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Evaluation of alternative age-based methods for estimating relative abundance from survey data in relation to assessment models

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ABSTRACT

Indices of abundance from fishery-independent trawl surveys constitute an important source of information for many fish stock assessments. Indices are often calculated using area stratified sample means on age-disaggregated data, and finally treated in stock assessment models as independent observations. We evaluate a series of alternative methods for calculating indices of abundance from trawl survey data (delta-lognormal, delta-gamma, and Tweedie using Generalized Additive Models) as well as different error structures for these indices when used as input in an age-based stock assessment model (time-constant vs time-varying variance, and independent versus correlated age groups within years). The methods are applied to data on North Sea herring (*Clupea harengus*), sprat (*Sprattus sprattus*), and whiting (*Merlangius merlangus*), and the full stock assessments are carried out to evaluate the different indices produced. The stratified mean method is found much more imprecise than the alternatives based on GAMs, which are found to be similar. Having time-varying index variances is found to be of minor importance, whereas the independence assumption is not only violated but has significant impact on the assessments.

1. Introduction

Many fish stock assessments are based on two key sources of input data: (1) The removals from the population due to commercial fishing and (2) indices of abundance based either on catch and effort data from commercial or recreational fisheries, or from independent scientific surveys (Maunder and Punt, 2004). An index of abundance is a relative measure of e.g. the biomass or number of individuals in a population and most often proportionality is assumed:

$$I_y = qN_y$$

In this paper the focus will be on the analysis of fishery-independent survey data to create age-disaggregated indices of abundance, as well as on the subsequent use of these as input for a stock assessment model.

Several quite different approaches to the analysis of survey data exist depending on the design of the experiment, see Kimura and Somerton (2006) for a review. A popular method is based on stratified analysis, where the region of interest is divided into smaller strata and assuming that abundance is homogeneous within strata. The area weighted mean abundance is then calculated for each stratum and summed to give an index for the whole region. The probably simplest procedure uses the arithmetic mean within strata (e.g. ICES, 2012c). A slightly more refined alternative is the use of delta-distributions (e.g. Pennington, 1983), where zero values are modelled separately and the positive values are assumed to be log-normal (or Gamma) distributed. Although departures from the assumed delta-distributions can be hard to detect for small to moderate sample sizes, which may lead to biased estimates (Smith, 1990; Myers and Pepin, 1990), the mean in the delta-distribution is a more efficient estimator when the nonzero values are well approximated by a lognormal distribution, specifically it is less sensitive to the occasional huge catches that are often found in marine data sets (Pennington, 1996).

Discrete valued distributions such as the negative binomial (Kristensen et al., 2006; Cadigan, 2011) and the Log-Gaussian Cox Process (LGCP) (Lewy and Kristensen, 2009) have also been applied, but age-disaggregated indices are typically not discrete valued, so these will not be considered in this study. More recently the Tweedie distribution (Tweedie, 1984) has been suggested as an alternative to delta-distributions (Candy, 2004; Shono, 2008).

When external factors other than changes in abundance affect the catch rate, these need to be corrected for in order to obtain an unbiased index (Maunder and Punt, 2004). To this end, more advanced methods such as generalized linear models (GLMs),

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generalized linear mixed models (GLMMs) and generalized additive models (GAMs) have previously been applied to correct for effects such as spatial position, depth, and time of day (Stefansson, 1996; Petrakis et al., 2001; Piet, 2002; Adlerstein and Ehrich, 2003; Beare et al., 2005). GAMs permit non-linear smooth relations between the response and the explanatory variables, so spatial stratification can conveniently be replaced by smooth functions of geographical coordinates (so-called splines). When stratification is used, there will be a trade-off between loss of spatial resolution due to the assumption of homogeneity within strata and problems with few or missing values when a too fine-grained stratification is used. When using GAMs, this trade-off problem is replaced with an easier problem of smoothness selection for the splines, which can be solved almost automatically using modern software packages (Wood, 2006a). Kernel density smoothing is an alternative but similar way of dealing changes in survey design (Chen et al., 2004). Sometimes the stratification is chosen such that it contains complex information about the seabed, under-water obstacles etc. (Cadigan and Tobin, 2010), which means a spatial smoother is less appropriate, but such situations will not be considered in this study.

Although useful on their own, one of the main uses of indices of abundance is to use them as input to an assessment model in combination with commercial catch data to obtain estimates of biomass and fishing mortality. The way that trawl survey data enters into many stock assessment models, can roughly be described as follows: (1) numbers-at-length data from individual hauls are preprocessed and reduced to a matrix of numbers-at-age (the index of abundance). (2) Each number in this matrix is taken as an observation of the relative abundance-at-age in the stock assessment model (often assumed independent and with constant CV through time). Although often separated for convenience, we will demonstrate that more information can be extracted from the data by combining the analyses: Instead of reducing the information from a survey to a matrix, we will use three matrices (by adding standard deviations and correlations), and by actually carrying out the stock assessments with different assumptions about the survey indices, we are provided with additional means to evaluate the impact of changes in the preprocessing step. This paper is therefore organized as follows: the first part of this paper deals with a comparison of the stratified mean method (SMM) with three variations of the Delta-GAM approach for calculating indices of abundance from trawl survey data, and second part of this paper deals with performing stock assessments using different assumptions on the error structure for the survey indices derived in the first part. Using bootstrap methodology we will show that there can be considerable positive correlations between abundance indices by age within the same year, and that including these correlations in a stock assessment model improves the model likelihood using the same number of parameters indicating improved precision in forecasts.

2. Materials and methods

2.1. Data

The data sets consist of 20 years (1992–2011) of biannual (Q1 and Q3) trawl survey data from the International Bottom Trawl Survey (IBTS) in the North Sea, downloaded from the DATRAS database (www.datras.ices.dk, data downloaded 2012-04-30). The survey is based on a stratified random design in which the North Sea is divided into so-called statistical rectangles each of size 1° longitude × 0.5° latitude, where (ideally) two hauls should be taken each quarter (each by different countries), each separated by at least 10 n.m. (ICES, 2010). Trawling is mostly performed during daytime, although some hauls are also taken during the night. Trawling time is 30 min. for all but a few hauls. The last major revision of the IBTS sampling protocol was performed in 1991, so no major changes occured in the period considered. The commercial catch-at-age data, natural mortalities, proportion mature, and weight-at-age used in the stock assessments are taken from ICES (2012a) for sprat and herring and from ICES (2012b) for whiting, and the number of age-groups used in the analyses are also the same as in these two sources. Numbers-at-length from the trawl surveys are first converted to numbers-at-age using the method described Berg and Kristensen (2012) and implemented in Kristensen and Berg (2012), see online Supplemental Materials for details. We refer the reader to ICES (2010) for a complete description of the IBTS survey design.

2.2. Stratified mean method

The survey index is calculated using the stratified mean method (SMM) by taking the mean catch per rectangle, and then the mean over all rectangles in the North Sea. This method is similar to the current way that survey indices for use in assessment are calculated for stocks in the North Sea (ICES, 2012c), and is thus a relevant baseline to compare with.

2.3. Delta-GAM and Tweedie

The delta-models consist of two parts: one that describes the probability for a non-zero catch (binomial response), and another that describes the distribution of a catch given that it is non-zero (positive continuous). The two parts may be fitted independently which eases computation. We will consider both the lognormal distribution and the Gamma distribution for the positive values. We assume the following relationship in both parts of the model between the expected response (μ, which is numbers-at-age or 1/0 for positive/non-positive catch depending on the model) and external factors:

$$g(\mu_i) = \mathrm{Year}(i) + U(i)_{\mathrm{ship}} + f_1(\mathrm{lon}_i, \mathrm{lat}_i) + f_2(\mathrm{depth}_i) + f_3(\mathrm{time}_i) \quad (1)$$

where Year(i) maps the ith haul to a categorical effect for each year, $U(i)_{\mathrm{ship}} \sim N(0, \sigma_u)$ is a random effect for the vessel collecting haul i, f_1 is a 2-dimensional thin plate regression spline on the geographical coordinates, f_2 is a 1-dimensional thin plate spline for the effect of bottom depth, and f_3 is a cyclic cubic regression spline on the time of day (i.e. with same start end end point). The function g is the link function, which is taken to be the logit function for the binomial model, and the logarithm for the strictly positive responses in the Gamma and Tweedie models. The lognormal part of the delta-lognormal model is fitted by log-transforming the response and using the Gaussian distribution with a unit link. Each combination of quarter age group are estimated separately.

The length to age conversion may produce numbers that are very close to zero, which poses problems for the log-normal distribution and Gamma distribution when the mean is far from zero (Myers and Pepin, 1990; Kimura and Somerton, 2006). This can be remedied by simply treating values below some small chosen constant k as zero, and thereby move these from the positive component of the delta-distribution to the zero component (Folmer and Pennington, 2000). A preliminary analysis using histograms of residuals from the positive part of the delta models indicated that $k = 0.01$ was a reasonable choice (not the often ad-hoc chosen value of $k = 1$, which resulted in clearly non-Gaussian residuals in positive part of the delta-lognormal model). A brief sensitivity analysis using $k = 0.05$ indicated that that exact choice of k is not important though. Both the Gamma and the lognormal distributions have quadratic variance functions, $Var[y_i] = \phi\mu_i^2$, which can be checked by plotting log(sample variance) versus log(sample mean) for homogeneous groups of data (see e.g. Brynjarsdóttir and Stefánsson, 2004).

The likelihood of the delta-distributions, can be found by fitting the model for the zero and positive observations independently