Methods for standardizing CPUE and how to select among them

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Abstract

A number of methods for estimating trends in relative abundance based on standardized catch-per-unit-effort (CPUE) are discussed, including general linear and additive models, habitat-based standardization, neural networks, and regression trees. Methods and criteria for testing among various standardization techniques are presented and recommendations for future research are presented.

Authors' Keywords: catch, effort, methods, cross validation, habitat-based standardization, HBS, CPUE, statistical test, stock assessment, fisheries management, review

Introduction

Catch-per-unit-of-effort (CPUE) is often the main piece of information used in fisheries stock assessments. CPUE is usually assumed to be proportional to abundance and therefore included in the stock assessment as a relative index of abundance. The stock assessment model (population dynamics model) is used to predict the relative index of abundance by multiplying the predicted absolute abundance by a constant of proportionality (often called the catchability coefficient, q). The stock assessment model parameters are then modified to match the predicted relative index from the model with the CPUE based relative index of abundance. This is commonly referred to as fitting to the CPUE index, and it is carried out using an iterative function minimizer. The measure of how closely the indices match is usually a likelihood (or least squares) function based on the normal or log-normal distribution.

Due to the importance of CPUE in many stock assessments and the assumption that CPUE is proportional to abundance, it is important that any other factors that may influence CPUE are removed from the index. The process of reducing the influence of these factors on CPUE is commonly referred to as standardizing the CPUE. There have been various methods developed to standardize CPUE. However, the most common method is the application of generalized linear models (GLM).

GLMs are convenient because they have a long history, they are well understood, and they have accepted methods to choose factors, or variables, in a model. Unfortunately, they are limited in their functional form to linear relationships. These relationships can be made more complex, such as by adding higher order terms or by adding interaction terms, but they remain linear approximations to what is generally a non-linear world.

Several authors have developed methods that attempt to overcome the limitations of GLMs, but few have attempted to determine if they provide improvements over GLMs or to develop appropriate tests. Here we attempt to (1) briefly review some of the different methods used to standardize CPUE and (2) describe methods that can be used to test for differences among them. Finally, we provide an initial guide to future research into standardizing CPUE and a guide to developing a CPUE based index for specific applications.

Methods to Standardize CPUE

General Linear Models

General linear models (GLM; e.g. Allen and Punsly 1984) are the most common method used to standardize CPUE. The CPUE is predicted as a linear combination of the explanatory variables. Variables can be either categorical or continuous. Often, continuous variables are grouped into intervals and included as categorical variables. This is done, e.g., to provide indicators for intrinsically nonlinear relationships, to reduce problems encountered with large numbers of zero observation strata [see also delta lognormal method below], or to create strata which reflect combinations of continuous variables with certain characteristics that taken together serve as classifications that have no meaning on an ordinal scale. Higher order terms and intrinsically linear terms can be included for continuous variables in GLM models. For example, if the relationship is assumed to be domed shaped, the CPUE could be related to the square of the explanatory variable. Interaction terms can also be added to the model to allow for interactions among explanatory variables when appropriate.

The main objective of the analysis is to estimate a year effect. The year effect is used to represent the annual relative levels of abundance and is used as the relative index of abundance to include in the stock assessment. The year effect is included in the GLM as a categorical variable. Interactions with the year effect would invalidate the year effect as an index of abundance. For this reason, most analyses do not consider interaction terms for the year effect.

In the process of fitting the GLM, it must be decided whether or not to include explanatory variables. If too few explanatory variables are included, then variation from factors that influence CPUE but which are not included in the model may be attributed to the year effect, i.e. attributed to changes in abundance. If too many explanatory variables are included in the model (i.e. the model is over-fitted), then some of the variation in CPUE that should be attributed to changes in abundance will in fact be attributed to the extraneous factors included in the model. In either case, the standardized CPUE and thus the index of relative abundance may be biased.

Delta-lognormal GLM

Many applications have a large number of unsuccessful units of effort [strata with positive effort and zero catch], and this can cause bias in the analysis. Standard GLM analyses based on log-transformation of the data require that no CPUE observation in a strata equal zero, and it is common practice to combine strata to eliminate zero catch observations or to add a constant to the data, so that CPUE is always greater than zero. Both of these approaches have disadvantages. When strata are collapsed, it is possible that important information contained in explanatory variables on levels not related to the collapsed strata may be compromised. This may reduce the performance of the GLM or require the development of alternate strata for certain explanatory variables in order to conduct the analysis. In the second approach, adding a constant may cause some bias in the estimated year effect. The delta-lognormal method (Pennington 1983, 1996; Lo et al 1992) has been used to overcome these problems in a GLM framework. This method models the zero catches separately and then models the positive catches using a GLM. The model for the zeros and the GLM are then combined to generate an index of abundance.

Nonlinear Models

GLMs are restricted in the relationship between the CPUE and the explanatory variables. In many situations nonlinear relationships may better describe the relationships between CPUE and explanatory variables.

General Additive Models

General additive models (GAMs) afford greater flexibility in expressing relationships between explanatory variables and CPUE, significantly expanding the range of possible relationships which may be considered during standardization procedures. An example of use of GAMs in the Pacific to standardize CPUE of swordfish and blue shark is provided by Bigelow et al (1999).

Neural Networks

Similar to GAMs, neural networks offer more flexible relationships between the CPUE and explanatory variables. Maunder and Hinton (submitted) developed a neural network approach to derive estimates of relative abundance for CPUE data. Their major development was to integrate the year effect as a categorical variable with a neural network. The Neural network was used to model the non-linear relationships between the explanatory variables and CPUE. Unlike GLMs for which the relationships are restricted to linear relationships (with the addition of higher order and interaction terms), neural networks allow the data to estimate these relationships. A good introduction to the relationship between neural networks and regression and terminology used in both is given by Warner and Misra (1996).

One problem with neural networks is that the there may be multiple solutions to the neural network using the common estimation techniques. These different solutions are obtained from different starting values for the weights. Initial investigations suggest that the different solutions provide similar estimates of the year effect (Maunder and Hinton submitted), to which may be applied simple methods to average the results.

Regression Trees

Regression trees are similar in concept to neural networks. Watters and Deriso (2000) used regression trees to standardize CPUE for bigeye tuna in the eastern Pacific Ocean. They suggest that the main advantage of regression trees is that they are ideally suited to detecting and extracting important and complex interactions of the explanatory variables.

Standardization model integrated with population dynamics model

The traditional approach of including CPUE data into stock assessment models uses a two-step approach. The first step is to standardize the CPUE using one of the approaches described here and the second step is to fit to the CPUE based index of relative abundance in the stock assessment model. Maunder (1998; 2001a) suggests that the two step approach usually does not fully propagate uncertainty from one analysis to the next. For example, most applications assume the same precision for individual estimates of annual relative abundance. Maunder and Starr (in press) investigate the biased caused by this assumption and describe two improved methods to include the precision of the annual relative abundance estimates.

An alternative approach to the two step procedure is to integrate the CPUE standardization into the stock assessment model (Maunder 2001b). In this method the standardization is integrated with the stock assessment model. Instead of estimating the year effect, the population dynamics model is used to represent the year effect. The parameters of the population dynamics model and those of the standardization model are estimated simultaneously while optimizing the objective function that combines the CPUE data and other data used in the stock assessment (e.g. catch-at-age data). Maunder (2001b) showed in an application using GLM standardization that the integrated method produced confidence intervals that were narrower and included the true value more often than if the two step procedure was used.

Habitat Based Models

Nonlinear models, neural networks, regression trees, and GAMs are more general in their functional forms when compared to GLMs, but they do not in general use analytical reasoning to define the functional form of the relationship between the explanatory variables and CPUE. Hinton and Nakano (1996) developed a general habitat-based standardization (HBS) method that provides an analytical framework, and by extension a statistical construct [see below], to incorporate understanding of the distributions of the environmental, fishing gear, and a species into the standardization of CPUE. They illustrated the method using data obtained from studies of the distribution of depth at which hooks on longlines are fished, the habitat preference of blue marlin, and the spatial distribution of temperature in the Pacific. The basic premise is that if a hook is fished in an environment that is preferred by the species, then it has a higher probability of capturing that species. This is particularly important, for example, when standardizing effort of longline gear targeting tuna, because the depth of the gear has increased over time as fishermen targeted bigeye tuna, which are generally found at deeper depths in the water column.

Bigelow et al. (2002) have used the habitat based standardization method (HBS) to create CPUE based indices of relative abundance for bigeye and yellowfin tuna in the Pacific Ocean. These indices have been used for assessments in both the western-central Pacific Ocean by SPC (Hampton 2002a,b) and the eastern Pacific Ocean by the IATTC (Maunder 2002; Maunder and Harley 2002). Maunder et al. (submitted) showed that the HBS standardized CPUE for these stocks was a statistically significant improvement over nominal effort.

Statistical Habitat Based Model

When the HBS method is applied using data on the distributions of a species and of fishing effort with respect to the environment as input for the model, the method is deterministic in nature. The fact that the model has an analytical basis does not mean that it will necessarily produce better estimates than other methods, such as a GLM, and whether it performs better or worse than competing standardization models when used in this way may be tested (Maunder et al (submitted)). However, Hinton et al (2001) and Hinton and Maunder (In Prep) have developed a statistical version of the HBS method that provides improved estimation of CPUE by estimating the parameters of the HBS model. The version used by Hinton et al (2001) incorporated the integrated model approach of Maunder (2001b) to provide maximum use of information in standardization and fitting of population dynamics models. The statistical HBS method uses the information on such as the habitat preference of a species as a prior that can be updated based on a better correspondence between the observed and predicted CPUE. In addition, the statistical HBS (statHBS) integrates a GLM based component that allows for additional explanatory variables, a gear retrieval component, and gear depth modification from shear. Because of the flexibility of this method, additional components, linear or nonlinear, can easily be added to the model.

Model Tests and Comparisons

The objective of many regression analyses is to provide a predictor of unobserved events given a set of observed explanatory variables. Therefore, the goal of the analysis is to choose the model that best predicts these unobserved events. The development of the model requires fitting the model to observed events. If the model is chosen that best fits the observed events, then it may not be a good predictor of unobserved events. This can be illustrated by the fact that a model with more parameters will always fit the data as well or better than a model with less parameters if the models are nested. However, the model with more parameters may be fitting the noise rather than the general pattern. Therefore, when applied to data for prediction, it may perform poorly. A model with fewer parameters may be a better predictor, as it predicts the overall trend and not the noise. The goal thus becomes selecting the model with the optimal number of parameters. Unfortunately, not all models are nested and it may be desirable to test among models with different structures, e.g. testing a GLM versus a neural network.

The methods used to standardize CPUE are based on predicting catch or CPUE, with the goal of providing an index of relative abundance, usually by estimating a year effect. Good prediction of catch or CPUE does not necessarily infer good estimation of the relative abundance, but it is generally assumed that the best model or fit provides the best available indicator of relative abundance. The year effect may explain variation caused by other factors, or other explanatory variables included in the analysis may explain variation that should be attributed to abundance. In either case, the estimated year effect may be a biased representation of the abundance. Therefore, it would be appropriate to develop tests based on the ability to estimate the year effect. Unfortunately it is not possible to know the actual abundance, and therefore the tests that can be used to evaluate methods are limited. Below we describe three categories of tests, the first two are based on the ability to predict catch, or CPUE. Dependence on these tests strictly assumes that models that best predict catch or CPUE are the best predictors of relative abundance. The third category is based on how consistent the estimates are with auxiliary information about the year effect. This category of tests examine a universe of available information beyond catch and effort data.

<u>Likelihood ratio, AIC, BIC, and Bayes Factors</u>

A majority of tests are based on maximum likelihood. The likelihood ratio test (LRT) tests if a more complex model, one with more estimated parameters, fits the data significantly better than a less complex model. The LRT requires that the models be nested. Nested means that the less complex model is equivalent to the more complex model with one or more of the parameters fixed (usually at zero, one, or equal to another parameter). The test criterion is based on the Chi-square distribution with the degrees of freedom equal to the difference between the number of parameters in the models.

The Akaike Information Criteria (AIC, Akaike 1973) and Bayes Information Criteria (BIC, Schwarz 1978) are used to determine which model best fits the data. The models do not need to be nested and can have the same number of parameters or different number of parameters. It should be noted that increasing the number of CPUE data points does not increase the number of parameters, unless there are more years of data or more explanatory variables are added to the analysis.

A third family of tests which is not restricted in application to nested models are Bayes factors (Aitkin 1991), which can be used to determine a significant difference between models with the same number of parameters. A more in-depth discussion of the application of these various methods to testing models used to standardize CPUE may be found in Maunder et al (Submitted).

Cross validation

Simple cross validation is an alternative to likelihood-based tests for selection among models. In simple terms, cross validations uses part of the data set (the training set) to estimate the parameters of the model (called training the model) and part of the data set (the test data set) to determine how well the predictions fit the data (testing the model). The model that best predicts the test data set is chosen as the best model. Unlike the likelihood based tests, cross validation does not make assumptions about the distribution of the errors, and it does not require the models to be nested. Cross validation can also be used to compare multiple models of different types. Many modifications to the simple cross validation have been proposed and used to make cross validation more efficient.

We suggest that a three-subset test can be used to test among models of different types. The first subset of the data is used to estimate the parameters of the model. The second subset of the data is used to determine the complexity of the model for each model type, e.g. what variables to include in a general linear model or how many neurons to include in a neural network. The third subset is used to select among the different types of models, e.g. neural network versus a GLM. The cross validation tests may be sensitive to the proportion of the data set used as the test data set, therefore it is important to determine the optimal size of the test data set for the particular application (Maunder and Hinton submitted).

System-based Testing

In general it is held that the measure of CPUE is the principal measure of relative abundance providing information to the population dynamics model, however in many models ancillary data on age or size structure or movement is included in an effort to improve the estimation of the status of a population or stock. Within the context of such a model it is possible to determine which of a series of CPUE estimates is most consistent with the additional information inputs and the model structure. For example, Kleiber et al (In Press) compared results obtained using CPUE series for blue marlin in the Pacific using MULTIFAN-CL (Fournier et al 1998) and found that CPUE from HBS provided significant improvements in precision of estimated parameters of interest to fisheries management. In other words, they found that in this instance results obtained using HBS were most consistent with the ancillary data used in the analyses.

McDonald et al (2001) described a method for estimating the weighting factors for multiple indices of abundance. The method is based on the normal likelihood function and the analytical maximum likelihood estimates of the standard deviation. However, they relaxed the commonly used assumption of statistical independence of surveys implied by univariate likelihood functions by using a multivariate likelihood function. Thus, they generalized the method to include correlation among the index errors. They described likelihood ratio tests to determine if correlation between index errors should be included in the analysis by restricting the multivariate likelihood function covariance matrix (i.e. setting some cells to zero). Analytical estimates of the variance and covariance parameters were described. Simulations showed that the tests correctly chose the appropriate correlation structure. The method of McDonald et al (2001) may provide a measure of the reliability of the standardized CPUE series based on the variance estimates obtained. This method was also suggested by White and Lubow (2002) and is described in Seber and Wild (1989) using iterative methods.

Model Selection and Future Research

Immediate needs of management and conservation, and current data availability will drive the model selection process at the first level. But in the process of providing scientific advice based on current data availability and appropriate models, it must never be left that the second level, continuing and anticipated future application requirements, is left untended.

Meeting Immediate Needs

We suggest the following approach to determining the most appropriate CPUE based relative abundance index to meet immediate management and conservation needs using available data in a cross validation method. First a candidate set of methods should be chosen. We suggest that a GLM-based method should always be included in this set of candidates because it is the most familiar model used to standardize CPUE and will provide a convenient point for comparison to other methods. Whenever a habitat-based model is used, we recommend that it should be a statHBS model.

Next, the data should be divided into two sets. If the application has a large data set (see Amari et al 1997) as are available for analyses of tunas and tuna-like species, then we suggest that the data set should be subdivided into one set containing 90 percent and one containing 10 percent of the data. The first set should be used to estimate the parameters of each candidate model using the optimal method for each model type. For example, in the case of a GLM, all of the data points in the 90 percent data set may be used in a stepwise selection procedure to determine the best GLM model. In the case of a neural network, a training and testing data sets are selected from the 90 percent, and the best neural network model is determined using cross validation (see section above). The final set of 10 percent of the original data should be used to compare among methods to determine which is the “best model” in terms of predicting catch or CPUE.

In addition to determining which of the models (e.g. GLM or neural network) was the best predictor of the final 10 percent data set, a standardized CPUE series may be generated from each and then compared for consistency with ancillary data by using the standardized CPUE series from each in a population dynamics model such as MULTIFAN-CL, as discussed above. A finding that the data is consistent with the ancillary data means that under the assumption that the dynamics model is correct, the information contained in the modeled CPUE is consistent with the other data and the assumed structure of the dynamics model. Thus, in this framework a comparison of two models that provide the best measures of relative abundance, e.g. our GLM and neural network, using measures of variance of parameter estimates or other dynamics-model diagnostics, is conditioned on the assumption that the dynamics model is the correct model.

Future Application Requirements

It is not sufficient to say that what has functioned in the past will continue to suffice for the future, for the certainty in resource management is that the status of the resource will change, due to changes in natural or anthropogenic stress or both, and that harvesters will make every effort to improve their economic return by seeking means to improve their catch rates. Thus, it is critical that research be devoted to developing and improving the understanding of factors which may change the relationship between catch and effort. We believe that future research will be driven by the need to maximize the information obtained from existing long-term databases, while at the same time anticipating the data that will be required to provide scientific advice for future management and conservation action.

We suggest that future research may be seen as consisting of five related components: (1) determining which of currently available methods for standardizing CPUE are generally applicable and the conditions under which they will perform better than other methods; (2) developing tests appropriate for determining which standardization methods provide the best index of relative abundance from a set of candidate methods; (3) determining the status of current data holdings, including identifying the nature and magnitude of deficiencies, and determining the priority for data collection for current model application; (4) defining what data should be collected in the future to attempt to capture changes in the relationship between catch and effort and to ensure the ability to maintain the information context and usefulness of long-term data series; and (5) exploring new methods for standardizing CPUE anticipating various changes in requirements of management and fisherman response.

The currently available standardization methods that are generally applicable can be examined using simulation analyses. These analysis should include many different combinations of population, catch, and effort trajectories, i.e. many possibilities which might represent some realized situation. This will allow the general performance of the methods to be determined using tests developed under (2) above. Methods that consistently perform poorly can then be rejected. Other methods can be further tested and improved.

The development of appropriate tests needs to start with a through review of the appropriate literature. Starting points include likelihood-based tests (Maunder et al submitted), cross validation tests (Maunder and Hinton submitted), and system-based tests (Kleiber et al In Press; McDonald et al 2001). The statistical literature contains a wealth of information on model testing, and this should be used to help improve the further development of model selection tests. The performance of candidate tests should be evaluated using simulation analysis.

Finally, it is important to know the limitations current data places on application of models and to anticipate the future by deciding what data should be collected into the future. For example, one of the most important factors for standardization of effort data from tuna longline fisheries is some measure of the depth at which the hooks on the longline are fished. Therefore, no matter which method is used to standardize the CPUE, the method will not perform well unless the appropriate explanatory variables are available. This information was not routinely collected prior to 1975 in the Japanese fishery (Hinton and Nakano 1996), and in some longline fisheries it is still not collected, which has been identified as a data deficiency in the information required for standardization models such as GLM and statHBS. One approach to setting data requirements is to collect all the possible information about the fishing process (e.g. the date, time, bait used, size of the boat, etc.), however this may not be all that is required, and in fact may include factors which have little or no bearing on catch and effort. For example, the analytical framework of the HBS model indicates that the habitat preference of the species and the environment may be as important as the depth of the longline. Basic research is needed on individual species, fishing technology, and the environment to determine what factors are most influential in determining CPUE.

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