches of target species to such a degree that their use was impractical. The difference observed, as well as the socio-economic implications in some cases lead the author to recommend rigorous field testing before implementation in the fishery.

For the southwestern Atlantic, Domingo et al. (2009) reported the results of experimental fishing trials to compare hooks (J-style *vs* circle) for the Uruguayan fleet operating in the region using mainly non-parametric hypothesis tests. The study used a total of 165 fishing sets (77,628 hooks), and the analysis was conducted by calculating the sea turtle CPUE for each fishing set, and then comparing the median CPUEs between hook styles with non-parametric Mann-Whitney tests. The same tests were also used to compare median sizes of the sea turtles captured with each hook style. A general reduction in catch numbers and catch rates was observed with circle hooks, but the observed differences were not statistically significant according to the Mann-Whitney tests that were used. Similarly, no significant differences were detected in the sizes captured with each hook style.

Pacheco et al. (2011) also used hypothesis tests to compare the hook performance between circle and J-style hooks for the Brazilian fleet operating in the western equatorial region. In this case the species catch composition by hook type was compared with chi-square tests, determining if different species were occurring in different proportions depending on the hook style used. For the analysis the authors included targeted species, as well as bycatches of sharks and sea turtles. In this study significant differences were detected in the percentages of occurrence of *D. coriacea*, with significantly higher proportions captured with J-style hooks.

Another example using hypothesis tests but in a different approach was used by Sales et al. (2010) for comparing the performance of 18/0 circle with 9/0 J-style hooks in sea turtles and fishes. In this case, the authors used contingency tables and a Mantel–Haenszel (MH) chi-square test to compare the catches with each hook style. This test uses *K* contingency tables for analysing the effects of two other variables on a dichotomous response, with *K* corresponding to the number of strata that is used *a priori* to separate the individuals. This removes the confounding effects from the *K* strata, and allows detecting differences in the other variables. In their study, an overall decrease in catch rates of *C. caretta* by 55%, and *D. coriacea* by 65% were observed when using circle hooks. On the contrary, circle hooks increased catch rates of tunas (bigeye and albacore), blue shark, and sharks from the genus *Carcharhinus*. No differences were detected for yellowfin tuna, mako shark, hammerheads and dolphinfish. Finally, a significant decrease in catch rates was observed for swordfish when using circle hooks.

Other studies have used statistical models, rather than hypothesis tests, to analyze the data, An approach with GLM lognormal models was used by Mejuto et al. (2008) for assessing the effects of different hooks and baits for five areas of operation of the Spanish longline fleet in the Atlantic Ocean (both in the North and South Atlantic). The approach used by this study was a lognormal GLM, using the nominal sea turtle CPUEs (in number) as response variable, and the effects of hook (3 types), bait (2 types), and zone (5 regions) as explanatory variables. In this case, the authors transformed the response variable into the log (CPUE+1) before applying the model. The log transformation normalized the data, and adding a small constant (+1) dealt with the zero values. The results showed that in general the factor region was the most important for explaining CPUE variability. The hook type was only significant for the billfishes group, while the bait was significant for *C.*

caretta, shortfin mako and several other fishes. For the sea turtle, effects of the bait were similar to other studies, with higher catch rates when squid was used instead of fish bait.

A different approach using binomial GLMs was used in a study conducted by MRAG, Lamans and AZTI to determine the effects of hook (circle vs. J-style) and bait (squid vs. mackerel) on swordfish and sea turtle catches in three separate regions: southern Atlantic, eastern and western Mediterranean (Anon 2008). In terms of methodology for analysing the sea turtles bycatches, that study used GLMs with logit link function, with the models formulated to predict the probability of capturing a turtle given that a hook is set. With this model, the binomial response (turtles caught / hooks without turtles, by set) was modelled as a linear combination of the categorical effects in terms of bait (squid vs mackerel) and hooks (J hook, 16/0 0º offset circle hook, 18/0 10º offset circle hook). In terms of general results, sea turtle bycatch was significantly affected by bait type, with turtles consistently caught more frequently on squid bait than on mackerel bait. However, in this study, there were no significant differences detected in sea turtle bycatch rates between hook types. There was, however, some indication that 18/0 circle hooks were less likely to be swallowed than J-style or 16/0 circle hooks.

More recently, Santos et al. (2012) applied a similar binomial GLM methodology for the Portuguese longline fleet targeting swordfish and operating in the Equatorial Atlantic region. In this particularly study, a total of 221 longline sets (> 305,000 hooks) were used, with 3 hook styles tested (J-style: EC-9/0-R; circle 0ºoffset: H17/0-M-S, and circle 10º offset: H17/0-M-R) and two bait types (squid and mackerel). The analysis was carried out with a GLM logistic-binomial model, with the response variable being the proportion of sea turtle captured in each fishing set, given the availability of hooks. In practice, this was calculated as a combined variable using the number of successes (N hooks with sea turtle captures) and the number of failures (N hooks without sea turtle captures), per fishing set. The model used a binomial error distribution and a logit link function. Possible interactions between the explanatory variables were tested with likelihood ratio tests, and the odds-ratios of the parameters, with their respective 95% confidence intervals, were calculated as the exponential values of the model parameters (because a logistic model was used). For the most captured species (*L. olivacea*), both variables were significant, with the fish bait resulting in a reduction in sea turtle interactions between 38-69%, and circle hooks reducing the interactions between 33-77%. For that same experiment, another paper presented the results of the same experimental fishing trials for other bycatch groups, specifically sharks, as well as for the targeted species (swordfish and tropical tunas) (Coelho et al. 2012a). Depending on the species, the results for those groups were similar or opposite than what was observed for the sea turtles. For example, swordfish catch rates were higher with J-style hooks baited with squid, while for the targeted tunas and blue shark only the bait effects were significant, but with opposite effect, i.e., higher catches of tuna with squid bait and higher catches of blue shark with mackerel bait.

5. Ecological Risk Assessment (ERA) methods

5.1 ERA methods and analysis

Ecological Risk Assessment (ERA) is an important technique with the objective of analysing and determining the vulnerability of a stock to a fishery in function of the productivity and susceptibility components. This type of analysis seems to be particularly useful and adequate for species that are in general considered data-poor species (such as is the case of most bycatch species), or in cases where several species in one same group (same taxonomic complex and/or impacted by the same fishery) are analysed in a comparative way. In the case of the sea turtles and ICCAT fisheries, such analysis could be applied, for example, to the six species of sea turtles that interact with ICCAT longline fisheries, with the final output producing a rank of the species productivity *versus* susceptibility (i.e. vulnerability) to the fishery. With this type of analysis, it is possible, for example, to identify species with high susceptibility to the fishery but where productivity (biological) information is still lacking, and that could help to establish needs in terms of management and research priorities.

ERA approaches can usually be categorized depending on the level of quantitative information used. One advantage of ERA analysis is that it is highly flexible, as depending on the quantity and type of available information the analysis can be based on different analytical levels. These are usually defined as:

1) *Level 1:* Qualitative analysis, particularly useful for data-poor fisheries and species, and those with limited knowledge on the interactions between the fisheries and the species. At this level the analysis is based mainly on expert knowledge;

2) *Level 2:* Semi-quantitative analysis, *useful* when more data is available;

3) *Level 3*: Fully *quantitative* approaches, when more information is available for a fully quantitative analysis.

One study that used a fully quantitative (level 3) approach within ICCAT fisheries is the work by Cortés et al. (2010) with pelagic sharks interacting with pelagic longline fisheries. The authors chose this quantitative approach because: 1) the biological information available was sufficient to estimate a direct measure of productivity, namely *r*, the intrinsic rate of population increase, and 2) the susceptibility component was estimated as the product of four conditional probabilities, also available for those species and the fishery (i.e. availability, encounterability, selectivity and post-capture mortality). The authors introduced uncertainty into the analysis by calculating the intrinsic rate of increase (*r*) with stochastic Leslie matrices that incorporated random errors (uncertainty) in the age at maturity, lifespan, age-specific natural mortality and fecundity matrix parameters.

Another example applied to ICCAT fisheries is the study by Arrizabalaga et al (2011) that was specifically carried out for bycatch species. That study followed a two stage approach with the objective of assessing the relative risk of species being negatively impacted. On that study it was possible to determine that based on their life history characteristics, marine mammals and coastal sharks caught in ICCAT fisheries showed the highest intrinsic vulnerability values. A productivity susceptibility analysis for the European Union (EU) tropical tuna purse seine fleet and the United States (US) pelagic longline fleet revealed two groups with high relative risk scores, the first including pelagic and coastal sharks (characterized by relatively low productivities), and the second group including teleosts that are characterized by higher productivities but also have high susceptibility to purse seine and longline gear.

Conducting and ERA analysis typically involves the following steps: 1) determine the portion of the fishery that is being evaluated (e.g. longline); 2) assign weights to the productivity and susceptibility indicators relative to that fishery (i.e. decide what components are more/less relevant); 3) collect data and rank productivity and susceptibility indicators for each species analysed; 4) calculate the overall productivity and susceptibility scores; 5) plot the productivity and susceptibility scores on XY scatterplots; 6) measure the vulnerability of each species as the distance from the plot origin to the productivity/susceptibility intersection. This final vulnerability measure can then be used to rank the species. The stocks that receive a low productivity and a high susceptibility score are considered to be the least sustainable (i.e. with higher vulnerability), while stocks with a high productivity and low susceptibility scores are considered the most sustainable (i.e. with low vulnerability).

Hobday et al. (2011) proposed an Ecological Risk Assessment for the Effects of Fishing (ERAEF) using a hierarchical approach for the analysis, and illustrated the methodology with an application to the trawl fishery in Australia. Hobday et al. (2011) started with an initial set of 600 species and 158 habitats that were analysed at the level 1, then the more vulnerable groups (159 species and 46 habitats) were analysed at a level 2, and finally a more reduced group of concern was analysed at the level 3.This analysis had the advantage of starting in a more general and less data intensive approach, with the groups of higher concern being subsequently analysed in more detail and in more quantitative approaches.

5.2. Productivity/Susceptibility parameters

Stobutzki et al. (2001a) defines productivity as the capacity of a species to recover once the population is depleted (i.e. a measure of resilience), and susceptibility as the likelihood or propensity of a species to be captured and suffer mortality from the fishery. One possible complication of conducting ERA analysis seems to be defining and deciding what attributes should be used in each of the components (P/S). For example, Stobutzki et al. (2001b) used 6 susceptibility and 5 recovery attributes for analysing sharks captured as bycatch in the Australian prawn fishery, while Cortés et al. (2010) used 1 productivity component (a general component (*r*) that combines biological information from other life history parameters), and 4 susceptibility components. Patrick et al. (2009), by the contrary, refer that while there is some redundancy in the productivity parameters (that largely reflect life history characteristics), the inclusion of multiple life history traits will allow a more comprehensive assessment of productivity.

Another complication and possible subjectivity in ERA analysis is to define the ranges and threshold values for the scores in each parameter. It seems that most recent studies have been using 3 categories for evaluating the attributes. Some adaptations on both the parameters used for each component, as well as in the ranges of values for the scores may have to be carried out prior to the analysis, so that the parameters are adapted for each specific taxonomic group and each specific fishery under analysis. **Tables 1 and 2** present the general guidelines in terms of productivity and susceptibility parameters, as well as the scoring thresholds, currently recommended by the NOAA/NMFS Vulnerability Evaluation Work Group (VEWG). These attributes are explained in detail in the NMFS/VEGS Report (Patrick et al. 2009) and were recently used by Patrick et al. (2010) for analysing the vulnerability of 162 U.S. fish stocks to overfishing.

The NMFS/VEGS also alert that the uncertainty associated with data-poor fisheries and populations can lead to errors and bias in the analysis. This working group created an index relative to the data quality, that provide an estimate of the uncertainty of individual vulnerability scores based on 5 levels, ranging from the best data (i.e. where there is a high belief in the accuracy of the score) to lower quality data (i.e. where there is less belief in the accuracy of the score), to no data available. **Table 3** present the values of these data quality indices, that can then be used as weights for the individual productivity and susceptibility attributes. One final recommendation in terms of ERA analysis is that because the analysis can be somewhat subjective, it should be conducted by a panel, in order to fully consider a variety of views and expert opinions.

5.3 Sea turtle biological/productivity data

Tables 4 through **9** compile and summarize currently available biological data that can be used in the productivity components for an Ecological Risk Assessment of sea turtles within ICCAT fisheries (as well as other fisheries). For the vulnerability components, there is a general need to compile CPCs data (either logbook or fishery observer data), in terms of sea turtle captures, overlapping (both horizontal and vertical) of the fisheries/fleets with the various sea turtle species, and estimation of mortality rates.

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Table 1: Productivity parameters and rankings as recommended by the NOAA/NMFS Vulnerability Evaluation Work Group (VEWG). These attributes are explained in detail by Patrick et al. (2009).

Productivity parameter	**Ranking**		
	High (3)	**Moderate (2)**	**Low (1)**
r	> 0.5	0.16 - 0.5	< 0.16
Maximum age	< 10 years	10 - 30 years	> 30 years
Maximum size	< 60 cm	60 - 150 cm	> 150 cm
VB growth coef (*k*)	> 0.25	0.15-0.25	< 0.15
Estimated natural mortality	> 0.40	0.20 - 0.40	< 0.20
Measured fecundity	> 10e4	10e2-10e3	< 10e2
Breeding strategy	0	between 1 and 3	≥ 4
Recruitment pattern	Highly frequent recruitment success (> 75% of year classes are successful)	Moderately frequent recruitment success (between 10% and 75% of year classes are successful)	Infrequent recruitment success (< 10% of year classes are successful)
Age at maturity	< 2 year	2 - 4 years	> 4 years
Mean trophic level	< 2.5	Between 2.5 and 3.5	> 3.5

Table 2: Susceptibility parameters (in terms of catchability and management) and rankings as recommended by the NOAA/NMFS Vulnerability Evaluation Work Group (VEWG). These attributes are explained in detail by Patrick et al. (2009).

Susceptibility Parameter	*Ranking*		
	Low (1)	*Moderate (2)*	*High (3)*
Catchability components			
Areal overlap	< 25% of stock occurs in the area fished	Between 25% and 50% of the stock occurs in the area fished	> 50% of stock occurs in the area fished
Geographic concentration	Stock is distributed in > 50% of its total range	Stock is distributed in 25% to 50% of its total range	Stock is distributed in < 25% of its total range
Vertical overlap	< 25% of stock occurs in the depths fished	Between 25% and 50% of the stock occurs in the depths fished	> 50% of stock occurs in the depths fished
Seasonal migrations	Seasonal migrations decrease overlap with the fishery	Seasonal migrations do not substantially affect the overlap with the fishery	Seasonal migrations increase overlap with the fishery
Schooling/aggregation and other behavioral responses	Behavioral responses decrease the catchability of the gear	Behavioral responses do not substantially affect the catchability of the gear	Behavioral responses increase the catchability of the gear [i.e., hyperstability of CPUE with schooling behavior]
Morphology affecting capture	Species shows low selectivity to the fishing gear	Species shows moderate selectivity to the fishing gear	Species shows high selectivity to the fishing gear
Desirability/value of the fishery	Stock is not highly valued or desired by the fishery (< \$1/lb; < \$500K/yr landed; < 33% retention)	Stock is moderately valued or desired by the fishery (\$1 - \$2.25/lb; \$500k - \$10,000K/yr landed; 33-66% retention)	Stock is highly valued or desired by the fishery (> \$2.25/lb; >\$10,000K/yr landed; > 66% retention)
Management components			
Management strategy	Targeted stocks have catch limits and proactive accountability measures; non-target stocks are closely monitored.	Targeted stocks have catch limits and reactive accountability measures.	Targeted stocks do not have catch limits or accountability measures; non-target stocks are not closely monitored.
Fishing rate relative to M	< 0.5	0.5 - 1.0	> 1.0
Biomass of spawners (SSB) or other proxies	B is > 40% of B0 (or maximum observed from time series of biomass estimates)	B is between 25% and 40% of B0 (or maximum observed from time series of biomass estimates)	B is < 25% of B0 (or maximum observed from time series of biomass estimates)
Survival after capture and release	Probability of survival > 67%	33% < probability of survival < 67%	Probability of survival < 33%
Fishery impact on habitat	Adverse effects absent, minimal or temporary	Adverse effects more than minimal or temporary but are mitigated	Adverse effects more than minimal or temporary and are not mitigated

Table 3: Data quality scores that can be used as weights for the individual productivity and susceptibility values, as recommended by the NOAA/NMFS Vulnerability Evaluation Work Group (VEWG) (Patrick et al. 2009).

Data Quality Score	*Description*	*Example*
1	Best data: Information is based on collected data for the stock and area of interest that is established and substantial	Data rich stock assessment, published literature that uses multiple methods, etc
2	Adequate Data: Information with limited coverage and corroboration, or for some other reason deemed not as reliable as Tier 1 data	Limited temporal or spatial data, relatively old information, etc
3	Limited Data: Estimates with high variation and limited confidence and may be based on similar taxa or life history strategy	Similar genus or family, etc
4	Very Limited Data: Expert opinion or based on general literature review from wide range of species, or outside of region	General data – not referenced
5	No Data: No information	

Table 4: Biologic parameters for the leatherback sea turtle, *Dermochelys coriacea*.

Parameter	*Dermochelys coriacea*		*References*
Maximum Size	up to 200 cm (record 260 cm CCL male)	NE Atlantic	Morgan (1989)
Size at maturity	150-162 cm CCL average	Atlantic	NMFS (2012)
	105-125 cm CCL minimum		Stewart et al. (2007), NMFS (2012)
Lifespan	30 yrs		Sarti-Martinez (2000)
Age at Maturity	13-14 yrs	E Pacific	Zug and Parham (1996), NMFS (2012)
	12-14 yrs	US Virgin Islands	Dutton et al. (2005), NMFS (2012)
	24.5-29 yrs (median age at maturation)	NW Atlantic	Avens et al. (2009)
Fecundity	100 eggs per nest several times during the nesting season; 8-12 days interval		NMFS (2012)
Breeding Strategy	2-4 yrs nesting interval		NMFS (2012)
VBGF (k)	k= 0.07 (0.05-0.09)	NW Atlantic	Avens (2009)
Population growth	Mean λ=0.96-1.2 (log-transformed regression)	Atlantic	TEWG (2007)
	Median λ=0.93-1.18 (Baysian state-space model)	Atlantic	TEWG (2007)

Table 5: Biologic parameters for the olive ridley sea turtle, *Lepidochelys olivacea.*

Parameter	*Lepidochelys olivacea*		*References*
Maximum Size	74 cm CL	Surinam	Plotkin (1995)
	79 cm SCL	Mexico Pacific	Reichart (1993)
Size at maturity	60 cm SCL	NC Pacific	Zug et al. (2006)
	62 - 74 cm CL	Surinam	Plotkin (1995)
Lifespan	18-20 yrs	Mexico Pacific	Reichart (1993)
Age at Maturity	13 yrs (10-18 yrs)	NC Pacific	Zug et al. (2006)
Fecundity	100-110 eggs per nest, 1, 2 or 3 times per season with 14-28 days interval		used by Abreu-Grobois and Plotkin (2008)
	2.5 nests/female/season and 105 eggs/nest		
Breeding Strategy	2-3 yrs nesting interval		Domingo (2006)
	Arribada, anual, dispersed and mixed		(Abreu-Grobois and Plotkin 2008)
Growth rate	W=0.0304L^1.727 (Females)	Mexico Pacific	Reichart (1993)
	W=0.0195L^1.820 (Males)		Reichart (1993)
Notes	Close phylogenetic affinities suggest that *L. olivacea* likely shares a similar growth rate and first age at sexual maturity with *L. kempii*		Zug et al. (2006)

Table 6: Biologic parameters of the Kemp's ridley sea turtle, *Lepidochelys kempii.*

Parameters	*Lepidochelys kempii*		*References*
Maximum Size	78 cm SCL	Atlantic	Marquez (1994)
Size at maturity	60 cm SCL	Atlantic	Caillouet et al. (1995), TEWG (2000)
	65 cm SCL	Atlantic	Zug et al. (1997), TEWG (2000)
Lifespan	>15 years in the wild 20 years in captivity	Atlantic	Marquez (1994)
Age at Maturity	10 yrs	Atlantic	Caillouet et al. (1995), TEWG (2000)
	8-13 yrs	Atlantic	Schmid and Witzell (1997)
	11-16 yrs	Atlantic	Zug et al. (1997)
	7-15 yrs	Atlantic	used by TEWG (2000)
	12 yrs	Atlantic	used by NMFS (2011)
Fecundity	2.5 clutches season with 14-28 day interval	NW Atlantic	used by NMFS (2011)
	97 average number of eggs/ nest	NW Atlantic	used by NMFS (2011)
Breeding Strategy	20% - annually	Atlantic	TEWG (2000)
	60% - 2 yrs nesting interval	Atlantic	
	15% - 3 yrs nesting interval	Atlantic	
	5% - 4 yrs nesting interval	Atlantic	
	2 yrs mean remigration interval	Atlantic	used by TEWG (2000), NMFS (2011)
Growth rate	7.5 ± 6.2 cm/yr mean growth rate	GOM	NMFS (2011)
	5.5 ± 6.2 cm/yr mean growth rate	NW Atlantic	
VBGF (k)	k= 0.317	Atlantic	Caillouet et al. (1995)
	k= 0.2	Atlantic	Zug (1990)
	k= 0.259	Atlantic	Marquez (1994)
	k= 0.1292	Atlantic	Schmid and Witzell (1997)
	k= 0.259	Atlantic	Coyne (2000)
Population growth	19% per year from 2010-2020	Atlantic	NMFS (2011)

Table 7: Biologic parameters for the hawksbill sea turtle, *Eretmochelys imbricata.*

Parameter	*Eretmochelys imbricata*		*References*
Maximum Size	53 to 114 cm SCL		Márquez (1990)
	62.5-91.4 cm SCL	Caribbean	Plotkin (1995)
Size at maturity	50% Females 76–80 cm SCL, and 100% > 80 cm SCL	Cuba	Moncada et al. (1999)
	68 cm SCL Males	Cuba	Moncada et al. (1999)
Age at Maturity	20 or more yrs	W Atlantic and Caribbean	NMFS (2007), Mortimer (2008)
	14.7 or more yrs	Puerto Rico	Diez and Van Dam (2002)
	20 yrs average Females (10 yrs smallest recorded)	Cuba	Moncada et al. (1999)
	12–15 yrs Males	Cuba	Moncada et al. (1999)
Fecundity	3 to 5 clutches per season with 14-16 days interval		NMFS (2007)
	130 eggs per nest		NMFS (2007)
Breeding Strategy	2 yrs nesting interval		Domingo (2006)
	2-3 yrs nesting interval	Atlantic	NMFS (2007)
Growth rate	0.59 to 9.08 cm yr–1 SCL growth rates	Puerto Rico	Diez and Van Dam (2002)
	2 to 4 cm/yr typical	Caribbean	NMFS (2007), Diez and Van Dam (2002)
	> 5cm/yr too	Caribbean	NMFS (2007), Diez and Van Dam (2002)

Table 8: Biologic parameters for the loggerhead sea turtle, *Caretta caretta.*

Parameter	*Caretta caretta*		*References*
Maximum Size	99 cm CCL	Mediterranean	Margaritoulis et al. (2003)
	105 cm SCL	NW Atlantic	Musick (2002)
Size at maturity	83-123 cm CCL		Baptistotte et al. (2003)
	>87 cm CCL (Females)		NMFS (2008)
	>83 cm CCL (Males)		NMFS (2008)
	> 70 cm CCL	Mediterranean	Margaritoulis et al. (2003), Casale et al. (2005)
Lifespan	> 57 yrs		NMFS (2008)
	62 yrs		Frazer (1983)
Age at Maturity	32-35 yrs	NW Atlantic	NMFS (2008)
	23.5 to 29.3 yrs by length-frequency	Mediterranean	Casale et al. (2011b)
Fecundity	3 to 5.5 nests per season with 12-15 days interval		NMFS (2008)
	100-126 eggs		NMFS (2008)
Breeding Strategy	2-3 yrs		Domingo (2006)
	2.5-3.7 yrs	NW Atlantic	NMFS (2008)
Growth rate	0.37 to 6.5 cm y^{-1} annual growth rate	Mediterranean	Casale et al. (2011b)
VBGF (k)	0.06 or 0.051	Mediterranean	Casale et al. (2011b)
	0.062-0.066; by AS method using Skeletochronology	Mediterranean	Casale et al. (2011a)
	0.052 or 0.072; by GR method using Skeletochronology	Mediterranean	Casale et al. (2011a)
Population growth	Mean λ= 0.913-0.988 (log-transformed regression)	NW Atlantic	TEWG (2009)
	Median λ= 0.899-0.986 (Bayesian state-space model)	NW Atlantic	TEWG (2009)
Notes	Nesting females in the Mediterranean are much smaller than in the Atlantic.		Margaritoulis et al. (2003)

Table 9: Biologic parameters for the green sea turtle, *Chelonia mydas*.

Parameter	*Chelonia mydas*		*References*
Maximum Size	120 cm SCL average adult size (71-153 cm SCL)		Monzón-Arguello (2011)
Size at maturity	>70-100 cm mean 99.5 cm SCL Females	Mexico	Hirth (1997)
	83.2-116.7 cm SCL nesting size Females mean 101.5 cm SCL (n= 90)	Florida	Witherington and Ehrhart (1989)
	69.2-116.5 cm SCL nesting size Females mean 100.1 cm SCL (n=1,146)	Atl. Costa Rica	Carr and Ogren (1960)
	100-134 cm CCL nesting size Females mean 118.6 cm CCL (n=1,188)	Atol das Rocas Brazil	Bellini et al. (1996)
	84.8–94.9 cm SCL Males	Atl. Costa Rica	Ross and Lagueux (1993), Troëng (2000)
Lifespan	32 yrs maximum reproductive life span	Georgia U.S.	Frazer (1983)
Age at Maturity	28 to 44.5 yrs Females	N Atlantic	Goshe et al. (2010)
	37 to 47.5 yrs males	N Atlantic	Goshe et al. (2010)
	30 yrs estimate based on mean nesting size	Florida	Mendonça (1981), Seminoff (2004)
	27 yrs estimate based on mean nesting size	Florida	Frazer and Ehrhart (1985), Seminoff (2004)
	35 yrs estimate based on mean nesting size	Ascension Island	Frazer and Ladner (1986), Seminoff (2004)
	36 yrs estimate based on mean nesting size	Suriname	Frazer and Ladner (1986), Seminoff (2004)
	33 yrs estimate based on mean nesting size	U.S. Virgin Islands	Frazer and Ladner (1986), Seminoff (2004)
Fecundity	1 to 7 clutches per season with a 12-14 days interval		NMFS (1991)
	110 to 115 Mean clutch size ; 136 eggs average	Florida	NMFS (1991)
Breeding Strategy	3 yrs nesting interval		Hirth (1997)
	2, 3, 4 yrs; occasionally 1 yr nesting interval		NMFS (1991)
VBGF (k)	Logistic k=0.0777604, Gompertz k=0.0433663 Females skeletochronology		Goshe et al. (2010)
	VBGF k=0.031422, Gompertz k=0.0576755 Males skeletochronology		Goshe et al. (2010)
	Logistic k=0.814536, Gompertz k=0.0510606 Combined skeletochronology		Goshe et al. (2010)
	k=0.074 Length-frequency MULTIFAN	Bahamas	Bjorndal et al. (1995)
	k=0.180 Length-frequency SASNLIN	Bahamas	Bjorndal et al. (1995)
Notes	Nesting females from the Mediterranean present smaller sizes than other populations		Monzón-Arguello (2011)
	Mature males are smaller than mature females in some populations		Hirth (1997)

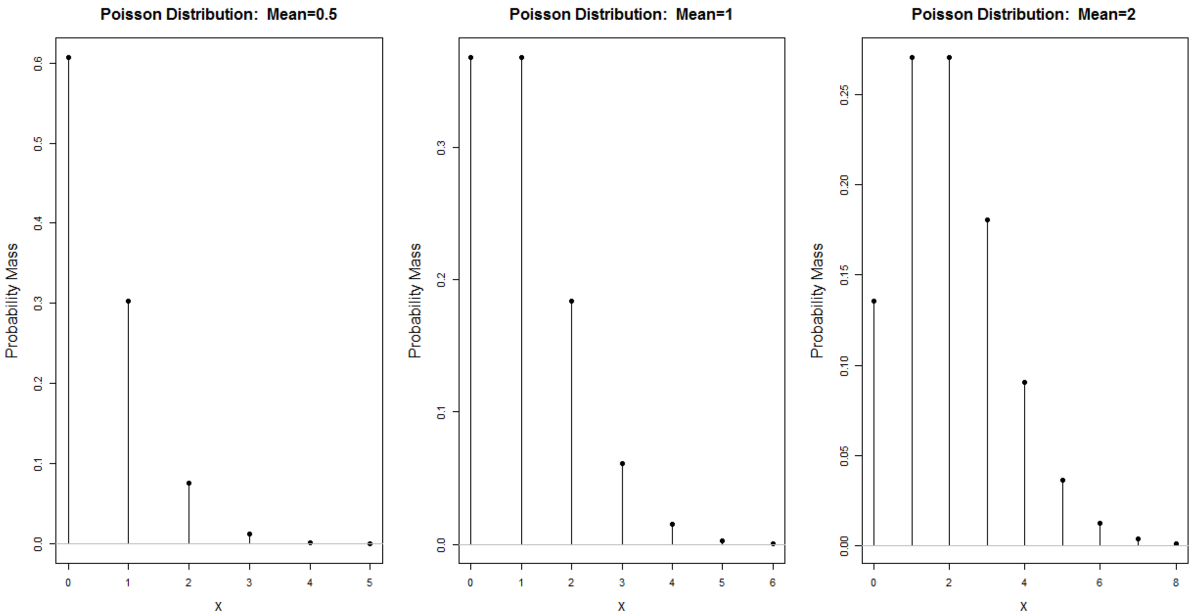

Figure 1: Probability Mass Functions of the Poisson distribution with lambda (mean) = 0.5 (left), 1 (centre) and 2 (right).

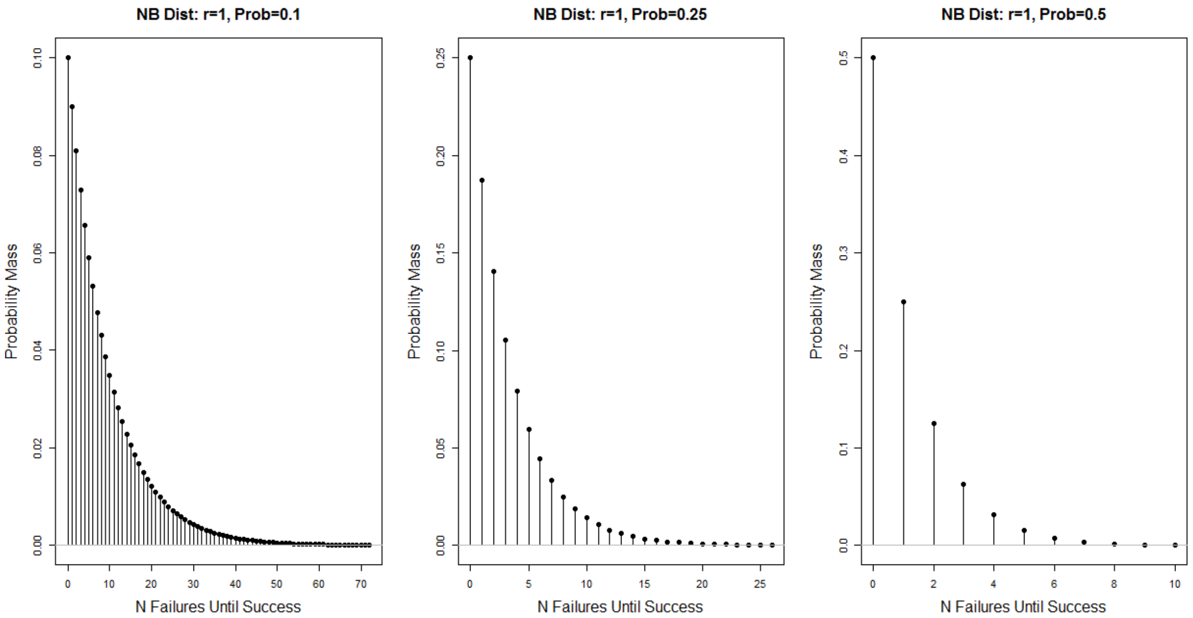

Figure 2: Probability Mass Functions of the Negative Binomial distribution with a probability of success = 0.1 (left), 0.25 (centre) and 0.5 (right).

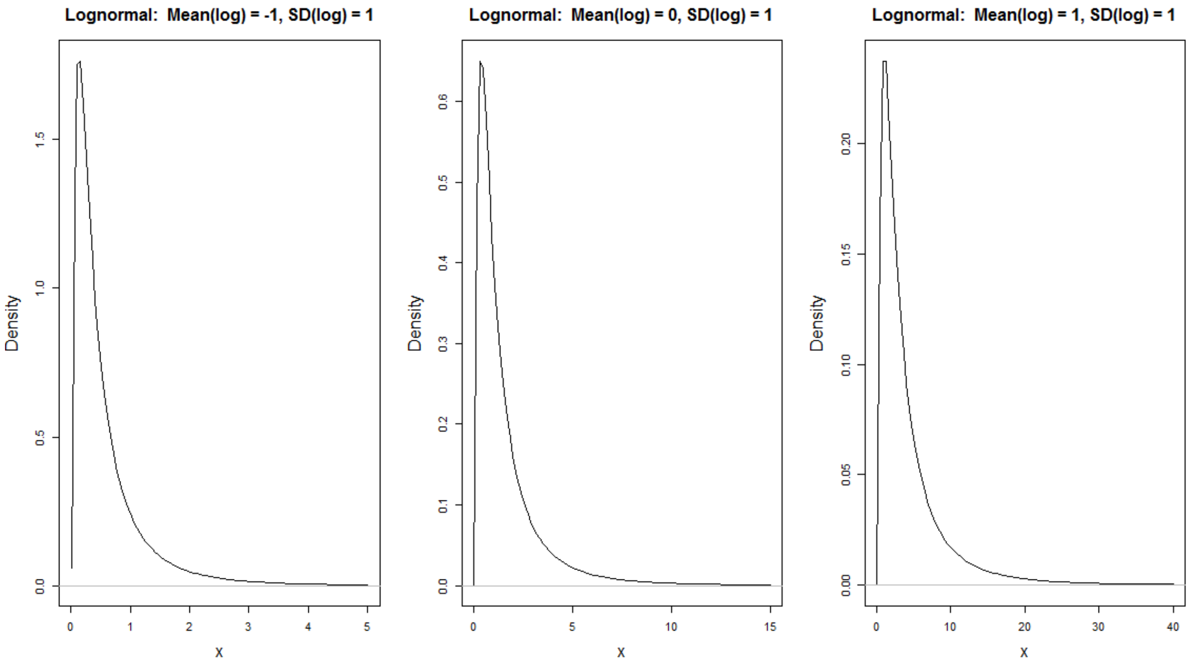

Figure 3: Probability Density Functions of the Lognormal distribution with a mean (log) = -1 (left), 0 (centre) and 1 (right). The mean and standard deviation of the distribution are in the log scale.

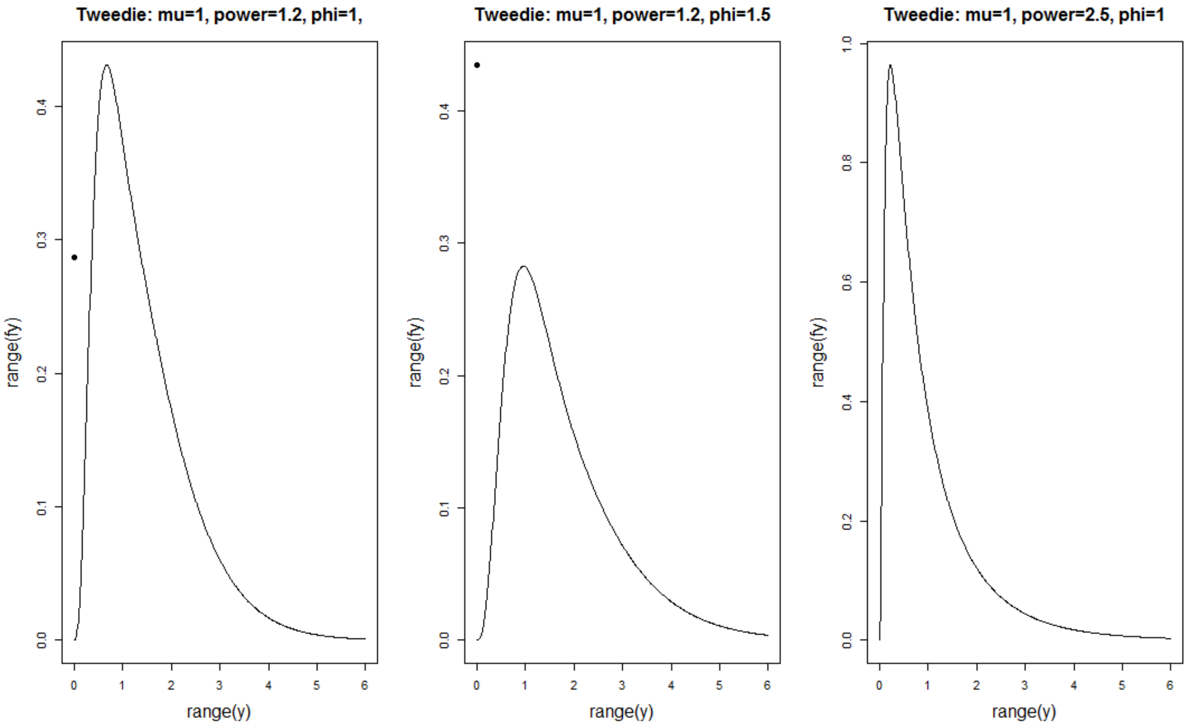

Figure 4: Probability Density Functions of the Tweedie distribution with μ=1, φ=1, *p*=1.2 (left); μ=1, φ=1.5, *p*=1.2 (centre) and μ=1, φ=1, *p*=2.5 (right). Note the mass of zeros when the power *p* takes values between 1 and 2. Plots built in R, using functions available in library "tweedie" (Dunn 2011).