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LIKELIHOOD PROFILES BY DATA COMPONENTS TO EVALUATE INFORMATION CONTENT OF INDICES OF ABUNDANCE FOR NORTH ATLANTIC SWORDFISH

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SUMMARY

We use likelihood profiling by data component, i.e. for each catch per unit effort (CPUE) series as a data exploratory tool. The approach allows the information on key parameters in each time series to be evaluated.

RÉSUMÉ

Nous avons recours au profilage des vraisemblances par élément des données, c.-à-d. pour chaque série de capture par unité d'effort (CPUE) comme outil exploratoire des données. L'approche permet d'évaluer l'information sur les paramètres fondamentaux dans chaque série temporelle.

RESUMEN

Se utilizaron perfiles de verosimilitud por componente de datos, a saber, por cada serie de captura por unidad de esfuerzo (CPUE) como herramienta exploratoria de datos. El enfoque permite evaluar la información sobre los parámetros clave en cada serie temporal.

KEYWORDS

Biomass Dynamic, Diagnostics, Stock Assessment

1. Introduction

Biomass dynamic models are widely used in ICCAT for stock assessment and advice parameters are estimated by setting to time series of total catch and standardised catch per unit effort (CPUE) from fisheries. The latter are assumed to track stock abundance. However it is not uncommon for such indices to contain sufficient information to estimate both parameters. Also indices may be connecting and fitting therefore may involve weighted averages of contradictory CPUE data. This generally produces parameter estimates intermediate than would be obtained from the data sets individually Schnute and Hilborn (1993), who point out that the most likely parameter values are not intermediary to conflicting values; instead, they occur at one of the apparent extremes. We therefore use the ASPIC biomass model to explore uncertainty due to contradictory trends in time series of catch per unit effort (CPUE). We do this by calculating likelihood profiles for the parameter K (carrying capacity or unfished biomass B0) and MSY (maximum sustainable yield).

Parameterising the assessment model in terms of MSY and K is preferred to r and K since providing management advice requires management target and limit reference points (Martell *et al*., 2007) and this way uncertainty in the reference points can be evaluated directly.

2. Materials and methods

We use Piner Plots (ISC/11/BILLWG-3/01) which show the likelihoods of the different data components for a profiled parameter. This allows an evaluation of what data series are affecting the parameter.

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2.1 Data

The data are from the North Atlantic Albacore assessment (SCRS2013-xxx), and comprise 4 long line CPUE time series one from Chinese-Taipei and the Japanese longline split into 3 periods to reflect changes in targetting.

2.2 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, summarising 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 CPUE series from the combined index are plotted in F**igure 1**; as estimated in 2009 (red) and 2013 (blue), error bars are the 10th and 90th Confidence Intervals. The indices are replotted from 1980 onwards in **Figure 2** to remove the large early values which otherwise make it difficult to compare recent trends. In F**igure 3** the three indices as used in the 2009 (top panel) and 2013 (bottom panel) assessments are presented. These are scaled so the mean is 1 as used in the stock assessment, note that the CIs cross. In **Figure 4** the variability over time is compared by plotted the 10th and 90th CIs divided by the mean; two effects are evident, i.e. that the variance in 2013 is much greater than in 2009 and that there appears to be a stepwise change in variability before the 1980s. **Figure 5** compares the standardised combined index (red) with the standardised index by flag; error bars are the 10th and 90th Confidence Intervals. This is repeated for the recent period in **Figure 6**. **Figure 7** plots the standardised indices of abundance as performed independently by flag.

For each series the Residual sum of square profiles for K by each index, i.e. data components are plotted for K and MSY in **Figures 8** and **9** for K and MSY. For the profiles of K only the Combined, Canada I & II and Portuguese indices gave a minimum. The indices from Morocco, Spain and USA imply that K is potentially very large. In comparison the Japanese index implies a very low value of K. For MSY the picture is more complicated, as there appears to low minima. For example in the case of Morocco. This implies MSY is low or very high. The estimated stock biomass is compared with the biomass predicted by the combined index (i.e. U=q) is shown in **Figure 10.** While the trajectory of yield and biomass is compared to the surplus production function in **Figure 11.**

4. Discussion

Common actions to address connecting trends are to down weight data which in the opinion of the stock assessors are not representative of stock trends or to run several scenarios then combine these in the Kobe advice plots. Both approaches can also be used with stock assessment methods that use other data, e.g. Stock Synthesis that can use size composition data. However, the approach would be similar to identify what sources of data are influencing parameter estimates and derived quantities such as the stock relative to BMSY benchmarks.

As pointed out by Schnute and Hilborn (1993) stock assessments sometimes, in retrospect, prove to be wrong, e.g. due to poor model assumptions or to data that do not reflect the biological process. Schnute and Hilborn (1993) demonstrated that when model or data errors are considered the most likely parameter values are not intermediary to conflicting values; instead, they occur at one of the apparent extremes.

This could be because important processes may be acting (e.g. SCRS2013-162) which could result in changes in distribution of the swordfish stock, catchability by the fisheries and potential population parameters such as virgin biomass (i.e. K) which are estimated as part of a stock assessment and used to provide reference points. Using all the standardised indices gave similar results to the combined index. However, using all actual indices as separate series allow a range of sensitivity analyses and hypotheses to be evaluated as in this study.

Rather than using a combined index an alternative is to integrate the standardisation of catch-per-unit-of-effort into stock assessment models. The typical stock assessment includes two steps, i.e. where a GLM is used to analyse the raw catch and effort data to estimate a year-effect and then a population dynamics model is fitted to the year-effect. However, Maunder (1998) suggested that this two-step approach has several disadvantages such as including loss of information, difficulty in appropriately representing the error structure of the CPUE data, inadequate transfer of uncertainty, and reduced diagnostic ability. Using a combined index will make this even worse.

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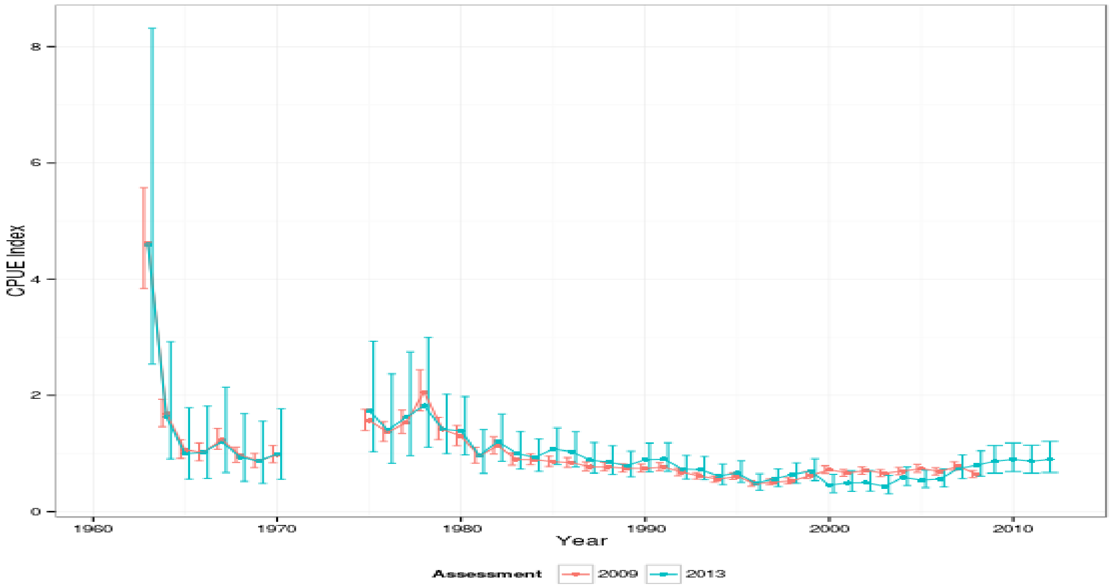


Figure 1. Combined index of abundance as estimated in 2009 (red) and 2013 (blue), error bars are the 10th and 90th Confidence Intervals.

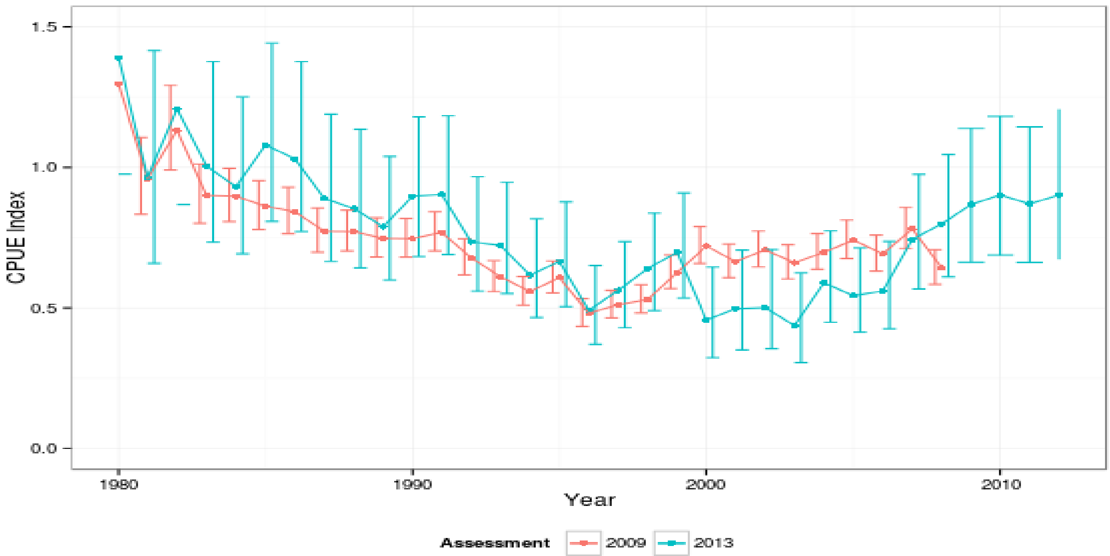


Figure 2. Combined index of abundance from 1980 onwards as estimated in 2009 (red) and 2013 (blue), error bars are the 10th and 90th Confidence Intervals.

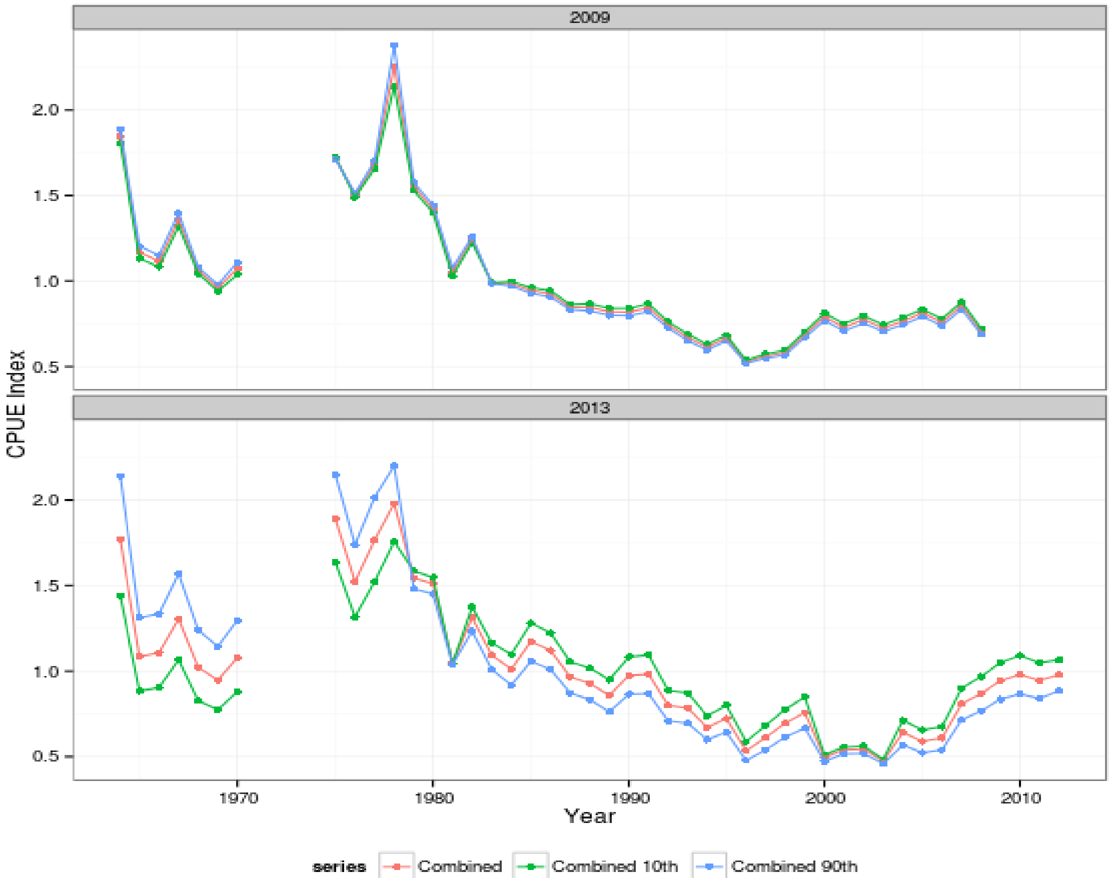


Figure 3. The three indices of abundance as used in the 2009 (top panel) and 2013 (bottom panel) assessments, scaled so the mean is 1 as used in the stock assessment; 10th CI (green), 90th CI (blue) and standardised index (red).

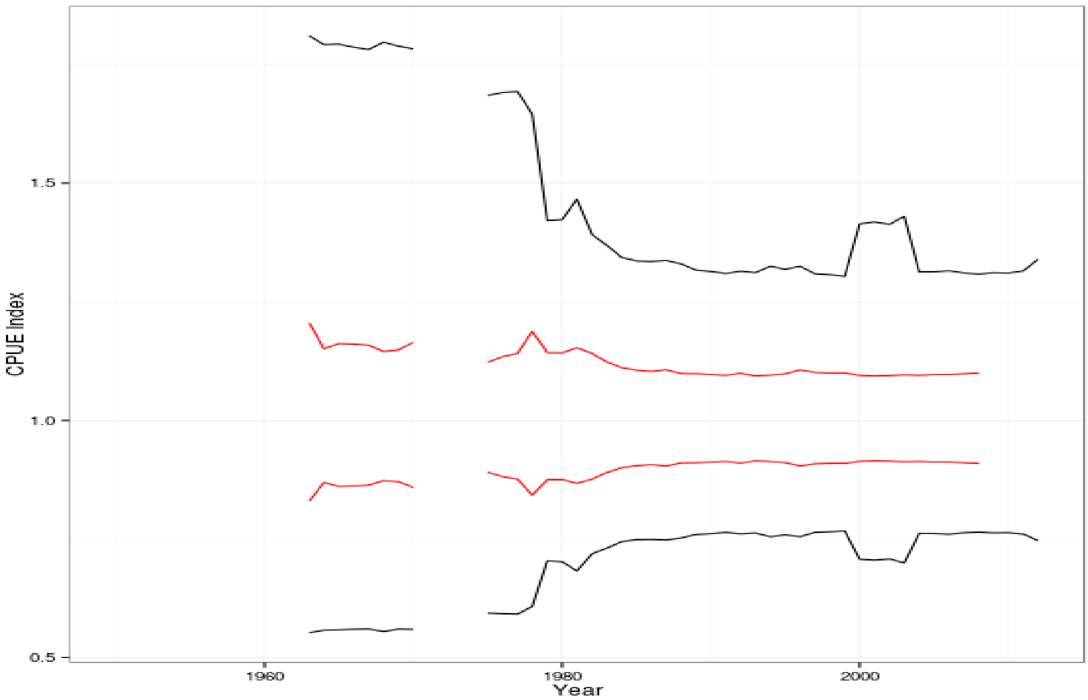


Figure 4. 10th CI (green) and 90th CI divided by the standardised index; 2009 indices (red), 2013 indices (black).

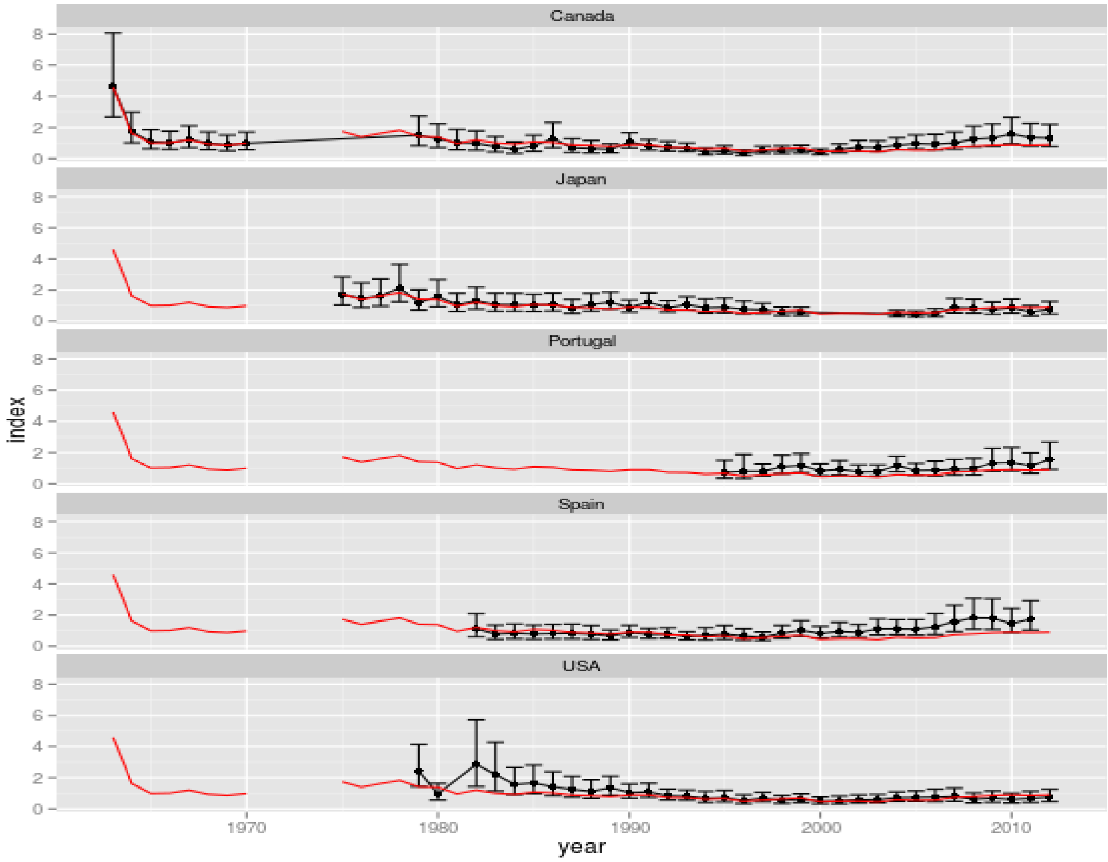


Figure 5. Comparison of the standardised combined index (red) with the standardised index by flag; error bars are the 10th and 90th Confidence Intervals.

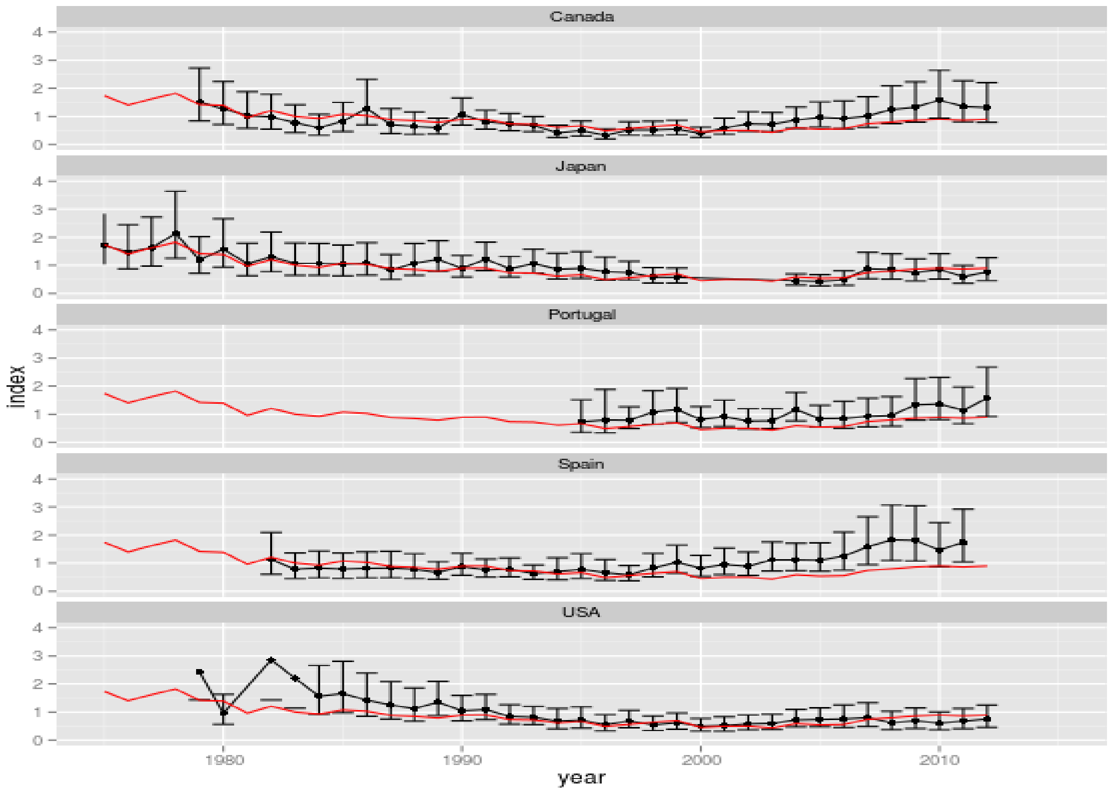
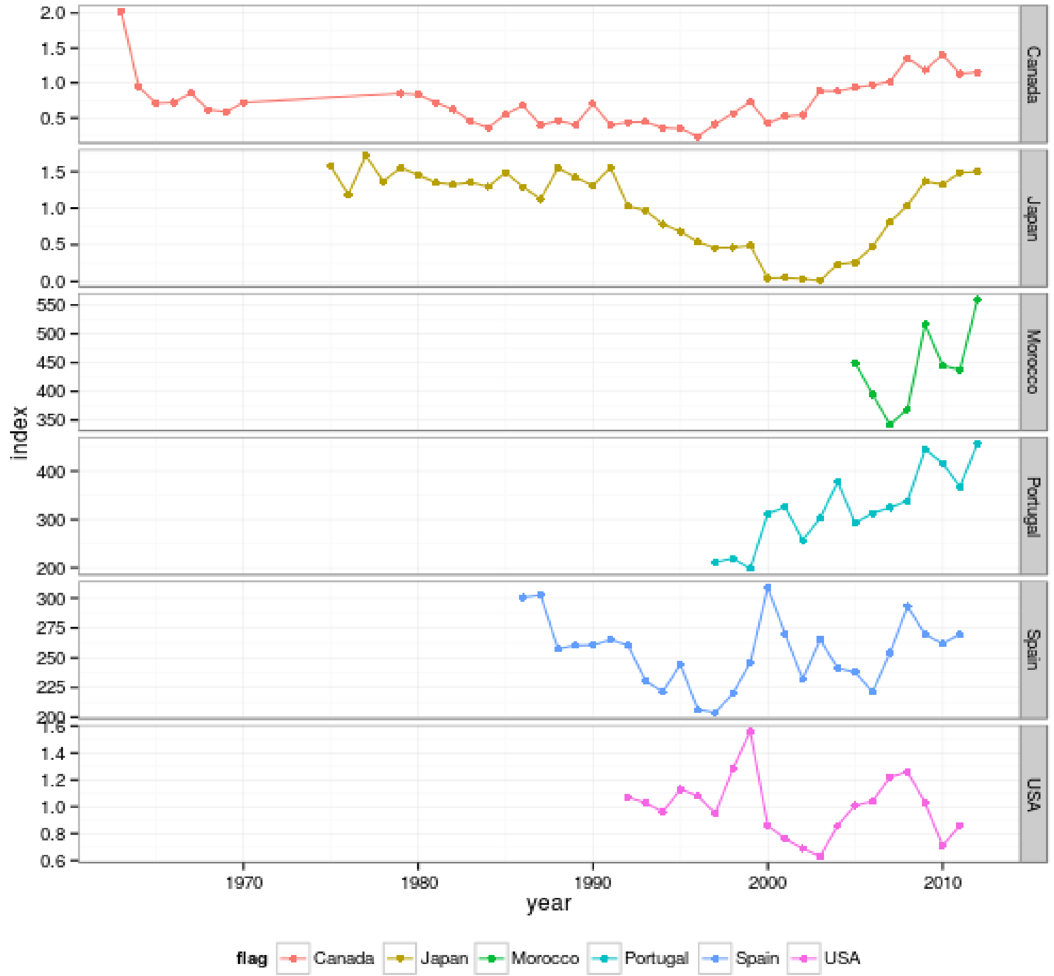


Figure 6. Comparison for the recent period of the standardised combined index (red) with the standardised index by flag; error bars are the 10th and 90th Confidence Intervals.



7. Standardised indices of abundance as performed independently by flag.

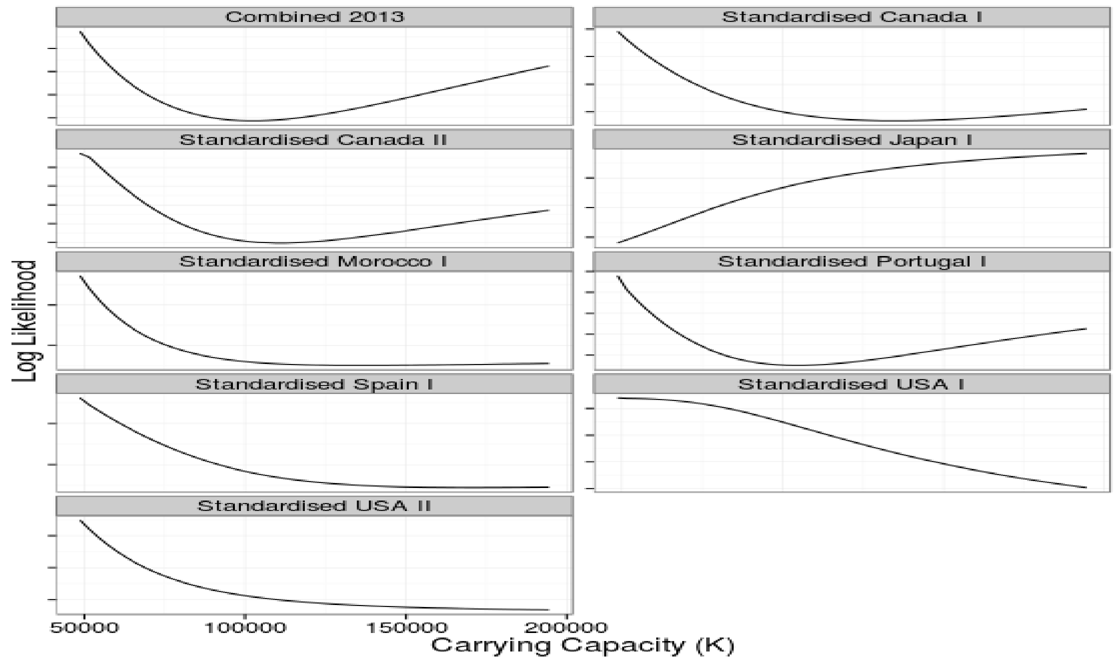


Figure 8. Residual sum of square profiles for K by each index, i.e. data components.

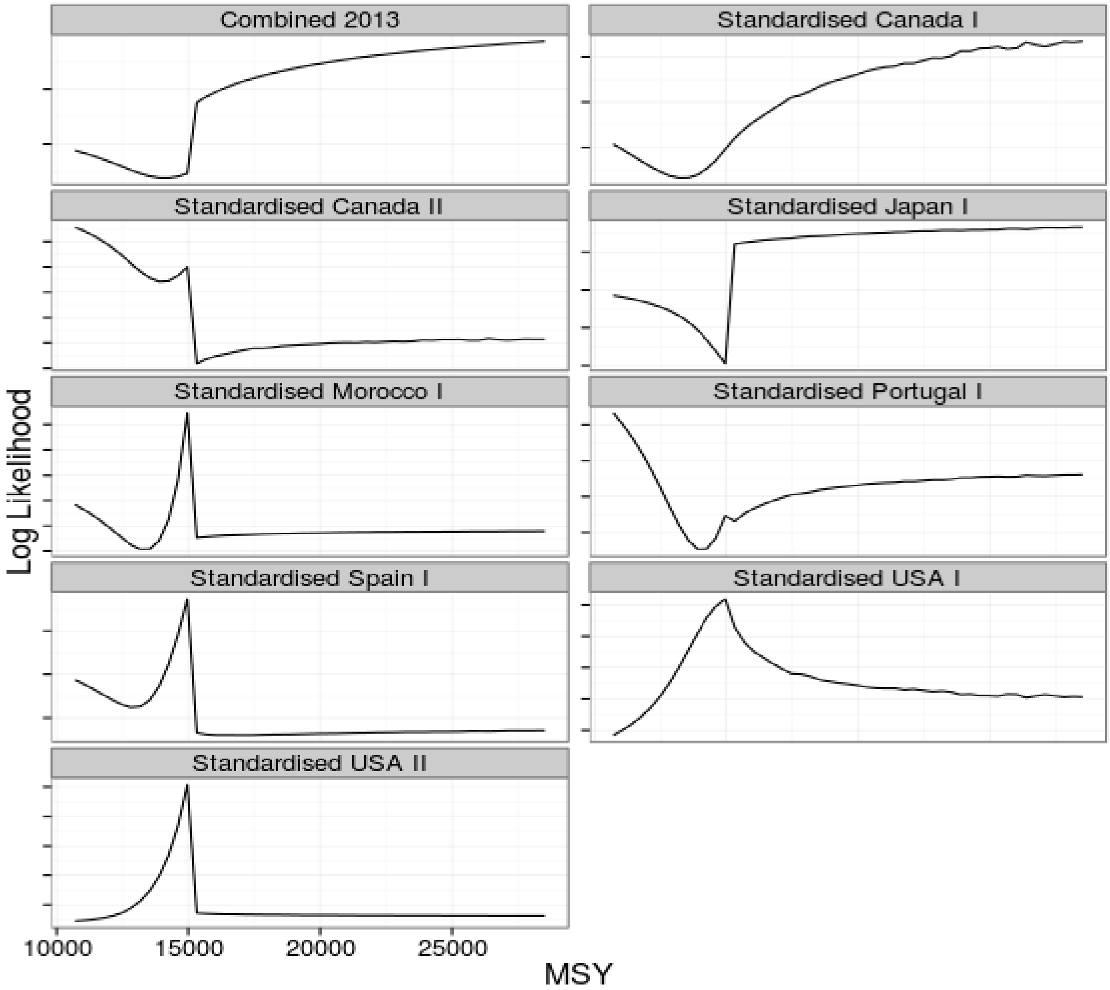


Figure 9. Residual sum of square profiles for MSY by each index, i.e. data components.

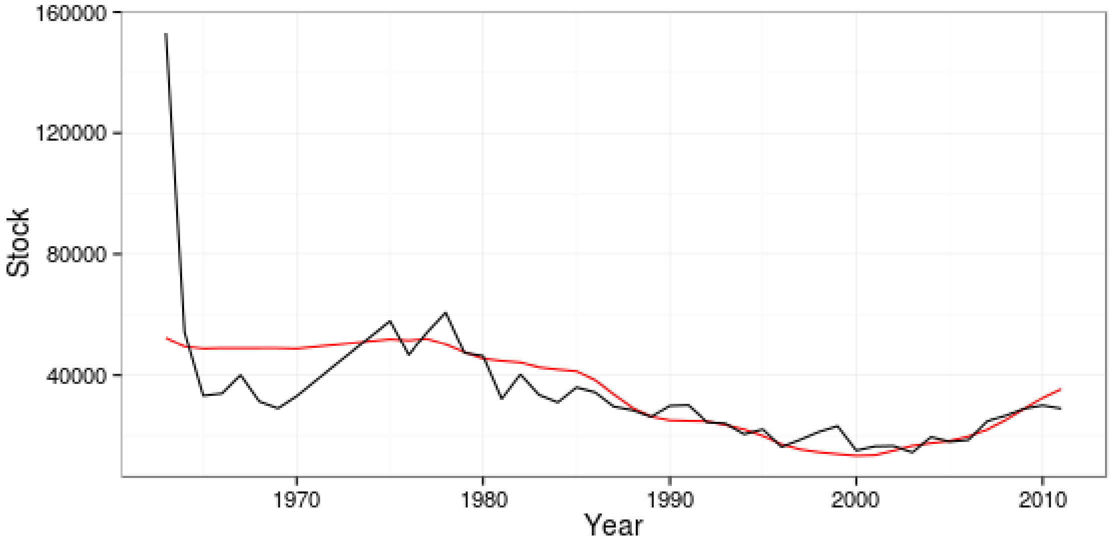


Figure 10. A comparison of the estimated stock biomass (red) with the biomass predicted by the combined index (black).

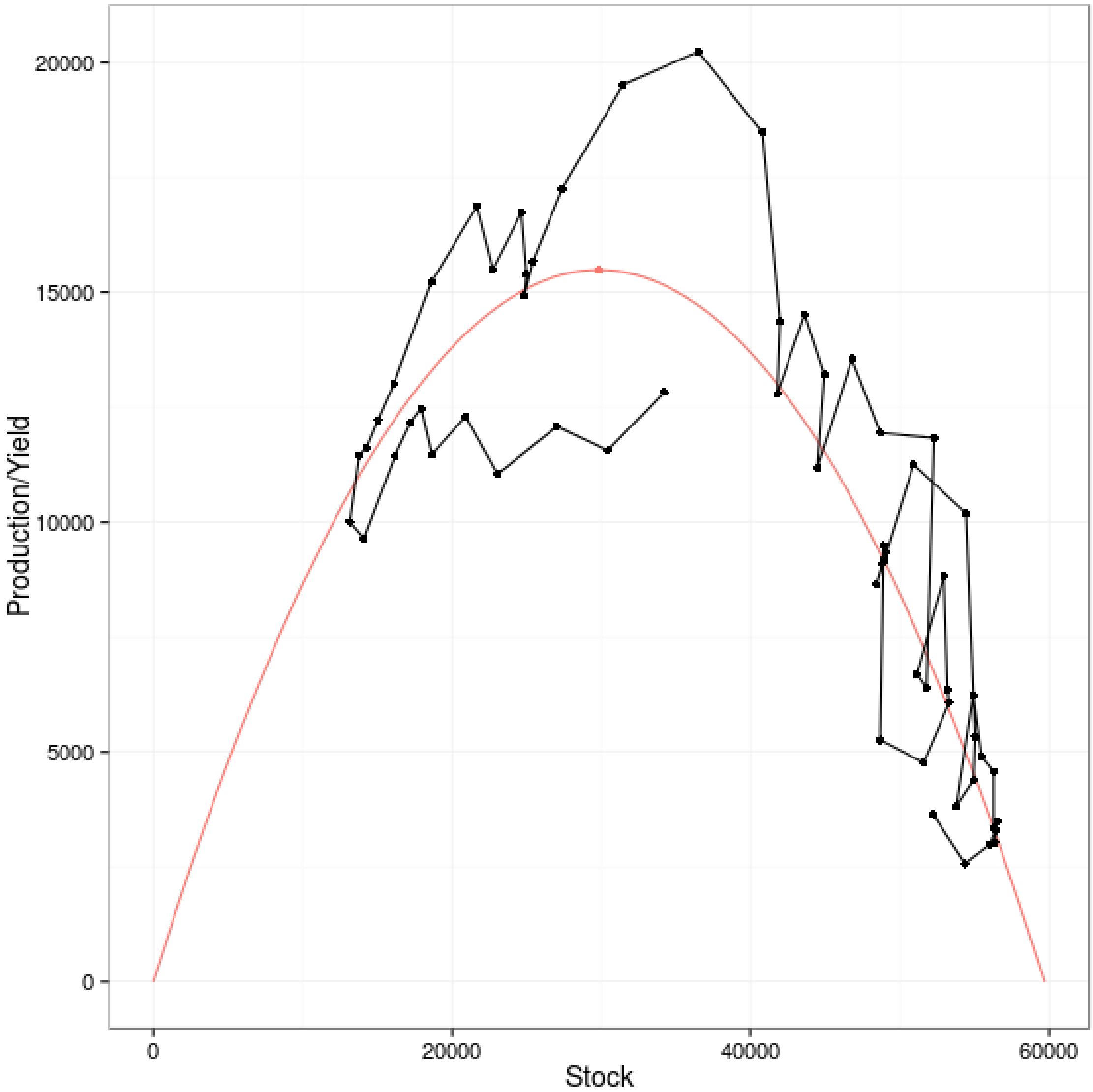


Figure 11. Plot of the surplus production function (red) with the estimated trajectory of yield and biomass (black).