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NORTH ATLANTIC SWORDFISH BIOMASS DYNAMIC STOCK ASSESSMENT REVISITED

Laurence T. Kell[1]

SUMMARY

North Atlantic swordfish was last assessed in 2013 using a biomass stock assessment model coded in the ASPIC software package. Since then ICCAT has developed a harvest control rule using Management Strategy Evaluation using a Management Procedure based on a biomass dynamic stock assessment package implemented in FLR. In this paper we compare the ASPIC and the R based assessments. We also include a range of diagnostics, including the Jackknife, not previously considered at the last assessment.

RÉSUMÉ

L'espadon de l'Atlantique Nord a été évalué pour la dernière fois en 2013 au moyen d'un modèle d'évaluation du stock de biomasse codé dans le progiciel ASPIC. Depuis lors, l'ICCAT a élaboré une règle de contrôle de l'exploitation au moyen de l'évaluation de la stratégie de gestion en utilisant une procédure de gestion basée sur un ensemble d'évaluation des stocks de dynamique de la biomasse mis en œuvre dans la FLR. Le présent document compare les évaluations basées sur ASPIC et R. Nous incluons également une gamme de diagnostics, y compris de type jackknife, *qui n'avait pas été pris en compte lors de la dernière évaluation.*

RESUMEN

La última evaluación de stock de pez espada del Atlántico norte fue en 2013 utilizando un modelo de evaluación de stock de biomasa codificado en un paquete de software ASPIC. Desde entonces ICCAT ha desarrollado una norma de control de la captura utilizando una evaluación de la estrategia de ordenación con un procedimiento de ordenación basado en un paquete de evaluación de stock de dinámica de biomasa implementado en FLR. En este documento se comparan las evaluaciones basadas en R y en ASPIC. Asimismo, incluimos una gama de diagnósticos, incluido el jacknife, que no se había considerado en la última evaluación.

KEYWORDS

Biomass Dynamic, Diagnostics, Jackknife, Management Procedure, Stock Assessment, Swordfish

1 ICCAT Secretariat, C/Corazón de María, 8. 28002 Madrid, Spain.

Introduction

Advice for North Atlantic is based on a biomass dynamic stock assessment model, the assessment model has been extensively tested using Multifan-CL using cross testing by generating data from Multifan-CL (Fraile *et al.*, 2017) and its performance as part of a management procedure has also been evaluated using MSE. The software used is the R package mpb (http://www.flr-project.org/) and was used to perform assessment advice for North Atlantic albacore (Fraile *et al.*, 2017) and bigeye Ortiz de Zárate *et al.*).

The package also includes ASPIC, for which it provides an R interface that includes an extensive suite of diagnostic and simulation tools.

It is proposed to run the mpb package to provide assessments for both the Northern and Southern stocks. Before doing this the estimates from the 2013 ASPIC assessment are compared to those obtained by biodyn algorithm in mp. Then a variety of diagnostics are run.

Diagnostics are important for evaluating stock assessment fits, the robustness of estimates of stock status and how uncertainties propagate through into advice. Diagnostics also make the stock assessment process more transparent and help to identify where more knowledge and better data are required. Diagnostics considered are i) likelihood profiles to check for convergence; ii) an evaluation of the information in the data to estimate the shape of the production function; iii) checking violation of assumptions by conducting an analysis of the residual; iv) the jackknife to identify problems with the data and model specifications; and v) hindcasting to evaluate prediction ability.

Material and Methods

Material

In 2013 a single catch per unit effort (CPUE) series was used (**Figure 1**), this was derived by standardising the catch and effort from the main fleets fishing North Atlantic swordfish.

Methods

Biomass Dynamics

In a biomass dynamic model the stock in the next year (Bt+1) is the sum of the current biomass (Bt) less the catch (Ct) plus the surplus production (Pt) i.e.

$$B_{t+1} = B_t - C_t + P_t$$

There are various forms of production functions (Pt), e.g. the symmetric logistic (Hassell, 1975) or the generalised Pella and Tomlinson (1969) forms. The logistic production function is probably not appropriate for tuna species, due to high steepness (Maunder, 2003) and a Pella-Tomlinson form with BMSY < 0.5B0 is perhaps more realistic, e.g.

$$\frac{r}{p} B_t - C_t + P_t$$

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 model was then fitted to the catch and CPUE series using maximum likelihood assuming measurement error in the CPUE.

Likelihood profiles

When fitting a model by maximising the likelihood, the solution is found at the maximum value of the likelihood function. Profiling the likelihood can therefore be used to check that the fitting algorithm has actually found a solution (i.e. it is at a maximum) and to compute how well a parameter is estimated (i.e. by deriving confidence intervals).

Residual analysis

Patterns in the residuals from the fits to the CPUE, may indicate biased estimates of parameters, reference points and stock trends. Therefore when fitting a model, the residuals should be checked to identify violations of the assumptions.

To check the distribution of the residuals the observed quantiles can be plotted against predicted quantiles from the assumed distribution. Q-Q plots do this by comparing 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 assumed; any systematic departure from a straight line may indicate skewness or over or under dispersion. In the assessment model it is assumed that an index is proportional to the stock, so when plotting the observed against the fitted values the points should fall around the y=x line. If they do not, then the index may not be a good proxy for the stock trend. Patterns in the residuals, e.g. by year due to changes in fishing practice, can be identified by plotting the residuals against year. It is also assumed that variance does not vary with the mean. This assumption can be checked by plotting the residuals against the fitted values. Estimates of variance obtained from bootstrapping and other techniques assume that residuals are independently and identically distributed (i.i.d.). This assumption can be validated by inspection of the residuals above. It is assumed that the residuals are not auto-correlated; plots of the residuals against each other with a lag of 1 to identify autocorrelation. Significant autocorrelations could be due to an increase in catchability with time; which may result in a more optimistic estimate of current stock status as any decline in the stock is masked by an increase in catchability.

Jackknife

Bootstrap sampling, subsampling, and the jackknife all rely on estimating the variance of a statistic by using the variability between resamples rather than using statistical distributions. Here we use the jackknife is applied to the CPUE series distribution to estimate bias and variance for a biomass stock assessment model using the Pella-Tomlinson production function.

The ordinary jackknife is a resampling method useful for estimating the variance or bias of a statistic. The jackknife estimate of a statistic can be found be by repeatedly calculating the statistic, each time leaving one observation from the sample out and averaging all estimates.

The jackknife estimate can be found by:

$$\theta_{(\cdot)} = \frac{1}{n}\sum_{i=1}^{n}\theta_{(-i)}$$

the variance by:

$V_J = \frac{n-1}{n}\sum_{i=1}^{n}\left(\theta_{(-i)} - \theta_{(\cdot)}\right)^2$ and the by:

$$Bias_{\theta} = (n-1)\left(\theta_{(\cdot)} - \theta\right)$$

where n is the total sample size, $\theta_{(-i)}$ is the statistic estimated without using the i^{th} observation, and $\theta_{(\cdot)}$ is the average of all jackknife estimates.

Hindcast

A major uncertainty in stock assessment is the difference between models and reality. The validation of model prediction is difficult, however, as fish stocks can rarely be observed and counted. Hindcasting and model-free validation can be used to evaluate multiple measures of prediction skill. In a hindcast a model is fitted to the first part of a time series and then projected over the period omitted in the original fit. Prediction skill can then be evaluated by comparing the predictions from the projection with the observations.

Results

Continuity run

The fits obtained using ASPIC and biodyn are compared in **Figure 2**, there is a slight difference in the parameter estimates and hence the predicted historical time series. When the sum of squares are compared the difference is due to ASPIC not having converged to the solution.

Shape of the production function

The configuration of ASPIC used in the last assessment assumed a logistic (i.e. Shaeffer) production function, i.e. a symmetric production function where the absolute change in production is equivalent either side of B_{MSY}. In contrast the Pella-Tomlinson production function includes a third parameter which allows the shape to change. In Figure 3 the estimated time series are compared, the main difference is the higher initial biomass for the skewed production function.

Figure 4 and 5 show the logistic and skewed Pella-Tomlinson production functions with the stock trajectories.

Likelihood profiles

The profiles or r and K for the logistic and skewed production functions are compared in **Figures 6 to 8**, respectively. The profile for p is then shown in Figure 8**, this suggests that p can be estimated and is close to 1 (i.e. the production function is of logistic form).

Residual Analysis

Next the residuals are examined for violation of assumptions. First the observed values are plotted against the fitted values to check whether the CPUE series are a good index of relative abundance (**Figure 9**),the blue line is a linear regression fitted to points, black the y=x line. The residuals are plotted by year in **Figure 10** to check patterns in time that may suggest the index is not tracking the stock. **Figure 11** shows quantile-quantile plots to compare residual distribution with the normal distribution. **Figure 12** plots the residuals against fitted value with to check the variance relationship. **Figure 13** plots the residuals with a lag of one against each other to check for autocorrelation, and finally the predicted stock trend by index (points), with biomass estimates (blue) and a local regression (black) are presented in **Figure 14** show the autocorrelation function.

The most striking feature is the high positive value of the first data point.

Jackknife

To evaluate the variance and bias of the model fits and the influence of individual observations the jackknife results are presented in **Figures 15 to 17** when the shape parameter is fixed. **Figure 15** shows the distribution of the parameters from the jackknife and the blue vertical lines the fit using all the data, while **Figure 16** shows the influence of individual points. **Figure 17** compares the jackknife estimates of uncertainty and bias to the bootstrapped values. **Figures 18** plots the individual parameter estimates obtained from the jackknife and **Figures 19** repeats the influential points analysis when the shape parameter is estimated and figure 19

Hindcast

Figure 20 shows the relationship between the observed and predicted CPUE values from the hindcast, and indicates that the assessment has good prediction skill.

Discussion

The estimation procedures in ASPIC and the R package mpb were compared, it was shown that the 2013 assessment had not actually found the solution, although the assessment procedure in mpb did find the solution.

Many stock assessment methods use linear regression for calibration when using CPUE as trends of relative abundance. Regression models are vulnerable to abnormal points, which may result in biased estimates of parameters, underestimation of uncertainty, and poor prediction skill. This is especially true when the number of observations are small as means there are fewer cases to counter them. Even if there are there many cases miscodes, excluding important explanatory variables, and changes in fishing behaviour can influence the regression model. It is important therefore to identify influential points and explore their impact

Abnormal points can be defined as when there is a large discrepancy between the observed Y and predicted Y value given their X value (outlier) and when they have an unusual X-value (leverage). Their influence is a function of their discrepancy and leverage, e.g.

Influence = Discrepancy * Leverage

Outliers and bias in parameter estimates were therefore evaluated using the jackknife

The shape parameter appeared to be estimable, however, the jackknife showed that this was mainly due to a point with high influence.

Conclusions

- The assessment procedure was better able to find the solution than ASPIC
- Although the shape parameter appeared to be estimable, the jackknife showed that this was mainly due to a single point that had strong influence. It is therefore probably better to fix the shape parameter based on life history relationships.
- The mpb package could be used to simulation test a HCR using MSE.

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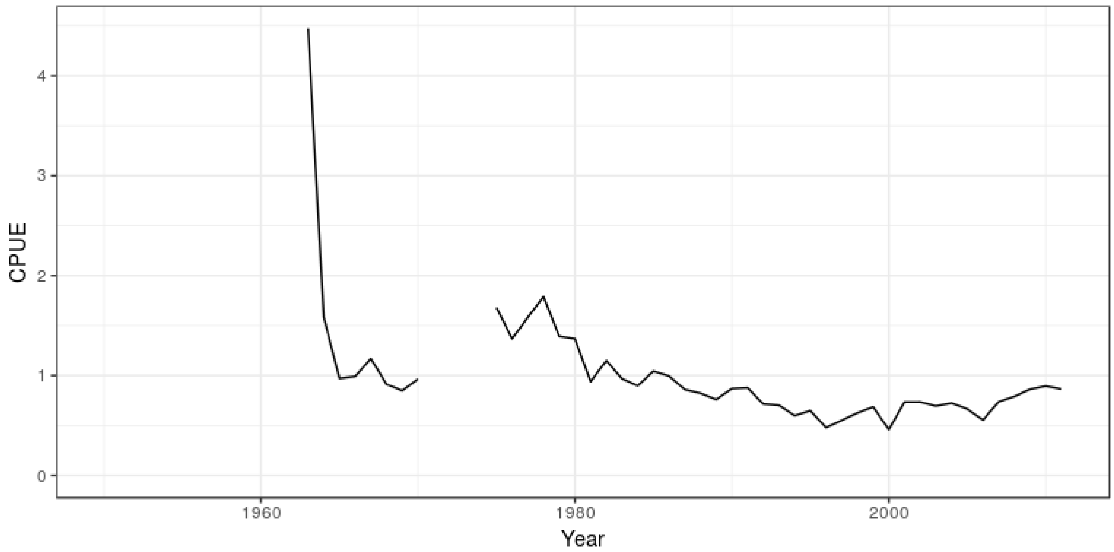

Figure 1. Time series of CPUE used in the 2013 assessment.

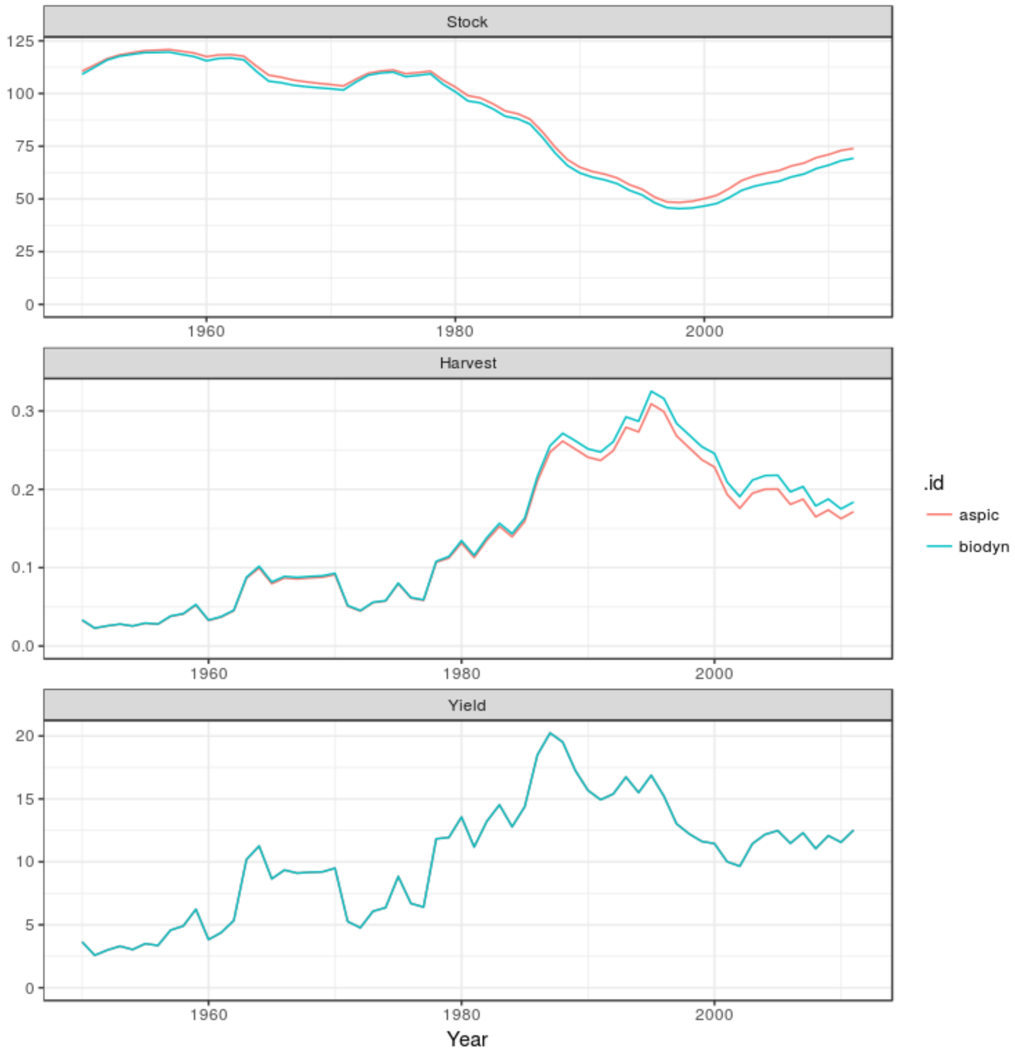

Figure 2. A comparison between the ASPIC fit and the biodyn procedure for the logistic production function, sum f squares were 2.54976 and 2.6027383 respectively.

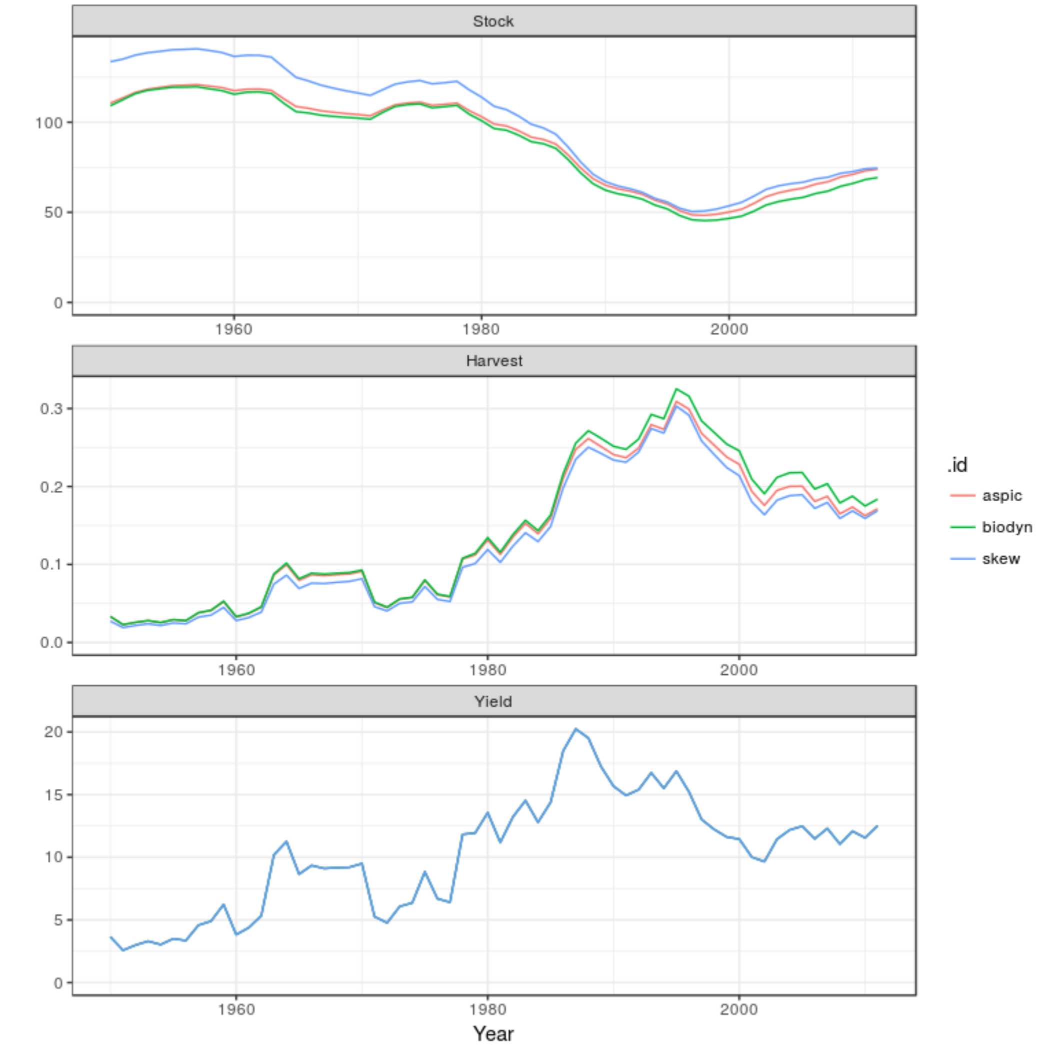

Figure 3. A comparison between the ASPIC fit and biodyn procedure for the logistic production function, and a Pella-Tomlinson production function where the shape parameter was set to 0.001.

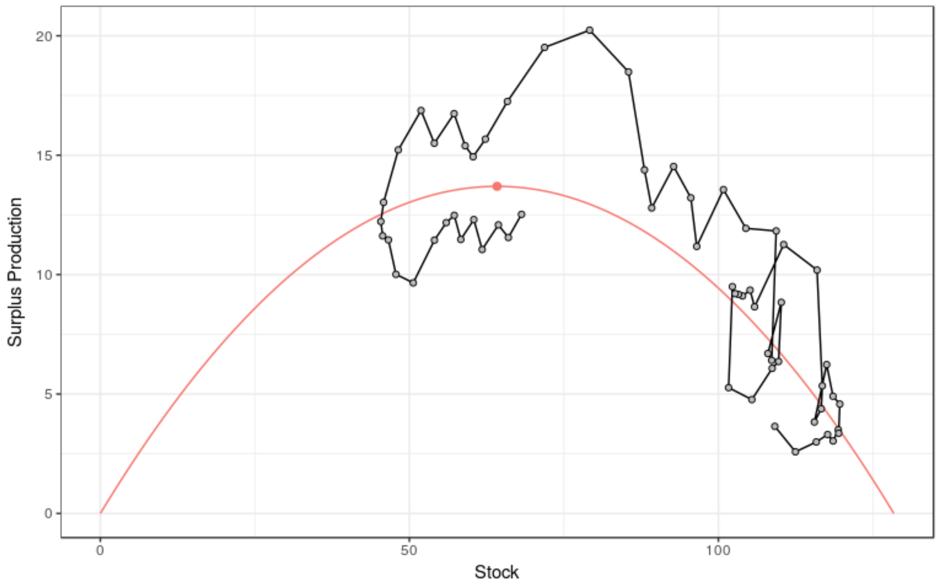

Figure 4. Production function for the logistic model, historic trajectory also shown.

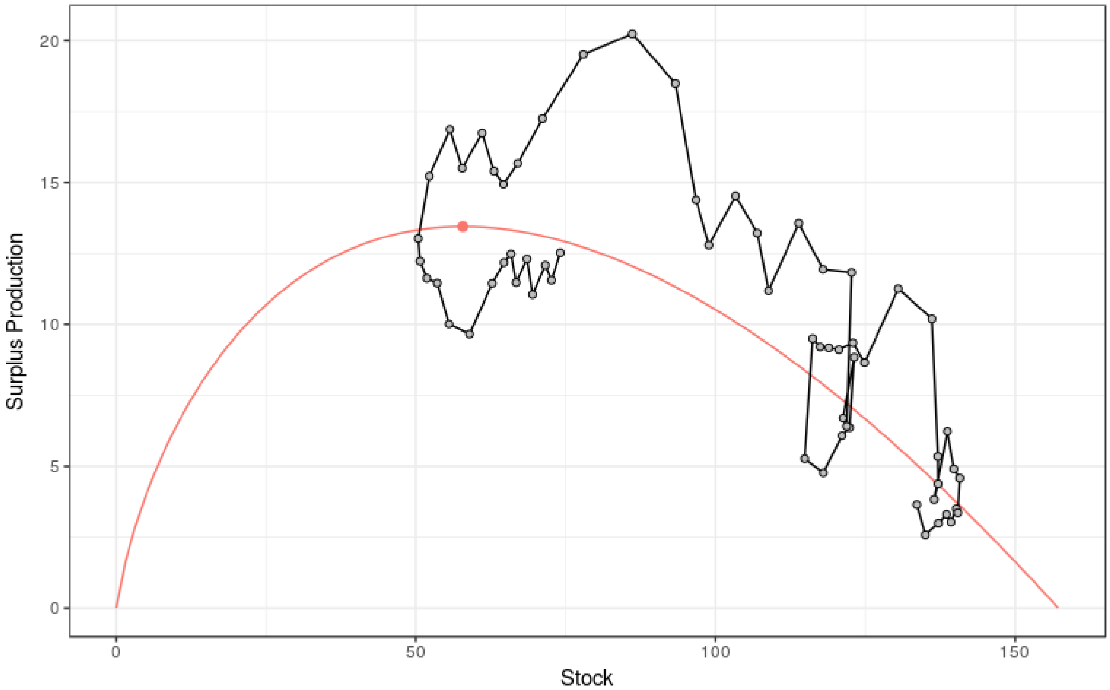

Figure 5. Production function for the Pella-Tomlinson production function with a shape parameter of 0.001, historic trajectory also shown.

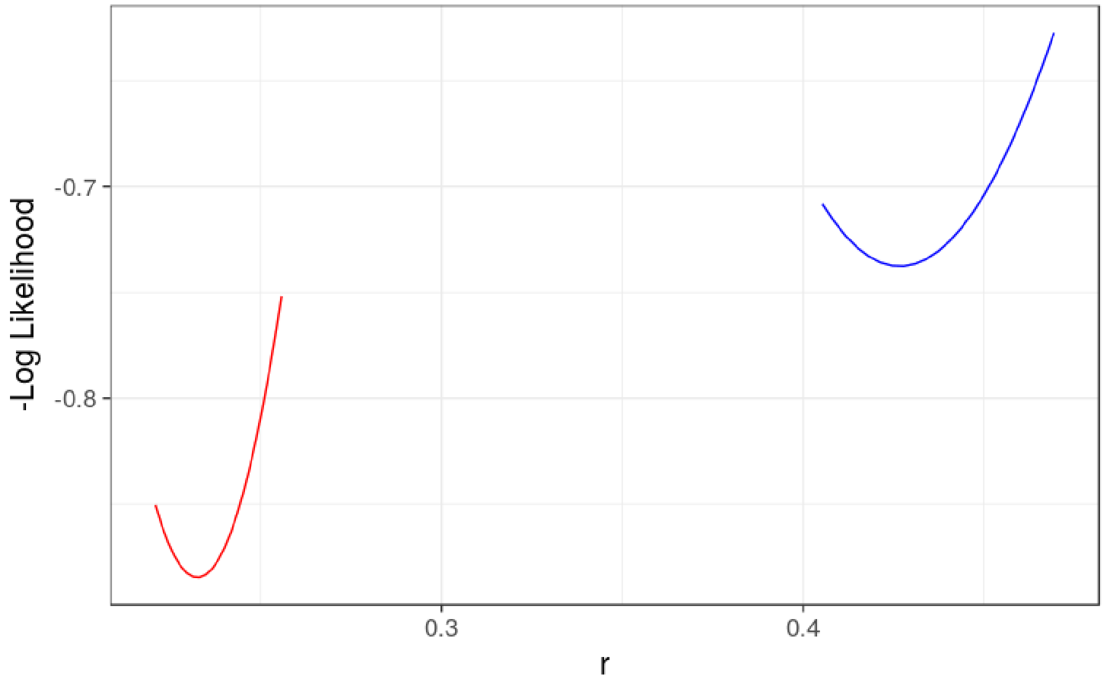

Figure 6. Likelihood profiles for r, symmetric (blue) and skewed (red) production functions.

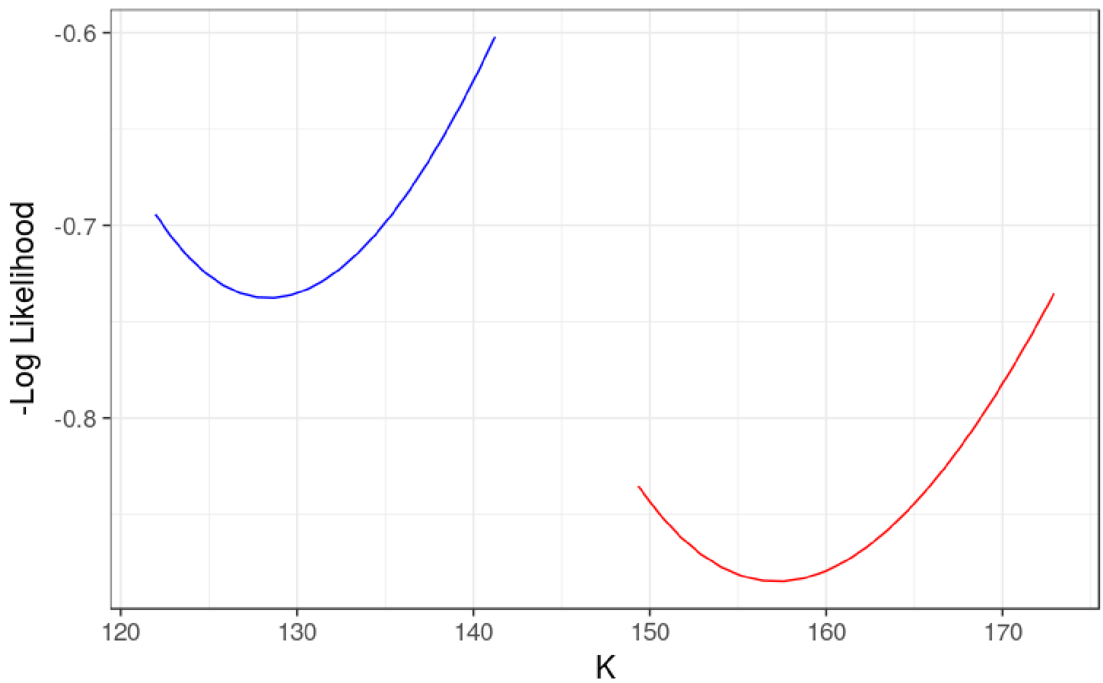

Figure 7. Likelihood profiles for K, symmetric (blue) and skewed (red) production functions.

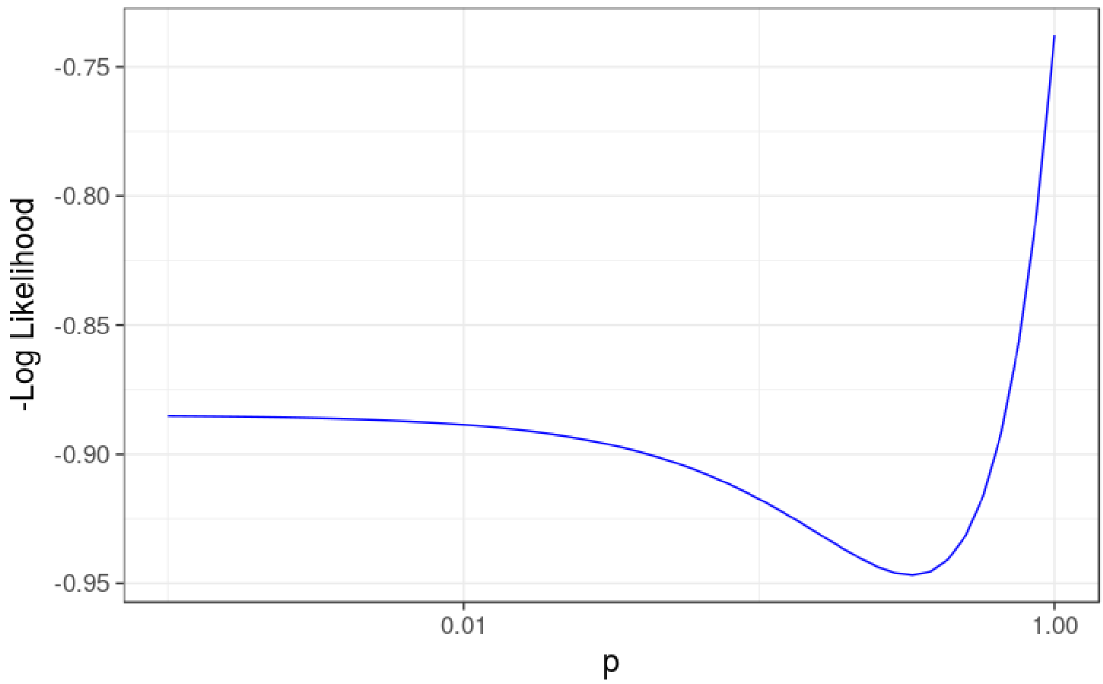

Figure 8. Likelihood profile for p.

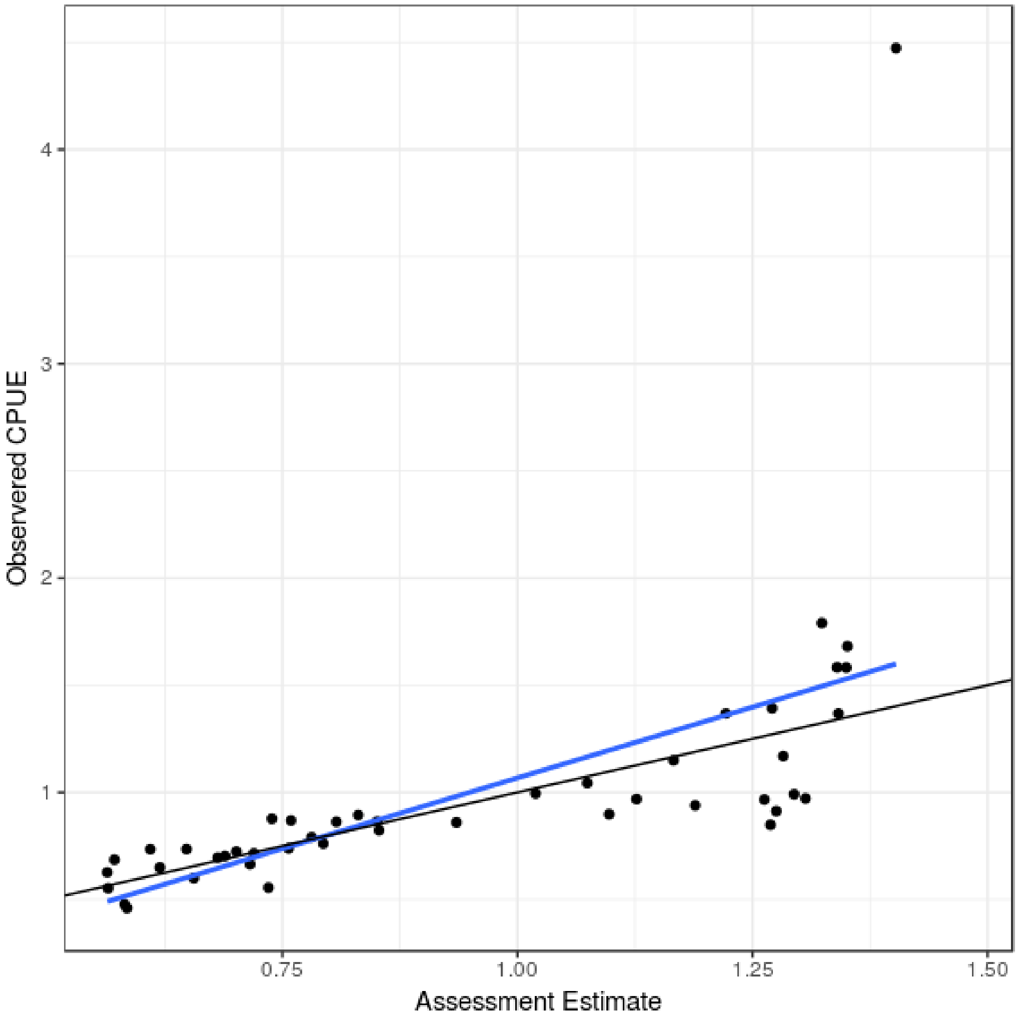

Figure 9. Observed against fitted CPUE points.

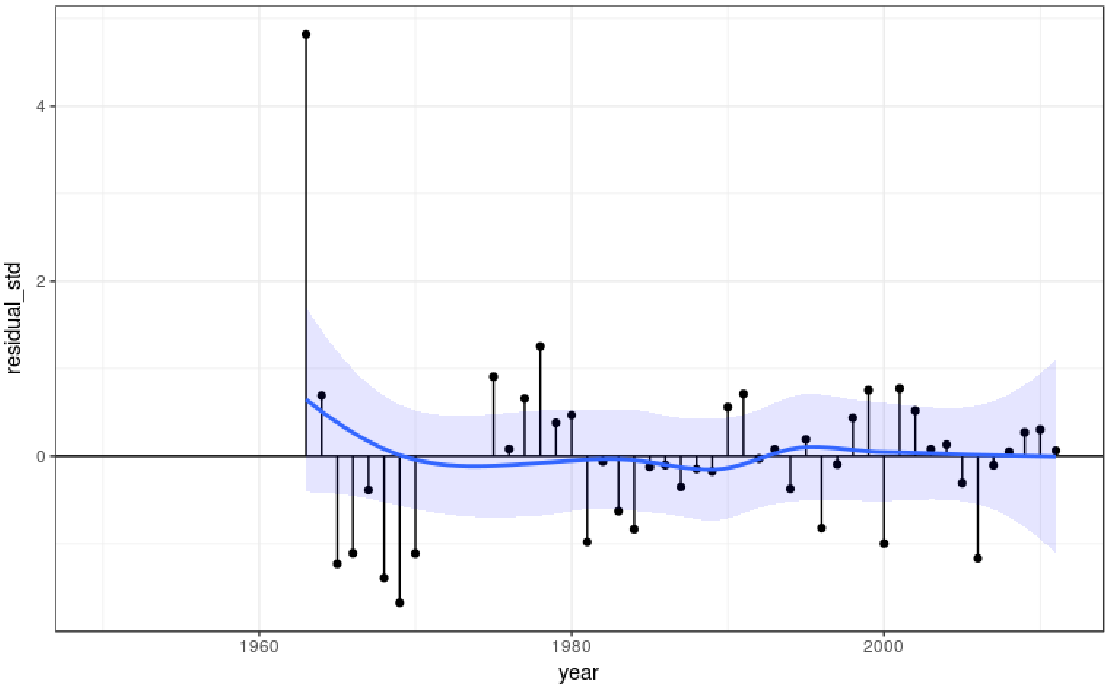

Figure 10. Standardised residuals by year.

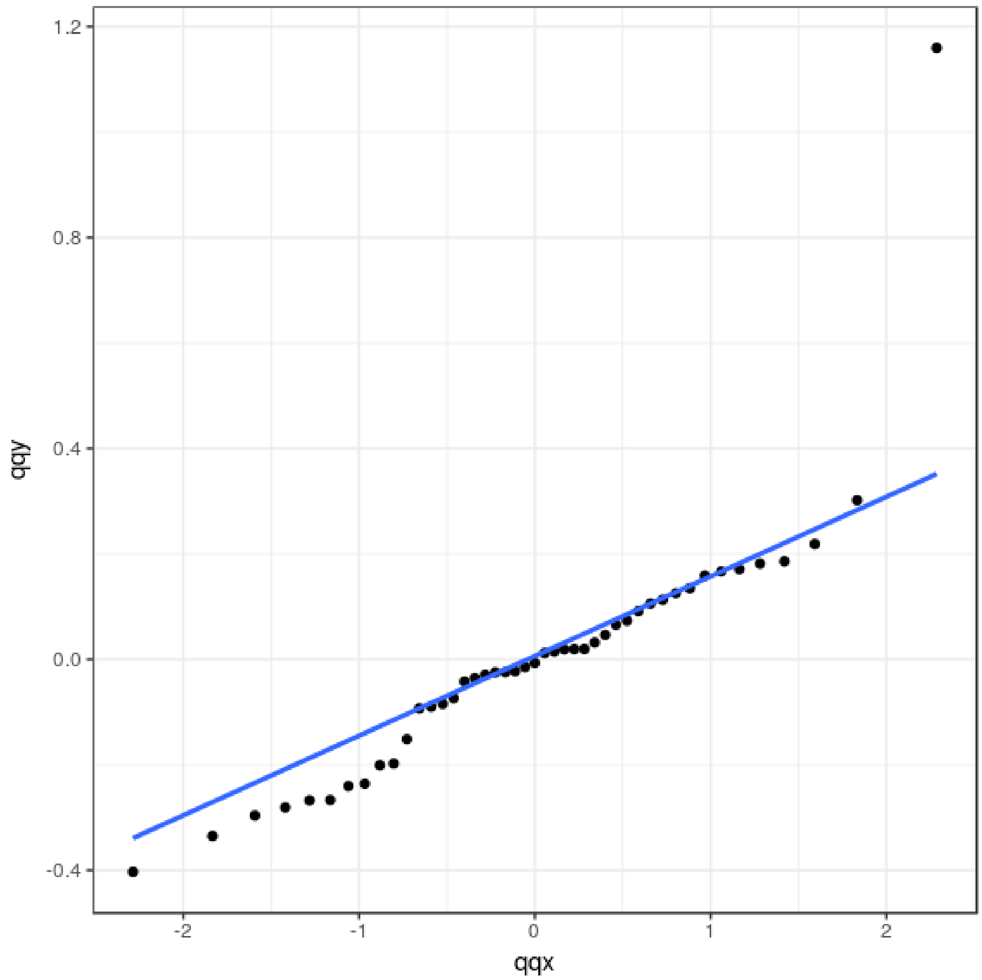

Figure 11. Quantile-quantile plot to check for normality.

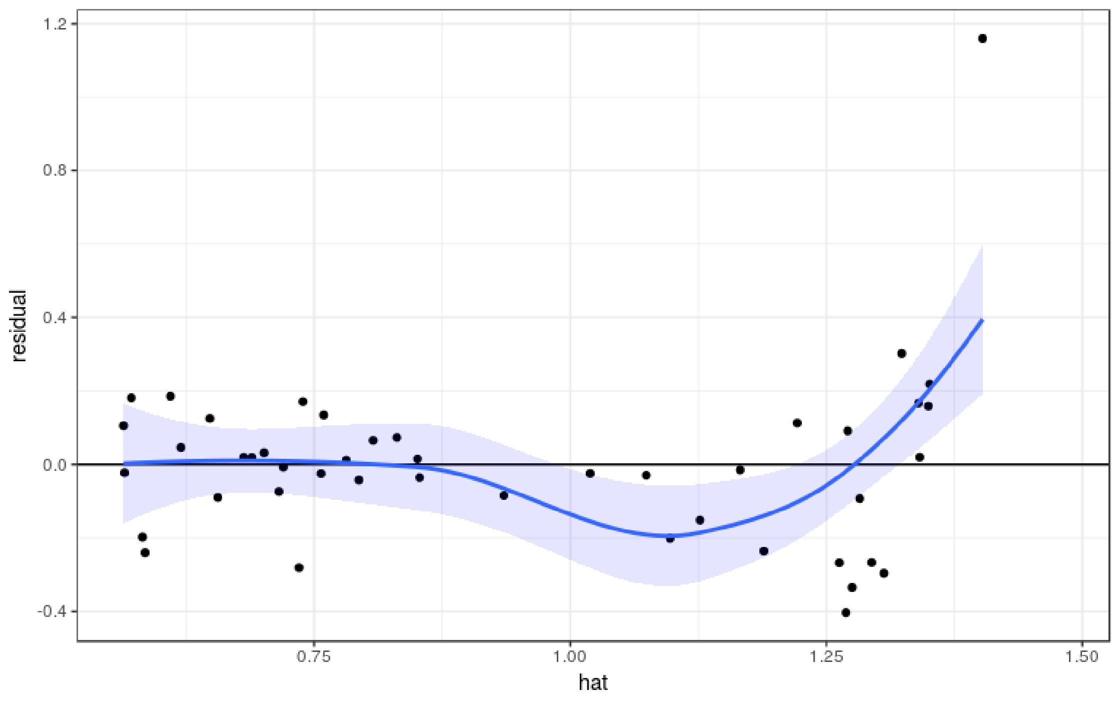

Figure 12. Plot of residuals against fitted values to check variance function.

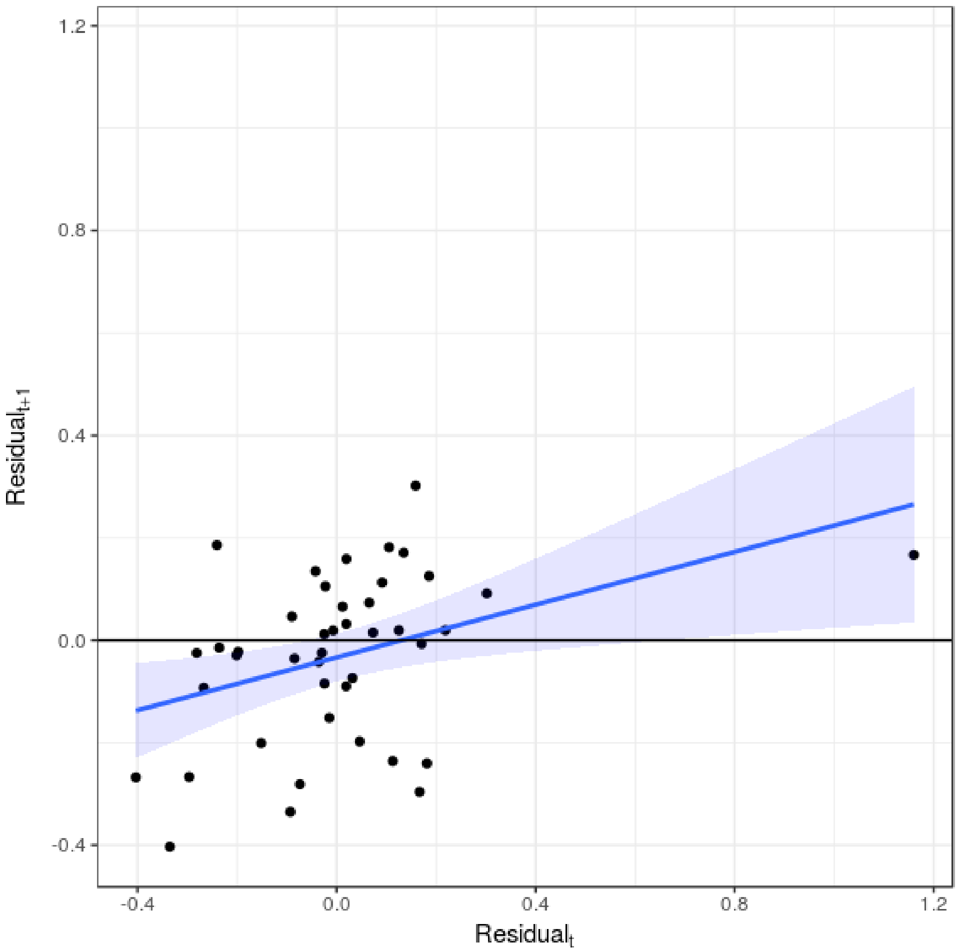

Figure 13. Check for autocorrelation.

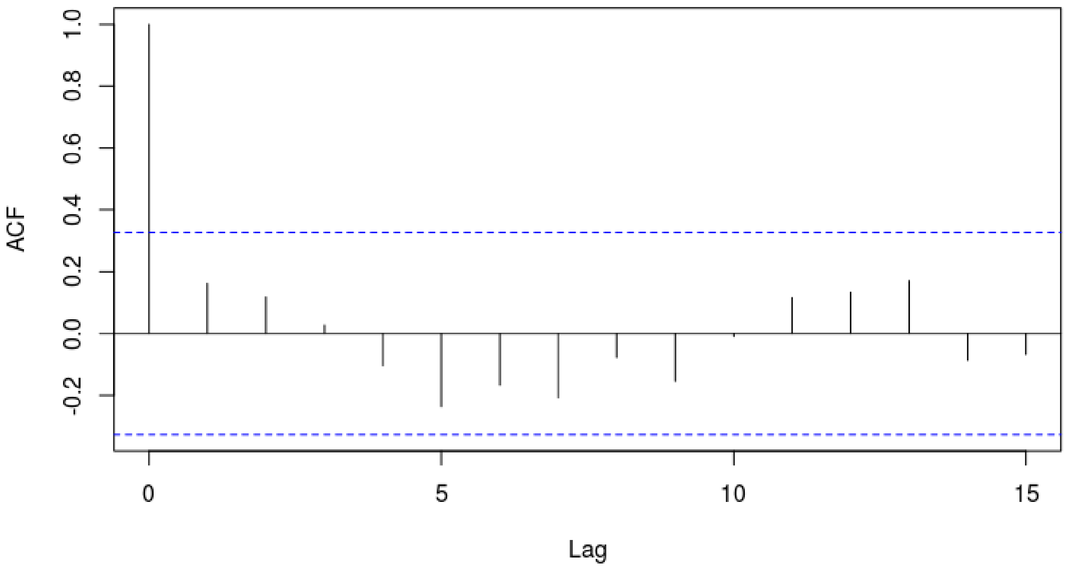

Figure 14. Autocorrelation function.

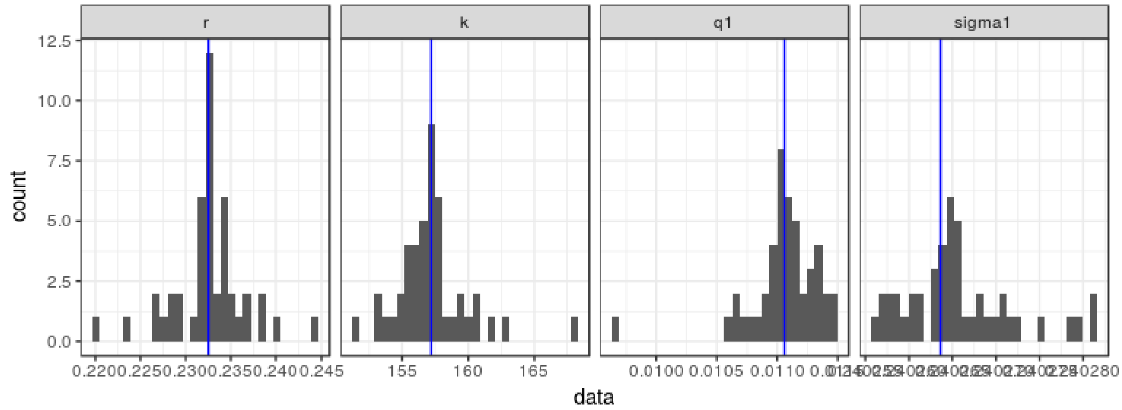

Figure 15. Parameters from jackknife, the blue vertical line indicates the fit using all points.

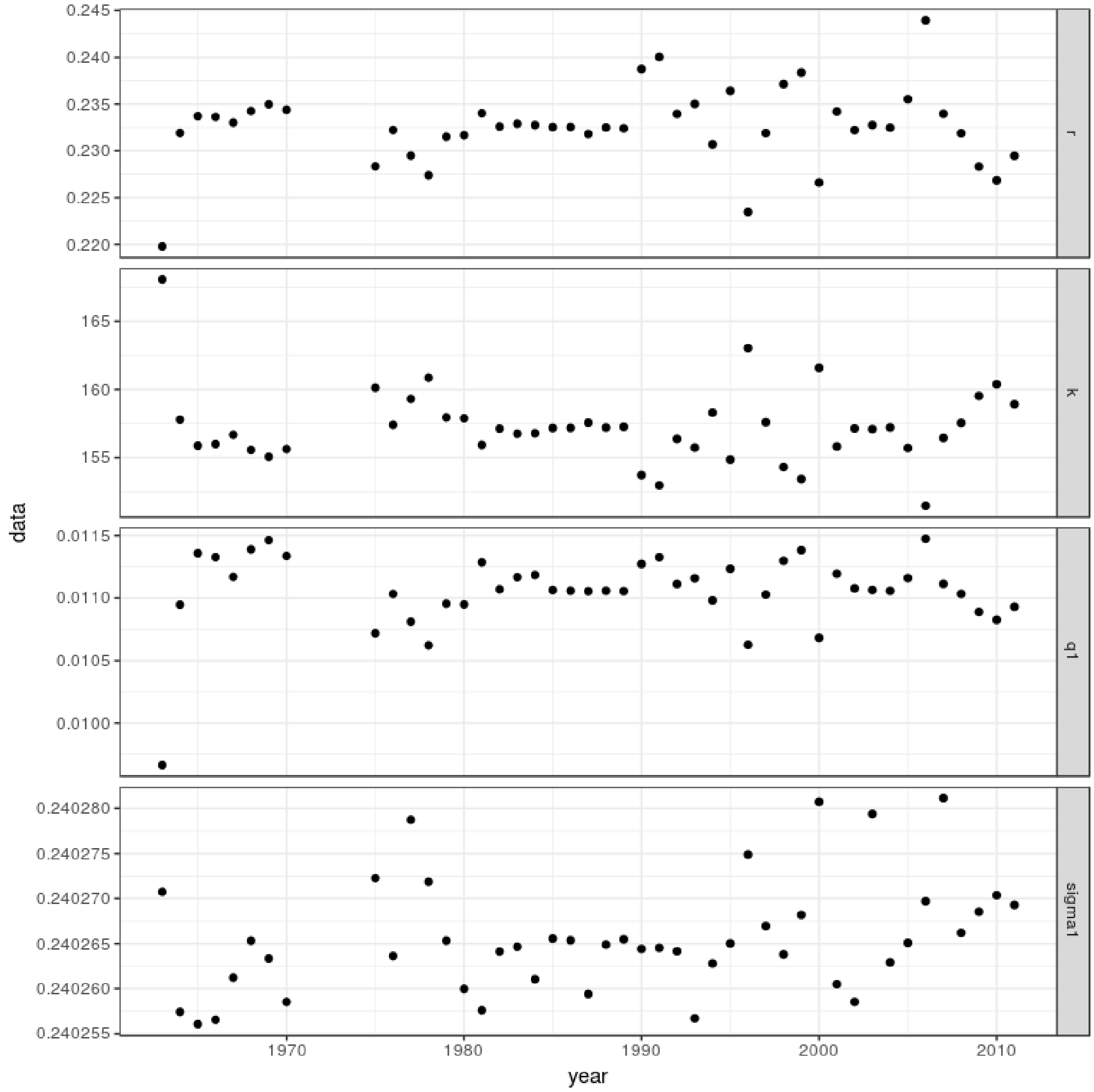

Figure 16. influential points

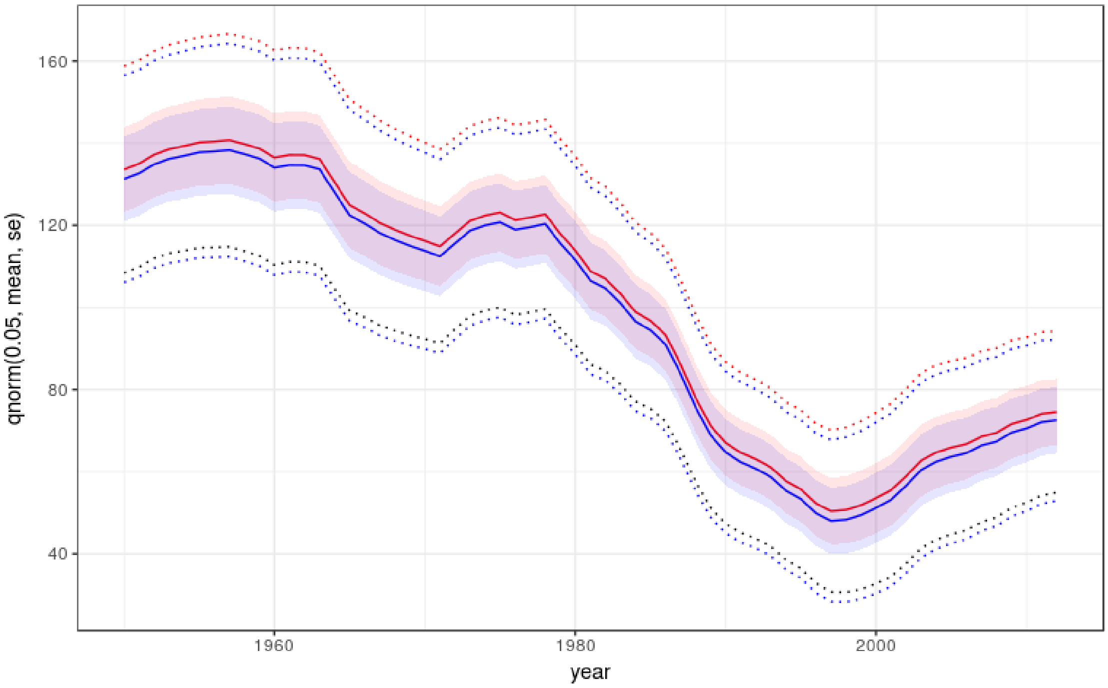

Figure 17. A comparison between ASPIC bootstrapped estimate of stock biomass, the bias adjusted estimates are shown in blue, ribbons correspond to the interquartile range and the dashed lines the 5^th and 95^th percentiles.

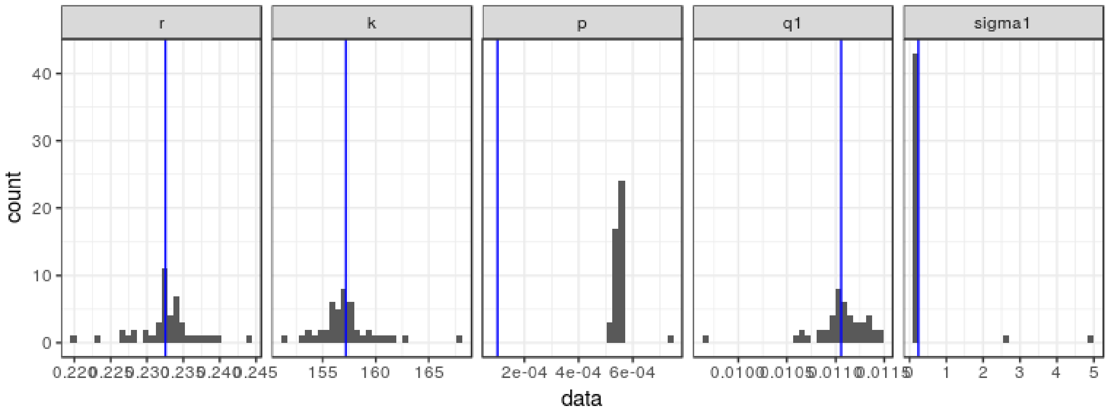

Figure 18. Parameters from jackknife, the blue vertical line indicates the fit using all points.

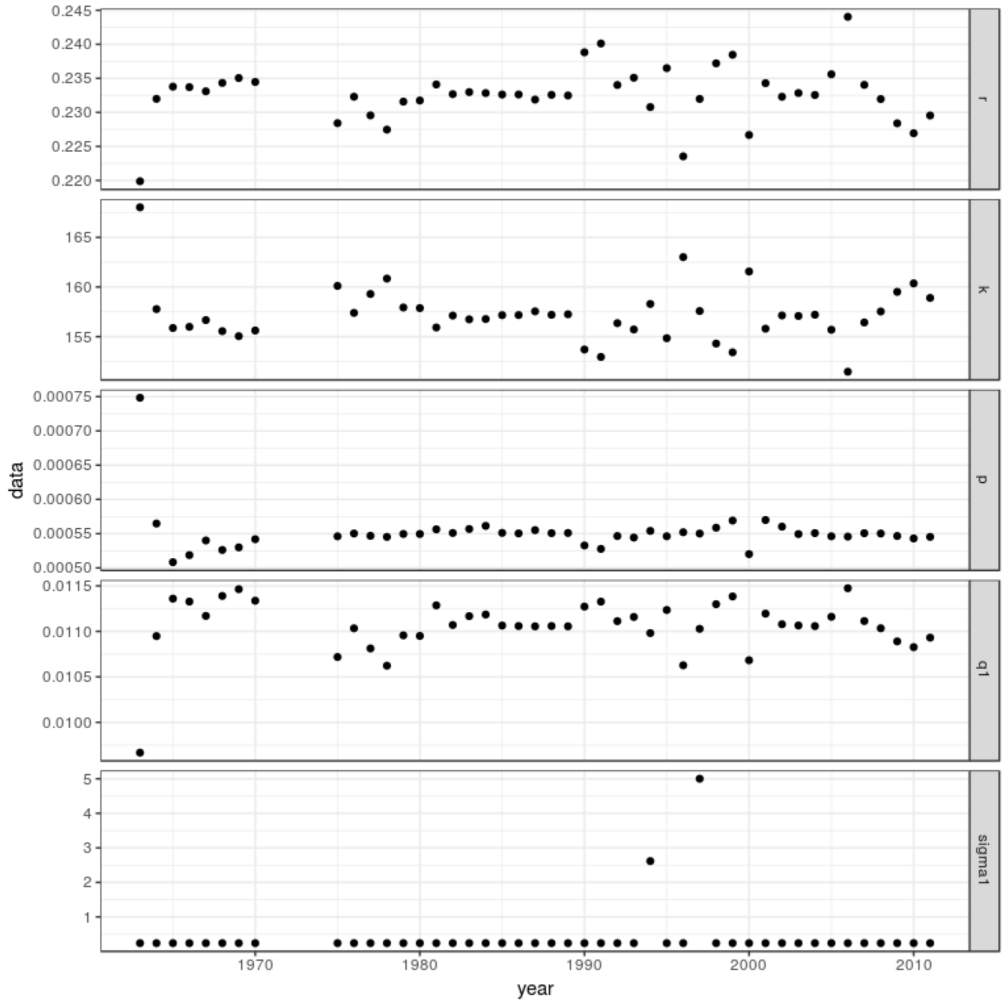

Figure 19. Influential points

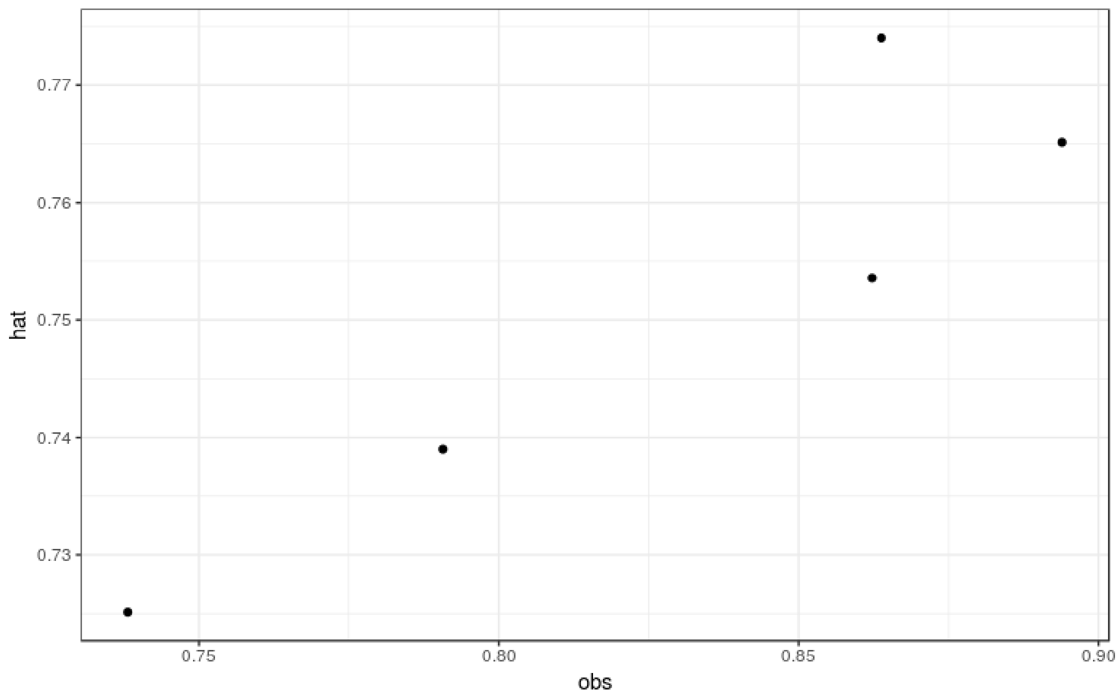

Figure 20. Relationship between the observed and predicted CPUE values.