A PRELIMINARY STOCK ASSESSMENT OF THE ALBACORE TUNA (THUNNUS ALALUNGA) STOCK IN THE NORTHERN ATLANTIC OCEAN USING A NON-EQUILIBRIUM PRODUCTION MODEL

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SUMMARY

Catch and catch per unit effort are used to fit a biomass dynamic stock assessment model. A variety of diagnostics, are then presented to check for violations of the model assumptions and to explore the information in the data. Potential problems are identified and ways to overcome or avoid them discussed.

RÉSUMÉ

La capture et la capture par unité d'effort sont utilisées pour ajuster un modèle d'évaluation des stocks dynamique de la biomasse. Divers diagnostics sont ensuite présentés afin de détecter le non-respect des postulats du modèle et d'explorer les informations dans les données. Les problèmes potentiels sont identifiés et les façons de les surmonter sont discutées.

RÉSUMÉ

La captura y la captura por unidad de esfuerzo se usan para ajustar un modelo de evaluación de stock de dinámica de biomasa. Se presentan posteriormente diversos diagnósticos para comprobar las infracciones de los supuestos del modelo y explorar la información de los datos. Se identifican posibles problemas y se discuten formas de superarlos o evitarlos.

KEYWORDS

Albacore, ASPIC, Assessment, Biomass Dynamic, Diagnostics, North Atlantic, Likelihood Profiles, Surplus Production, R, FLR

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1. Introduction

In order to investigate the northern albacore stock we run a non-equilibrium production model with the input data agreed at the last Data Preparatory meeting held in Madrid (April 2013). We then present a preliminary assessment of the state of northern albacore stock.

A set of common diagnostics were presented in at the working group on stock assessment (SCRS2013-36) that can be used for different stock assessment models. In this paper we apply these diagnostics as part of the North Atlantic albacore biomass dynamic Prager (1992) assessment. The same diagnostics were also used for the Southern Stock (SCRS/2013/037) and the Northern and Southern stocks of swordfish. A range of stock assessment models are used by the SCRS, from biomass dynamic models using catch biomass and effort data with only a few parameters to statistical catch-at-size models with over a 1000 parameters. Despite these differences they are being used for the same purpose i.e. to estimate population parameters from fisheries dependent data. The stock assessment process assumes that the input data can be evaluated and fits compared ensuring some consistency when decisions are being made about model choices.

This paper is not intended to be used as a check list but an example of what to look at, how to do it, potential problems, consequences and how to overcome, but even better to avoid them, i.e. the intention is not to provide strict guidelines but to look at some methods that can be used for a range of stock assessment models that use indices of abundance such as Catch per Unit Effort (CPUE) for fitting.

2. Material and Methods

A Stock Production Model Incorporating Covariates (ASPIC) is a non-equilibrium implementation of a biomass dynamic model based on surplus production model. ASPIC uses time series of indices of abundance and catch biomass to estimate stock status and uses bootstrapping to construct sampling distribution for a statistic of interest, e.g. stock status, the biomass that would provide the maximum sustainable yield (B_{MSY} and MSY). The model was fit to five time series of catch and catch per unit of effort (CPUE) fisheries data covering 15 distinct fishing fleets (**Table 1**). The main assumptions of ASPIC are that population dynamics are surplus production function e.g. Pella and Tomlinson (1969). Where biomass of a stock next year (Bt+1) as the sum of the biomass this year Bt less the catch (Ct) plus the surplus production (Pt) where (r) is the intrinsic rate of increase, (K) the carry capacity (p) the shape of the surplus production function. If p < 1 then the curve is skewed to the left.

The dynamics i.e. productivity and reference points and the response of the stock to perturbations, are determined by r and the shape of the production function p; if p = 1 then MSY is found halfway between 0 and K, as p increases MSY shifts to the right.

It is also assumed that catches and catch per unit effort (CPUE) are from a single homogeneous stock and that the CPUE represent stock trends in abundance. If there are zero or negative correlations between the indices, then this means that a basic assumption of ASPIC is violated, either because factors other than stock abundance are determining catch rates or that the indices are fishing different stock components.

2.2 Diagnostics

In addition to the results of a preliminary stock assessment of the northern stock of albacore a set of diagnostics are presented. Large statistical stock assessment models require more diagnostics than simple models, but similar questions need to be answered and the goodness of fit for the different models compared. Therefore, in this paper we give examples of a range of diagnostics that can be applied to both simple and complex models. These diagnostic methods fall into two main categories i.e. exploratory data analysis and fits to data, e.g. residual plots, likelihoods, sensitivity tests, retrospective/cross validation.

2.3 Software

Software used was a biomass production model implemented as a package in R, this allows it to be used with a variety of other packages for plotting, summarizing results and to be simulation tested, e.g. as part of the FLR tools for management strategy evaluation (Kell *et al.*, 2007).

3. Results

The results are not intended to be used as stock assessment, i.e. to provide advice on stock status. The aim of the analysis is to provide a set of diagnostics to allow check of the validity of the data and results. 3.1 Input data analysis. The indices are plotted by year in Figure 1, points are the observed index values, the blue line is a less fitted to the points by index and red line is a GAM fitted to year as a smooth term and fleet as a factor. In other words, the red line shows a common trend and the blue line the trend suggested by the individual index. The differences between an index and the average trend can be seen by comparing the blue and red lines. We can see periods where there are different trends among fisheries, especially in the last years of the data series. To check the assumptions that the indices are unbiased estimates of stock trends, i.e. do not suggest contradictory trends, the correlations between indices and groups of indices are evaluated in Figures 2 and 3. Figure 2 plots the indices against each other, the blue line is a linear regression fitted to the points. In Figure 3, the colour shows the correlations between the indices (i.e. red negative and blue positive correlations) while the size of bubbles and depth of colour show the strength of the correlation. The order of the indices and the rectangular boxes are chosen based on a hierarchical cluster analysis using a set of dissimilarities for the indices being clustered. However sometimes even indices overlap for only a few years, and there may be negative correlations due to chance. It can be seen that there is a negative correlation between the Japanese and China-Taipei longline fleets, which may cause problems during when fitting and bootstrapping.

3.2 Residuals Analysis

An important way of checking a model fit is to look at the residuals to look for differences between the observed data and model predictions, i.e. a check for violation of models assumptions.

3.2.1 Fit to indices

The contradictory trends in the data, are further explored by plotting the observed against the fitted values, **Figure 5**. Since ASPIC assumes that an index is proportional to the stock the points should fall around the y = x line, it can be seen that in only one case this is appears to be the case. This may suggest that there are alternative stock hypotheses and that several scenarios should be run or else that the indices be explored to provide justification for excluding specific series. Patterns in the residuals are also evident, e.g. by plotting them against year in **Figure 6** with a lowest smoother to help identify patterns.

ASPIC assumes that the residuals are normally distributed with no autocorrelation, these assumptions are evaluated in **Figures 8 and 9**. The Q-Q plots in **Figure 8** compare a sample of data on the vertical axis to a statistical population on the horizontal axis, in this case a normal distribution. If the points follow a strongly nonlinear pattern this will suggest that the data are not distributed as a standard normal i.e. X N(0; 1). Any systematic departure from a straight line may indicate skewness or over or under dispersion.

Figure 9 plots the residuals against each other with a lag of 1 to identify autocorrelation. There are significant autocorrelations particularly for the Japanese and Taiwanese longlines, this could be due to an increase in catchability with time. This may result in a more optimistic estimate of current stock status as any decline in the stock is masked by an increase in catchability. It is also assumed that variance does not vary with the mean, this assumption is evaluated in **Figure 7** where the residuals are plotted against the fitted values. Any violation of the assumptions may result in biased estimates of parameters (and hence reference points and stock trends). In addition variance estimates obtained from bootstrapping assume that residuals are Independently and Identically Distributed (i.i.d.) and bootstrapped statistics may provide biased sample distributions.

3.2.2 Likelihood

Figures 10 and 11 plot residual sum of squares profiles for K and MSY to check that a solution has been found.

3.2.3 Sensitivity

Figure 12 performs a sensitivity analysis, by varying B0 to evaluate its effect of stock trends. This shows that the results are robust to the assumed B0 value.

3.24 Assessment

Figures 13, 14 and 15 show bootstrapped results showing biomass and fishing mortality relative to their corresponding estimated MSY values and kobe phase plots.

4. Discussion and Conclusions

We have presented a preliminary assessment for North Atlantic albacore using a dynamic biomass production model. focusing on diagnostic methods. The work is intended to provide examples of the steps that can be followed for a range of stock assessment models.

Various potential problems were identified, for example contradictory trends in the CPUE time series. This in turn resulted in patterns in the residuals that meant that the estimated parameters and that samples of statistics obtained from bootstrapping may be biased. Potential solution to this problem could be to create scenarios by index or groups of index showing similar trends or to explore a priori reasons for excluding indices. Alternatively the patterns seen could be due to model misspecification, i.e. seasonally or spatial factors not included in the assessment.

The diagnostics presented were done using R (e.g. the diags package). Although the results are from ASPIC, the same plots can be generated for any stock assessment methods that uses fits to CPUE series for calibration.

The paper was not intended to be used as a check list but an example of what to look at, how to do it, potential problems, consequences and how to overcome, but even better to avoid them, i.e. the intention is not to provide strict guidelines but to look at some methods that can be used for a range of stock assessment models.

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Figure 1: Plot of indices of abundance, points are the observed index values and the blue a lowest $_{\rm fi}$ t to the points by index. The red line is GAM $_{\rm fi}$ tted to lo(year) and fleet.



Figure 2. Pairwise scatter plots of the indices of abundance, blue lines are linear regressions _{fi}tted to the points, the shade area is the standard error of predicted means and the red line is the mean of the points on the y-axis.



Figure 3. A plot of the correlation matrix for the indices, blue indicate a positive correlation and red negative. the order of the indices and the rectangular boxes are chosen based on a hierarchical cluster analysis using a set of dissimilarities for the indices being clustered.



Figure 4. Trajectories of _{fi}shing mortality, stock biomass and yield.



Figure 5. Observed CPUE verses _{fi}tted, blue line is a linear regression _{fi}tted to points, black the y=x line.



Figure 6. Residuals by year, with lowest smoother and SEs.



Figure 7. Plot of residuals against _{fi}tted value, to check variance relationship.



Figure 8. Quantile-quantile plot to compare residual distribution with the normal distribution.



Figure 9. Plot of autocorrelation, i.e. residualt+1 verses residualt.



Figure 10. Likelihood pro_{fi}le for K to check that solution is found.



Figure 11. Likelihood pro_{fi} for MSY to check that solution is found.



Figure 12. Sensitivity analysis, where B0 is varied to evaluate its effect of stock trends



Figure 13. Bootstrap results, showing biomass relative to BMSY and harvest rate relative to $F_{MSY.}$



Figure 14. Kobe Phase plot of bootstrapped results for the last data year.



Figure 15. Kobe Phase plot of bootstrapped results for the last data year showing the 0.5, 0.75 and 0.9 Con_{fi} dence Intervals.