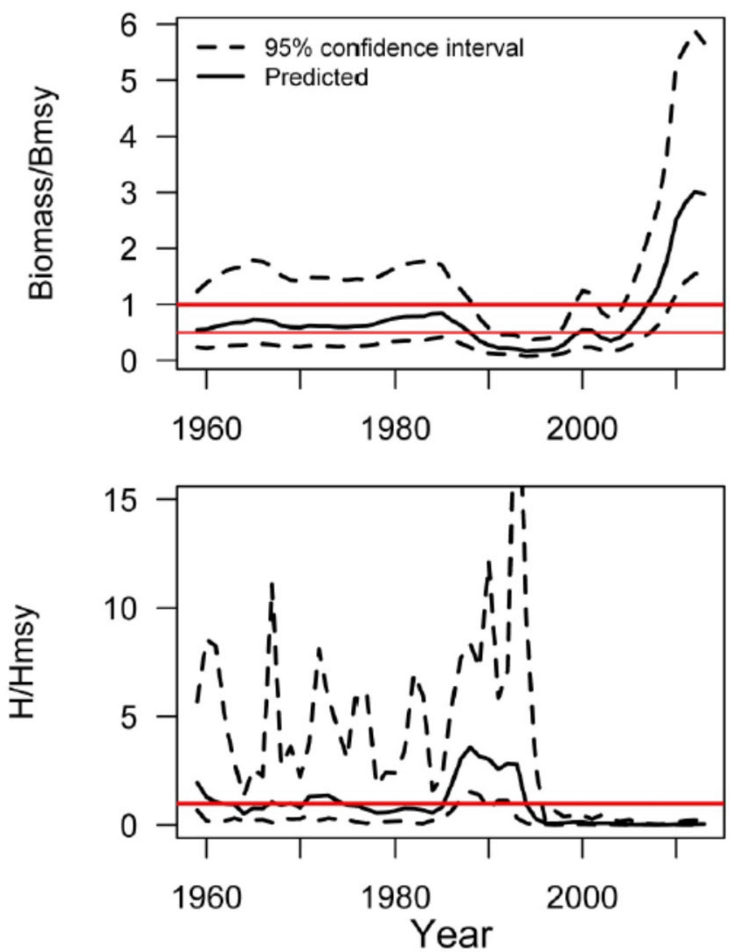
Marine Institute

Lecture 7: Population Model Estimation and Inference



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F6004 Lecture 7 Outline

Population Model Estimation and Inference (Haddon Text Chapter 10; Jennings et al Ch 7)

1) Estimation of Surplus Production Models
    a. Parameter constraints versus estimation
    b. Parameter correlations and model identifiability
    c. Stock status evaluations
2) Implications of process error
3) A little more on Bayesian methods
4) 3LN redfish case study

Recall: Surplus Production Models (SPMs)

- SPM - simplest analytical method that provides for a full stock assessment
- The overall effects of recruitment, growth, and mortality are combined into a single production function
- Age, size, sex, and other differences are ignored
- Only need a time series of total catch data, and a relative abundance index time series (CPUE or survey)
- We start with estimation of the Schaefer SPM.

SPMs for exploited stocks

- The Schaefer SPM is $B_{t+1} = B_t + rB_t\left(1 - \frac{B_t}{K}\right) - C_t$
- Where C_t are the annual fishery catches
- If we divide both sides of this equation by K, and let $P_t = B_t/K$, then $P_{t+1} = P_t + rP_t(1 - P_t) - C_t/K$
- The parameters to estimate are B_o (or P_o), r, and K.
- Using $C_t = H_tB_t = H_tP_tK$

$$P_{t+1} = P_t + rP_t(1 - P_t) - H_tP_t$$

The P version of SPM

Estimation

- Typically we treat the catches C_t as fixed variables, i.e. covariates (but not in F6005!).
- But we still need additional information.
- Unfortunately we rarely get direct estimates of B_t to use for estimating the SPM parameters r and K.
- However, surveys often provide an index (I) of stock biomass, where $I = qB$ and q is an additional parameter to estimate.
- q is often referred to as the survey catchability.

Estimation

- Need several surveys over a period of years.
- Better if there are annual surveys available, I_t.
- The common statistical model is

$$I_t = qB_t\exp(\varepsilon_t), \text{ where } \varepsilon_t \sim N(0,\sigma^2).$$

- This is referred to as the observation error (OE) approach.
- It is important that q not depend on t.
- The σ^2 reflects survey variance and other variation related to how well the survey covers the stock range

OE Estimation

- σ^2 is another parameter to estimate; so there are 5 in total: *Bo*, *r*, *K*, *q*, and σ^2.
- We cannot replace σ^2 with the survey variance estimates that you can get based on the random sampling design (which ever one is used)
- because the survey variances do not reflect all of the model variation
- In particular, if part of the population is not available to the survey then the survey variance does not reflect this. There is model process error also.

OE Estimation

- In practise the fraction of the population available to the survey will vary from year to year – hopefully at random and without a trend.
- It would be good to incorporate survey variances, but that is a topic to consider in F6005
- And how useful are estimates of survey variance??

OE Estimation

- In practise it is often assumed that *Bo = K*.
- Both *Bo* and *K* affect the scale of biomass estimates, which is the source of confounding.
- However, *Bo = K* assumption requires verification
- although Punt (1990) suggested that even in situations in which *Bo/K* is substantially different from 1, better estimation performance is achieved by fixing *Bo = K* than by estimating *Bo*.
- This reduces the number of parameters to 4

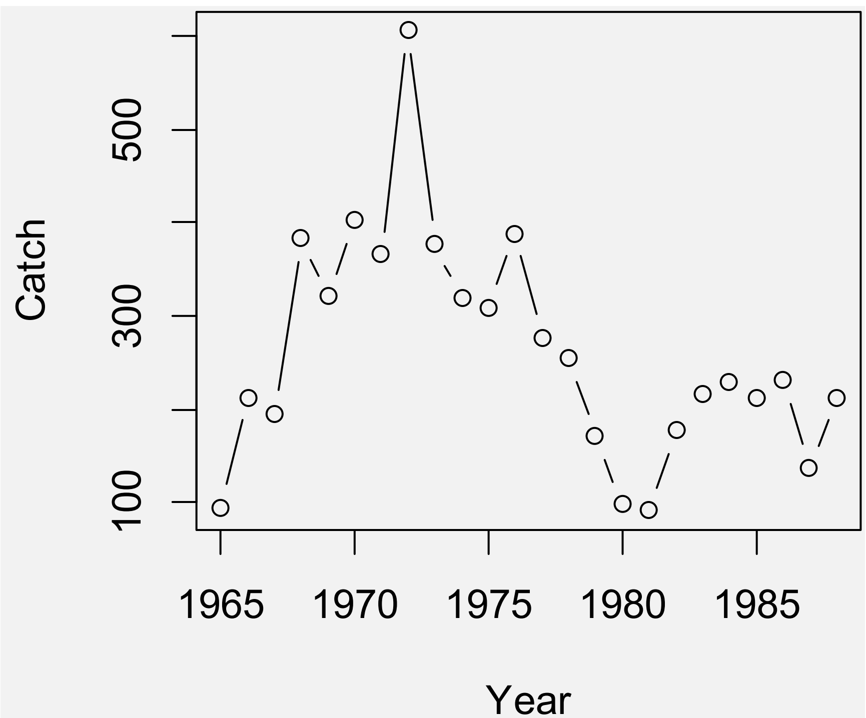
OE Estimation

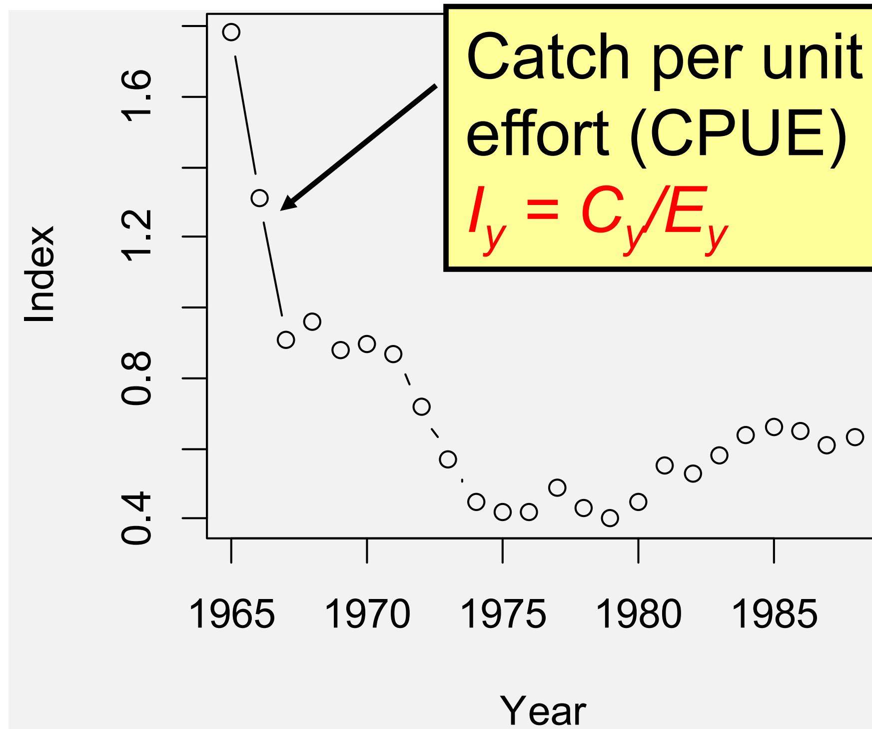
- We don't have to estimate the σ^2 parameter using a nonlinear optimizer
- We can estimate σ^2 after the SPM parameters are estimated
- so there are really only 3 parameters to estimate.
- I will show how to do this in R using nls()
- It is possible to eliminate q from the estimation as well, but I won't bother explaining that (e.g. see Polachek et al (1993).

Read Data

```
hake.data = read.table('hake_data.txt',header=T)
> names(hake.data)
[1] "Year"  "catch" "index"
> hake.data$log.index = log(hake.data$index)
```

data from Polachek et al (1993).





Catch per unit effort (CPUE)
$I_y = C_y/E_y$

R code for SPM

```
spm = function(r,K,catch){
 n=length(catch)
 B=rep(NA,n);
 B[1]=K
 for (i in (2:n)){
  B[i]=B[i-1]+r*B[i-1]*(1-B[i-1]/K)-catch[i-1]
  }
  B[B<0]=1e-10
return(B)
}
```

Create a vector to store biomasses in

A “fix” for infeasible negative values

R code for OE Estimation

```
spm_fit = function(logq,logr,logK,catch){
  B = spm(exp(logr),exp(logK),catch)
  return(data.frame(B=B,EI=exp(logq)*B))
}
```

Returns biomass plus predicted index

Avoid negative q's

EI

```
spm.fit <- nls(
    log.index ~log(spm_fit(logq,logr,logK,catch)[,2]),
    data = hake.data,
    start = list(logq = -5, logr=log(0.3), logK = log(4000))
)
```

Do the estimation

Results of nls() Fit

Formula: log.index ~ log(spm_fit(logq, logr, logK, catch)[, 2])

Parameters:

	Estimate	Std. Error	t value	Pr(>|t|)	
logq	-7.75794	0.11459	-67.700	< 2e-16	***
logr	-0.99251	0.11508	-8.625	2.42e-08	***
logK	7.94459	0.08274	96.024	< 2e-16	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

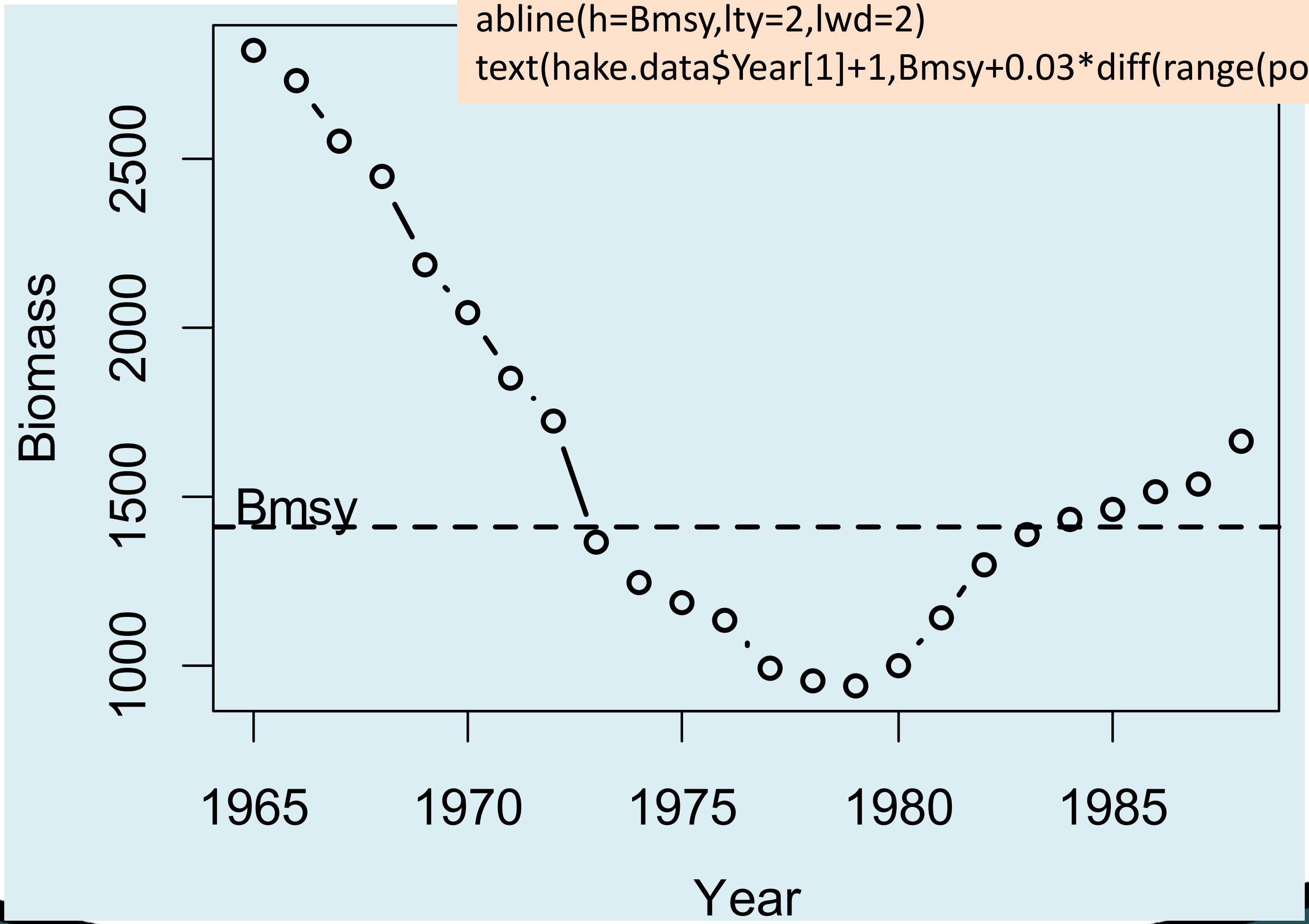
Residual standard error: **0.1331** on **21** degrees of freedom

the estimate of σ

Number of iterations to convergence: 7
Achieved convergence tolerance: 2.442e-06

Stock Size

```
parm.est = coef(spm.fit)
pop.est = spm_fit(parm.est[1],parm.est[2],parm.est[3],hake.data$catch)

par(mar=c(3.5,3.5,1,1),mgp=c(2.5,1,0))
plot(hake.data$Year,pop.est[,1],xlab='Year',ylab='Biomass',type='b',lwd=2)
Bmsy = exp(parm.est[3])/2
abline(h=Bmsy,lty=2,lwd=2)
text(hake.data$Year[1]+1,Bmsy+0.03*diff(range(pop.est[,1])),"Bmsy")
```



Results

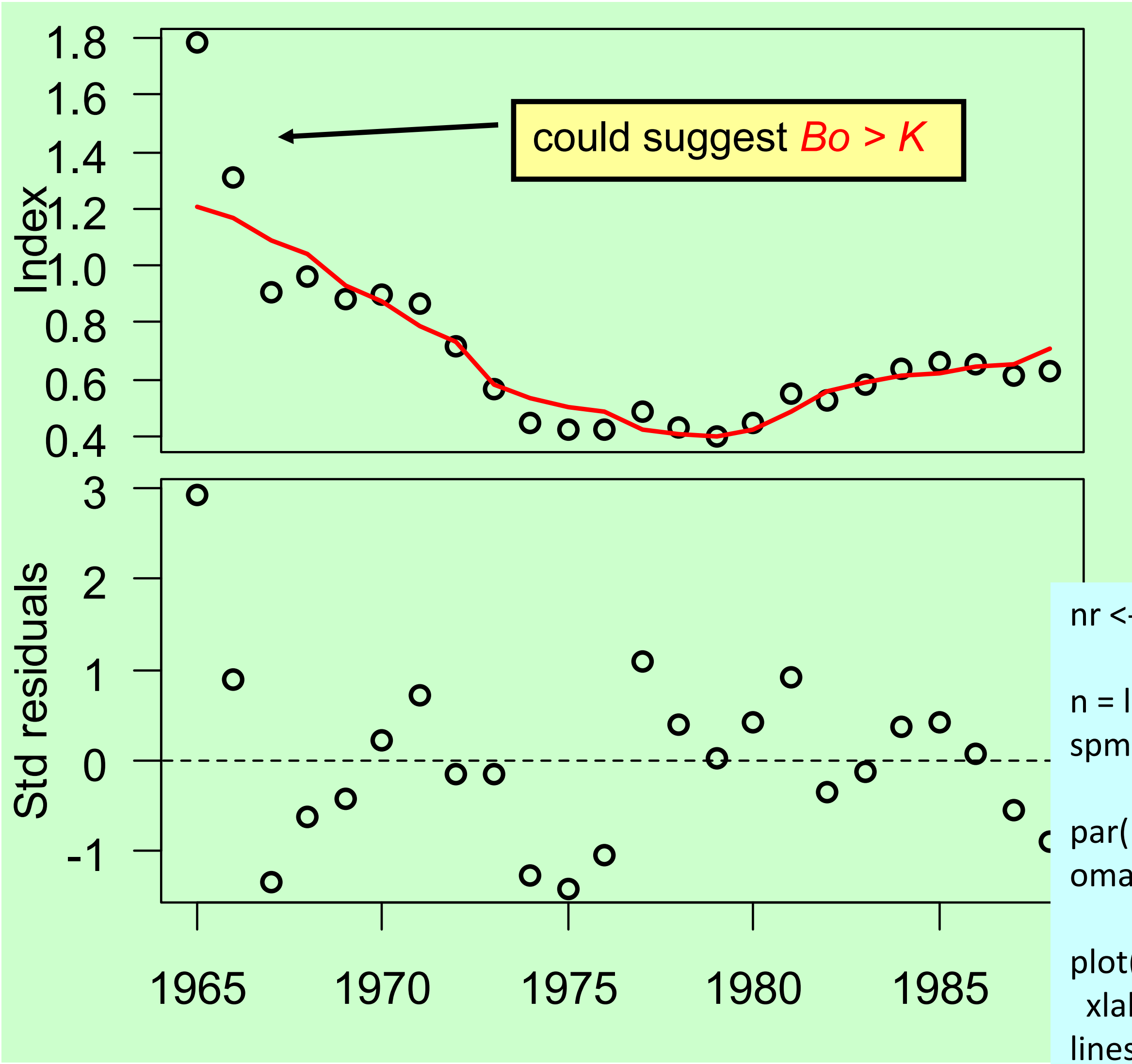
```
> spm.profile = confint(spm.fit)
Waiting for profiling to be done...
> print(spm.profile)
          2.5%      97.5%
Logq -8.002125 -7.5478249
logr  -1.246174  -0.7767502
logK  7.791673   8.1248761
```

estimate of exp parms

and 95% CI's

```
> print(exp(parm.est))
            q            r             K
4.273361e-04 3.706456e-01 2.820278e+03
> print(exp(spm.profile))
          2.5%        97.5%
q 3.347506e-04 5.272557e-04
r 2.876031e-01 4.598982e-01
K 2.420364e+03 3.377450e+03
```

Fit



Remember: I fit to logs

```
nr <- nlsResiduals(spm.fit)

n = length(hake.data$index)
spm.predict = exp(predict(spm.fit))

par(mfrow=c(2,1),mar=c(0,3,0.5,1),
oma=c(3,0,0,0),mgp=c(2,1,0))

plot(hake.data$Year,hake.data$index,
  xlab='Year', ylab='Index',type='p',lwd=2,xaxt='n')
lines(hake.data$Year,spm.predict,lwd=2,col='red')

plot(hake.data$Year,nr$resi2[,2],xlab='Year',
    ylab='Std residuals',type='p',lwd=2)
abline(h=0,lty=2)
```

2nd column returned by nlsResiduals() are standardized

R code for OE Estimation

```
spm = function(r,K,catch){
 n=length(catch)
 B=rep(NA,n);
 B[1]=2*K
 for (i in (2:n)){
  B[i]=B[i-1]+r*B[i-1]*(1-B[i-1]/K)-catch[i-1]
  }
  B[B<0]=1e-10
return(B)
}
```

Results, *Bo=2K*

Formula: log.index ~ log(spm_fit(logq, logr, logK, catch)[, 2])

Parameters:

I assigned the nls() result to spm.fit1

	Estimate	Std. Error	t value	Pr(>|t|)	
logq	-8.00747	0.10207	-78.45	< 2e-16	***
logr	-1.04059	0.07856	-13.24	1.15e-11	***
logK	8.00415	0.06229	128.50	< 2e-16	***

--- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: **0.0971** on **21** degrees of freedom

σ is much smaller

Compare *Bo=K* and *Bo=2K*

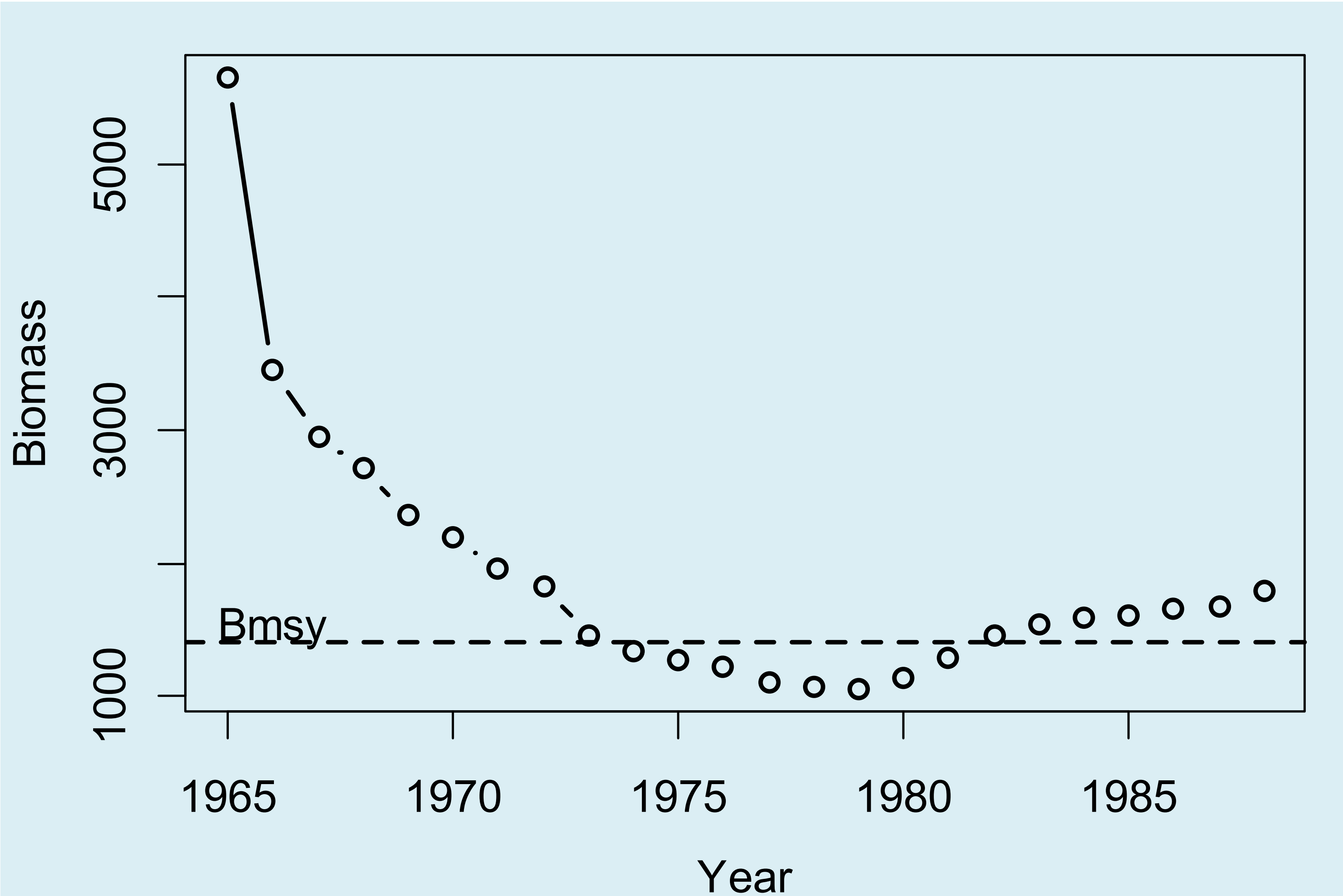

```
> print(parm.est)
           q            r            K
3.329674e-04 3.532459e-01 2.993345e+03
> print(exp(spm.profile))
          2.5%       97.5%
q 2.624792e-04 4.060017e-04
r 2.945740e-01 4.129283e-01
K 2.656434e+03 3.476342e+03
```

these CI's are not as wide

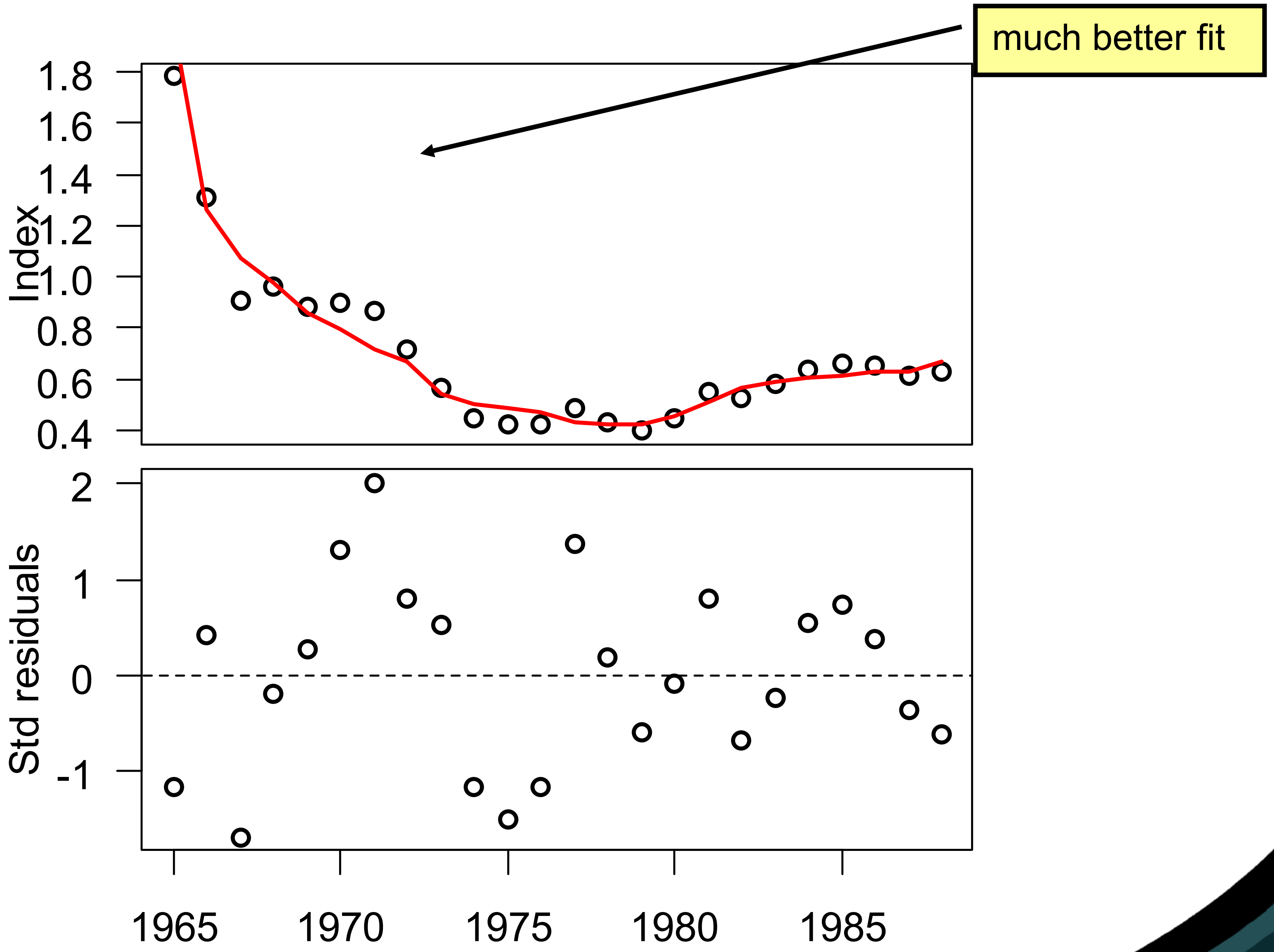
Bo = K

```
> print(exp(parm.est))
           q            r            K
4.273361e-04 3.706456e-01 2.820278e+03
> print(exp(spm.profile))
          2.5%       97.5%
q 3.347506e-04 5.272557e-04
r 2.876031e-01 4.598982e-01
K 2.420364e+03 3.377450e+03
```

Stock Size *Bo=2K*

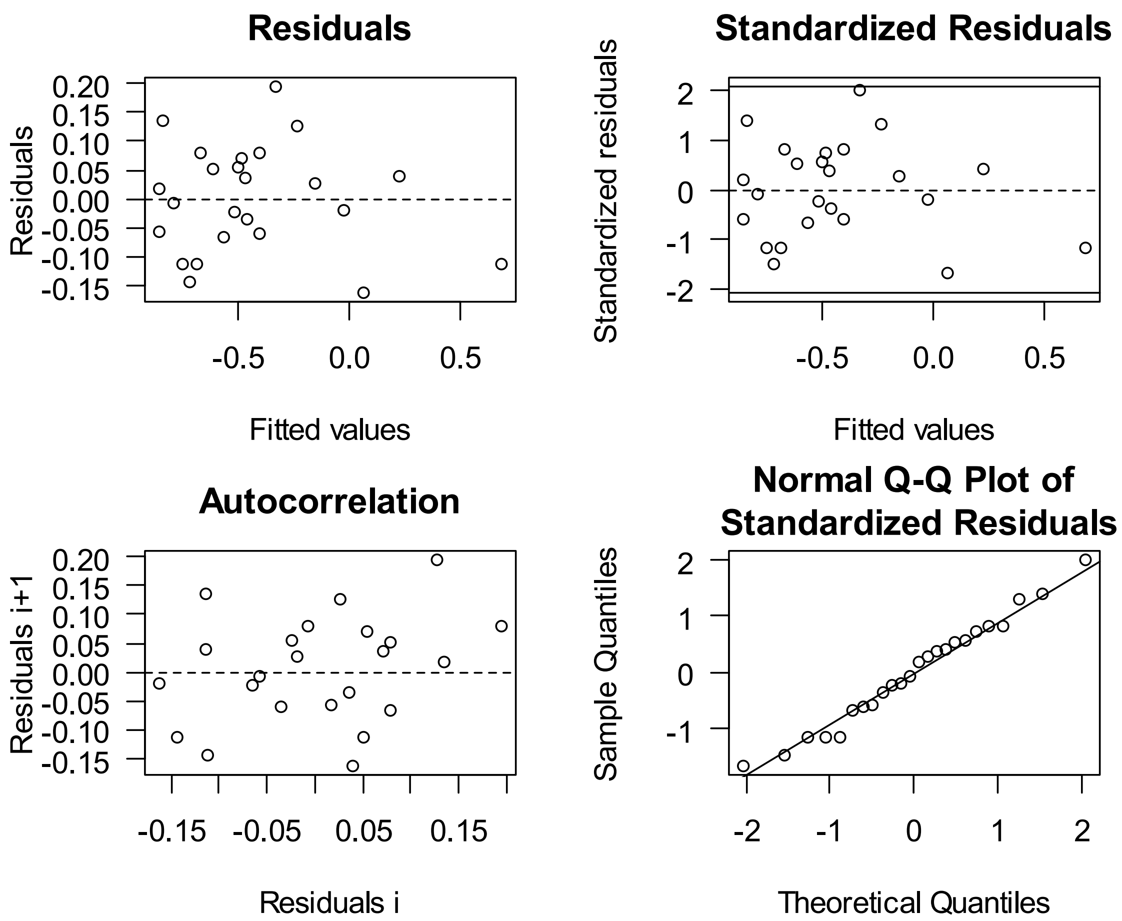


Fit, *Bo=2K*


much better fit
Index
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
Std residuals
2
1
0
-1
1965
1970
1975
1980
1985

Residuals, *Bo=2K*

all looks good

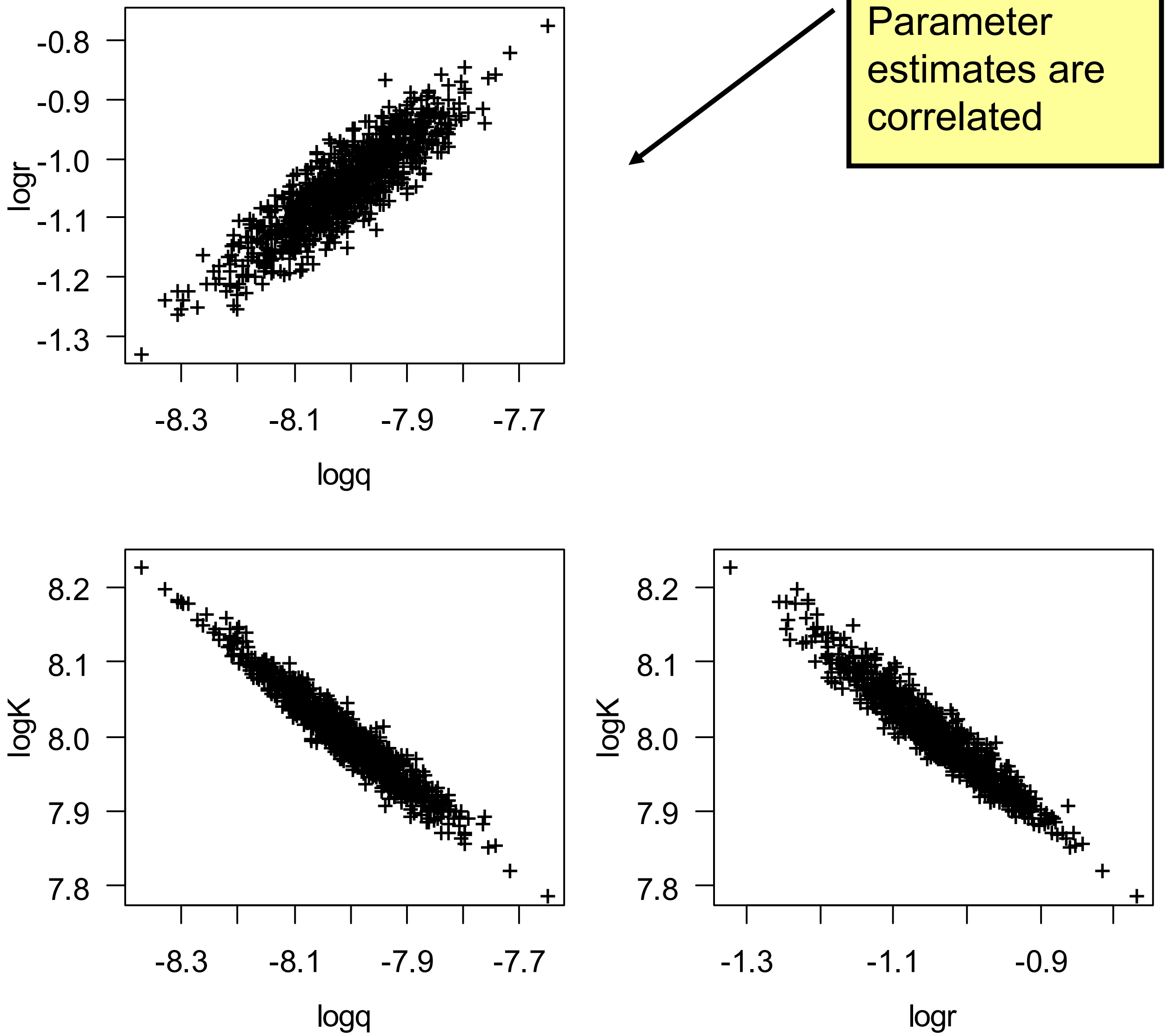



```
library("nlstools")
nr <- nlsResiduals(spm.fit1)
par(mar=c(4,4,3,2),mgp=c(3,1,0))
plot(nr, which = 0)

test.nlsResiduals(nr)
------
      Shapiro-Wilk normality test

data:  stdres
W = 0.98012, p-value = 0.898



------
      Runs Test

data:  as.factor(run)
Standard Normal = -0.83485, p-value =
0.4038
alternative hypothesis: two.sided
```

Bo = K??

- There is information that suggests *Bo > K* for Namibian hake
- We could estimate *Bo* separately from *K*.
- It would help if we had information on fishing prior to 1965
- i.e. is a reasonable that $Bo=B_{1964}$ is greater than carrying capacity?

Bootstrap, *Bo=2K*

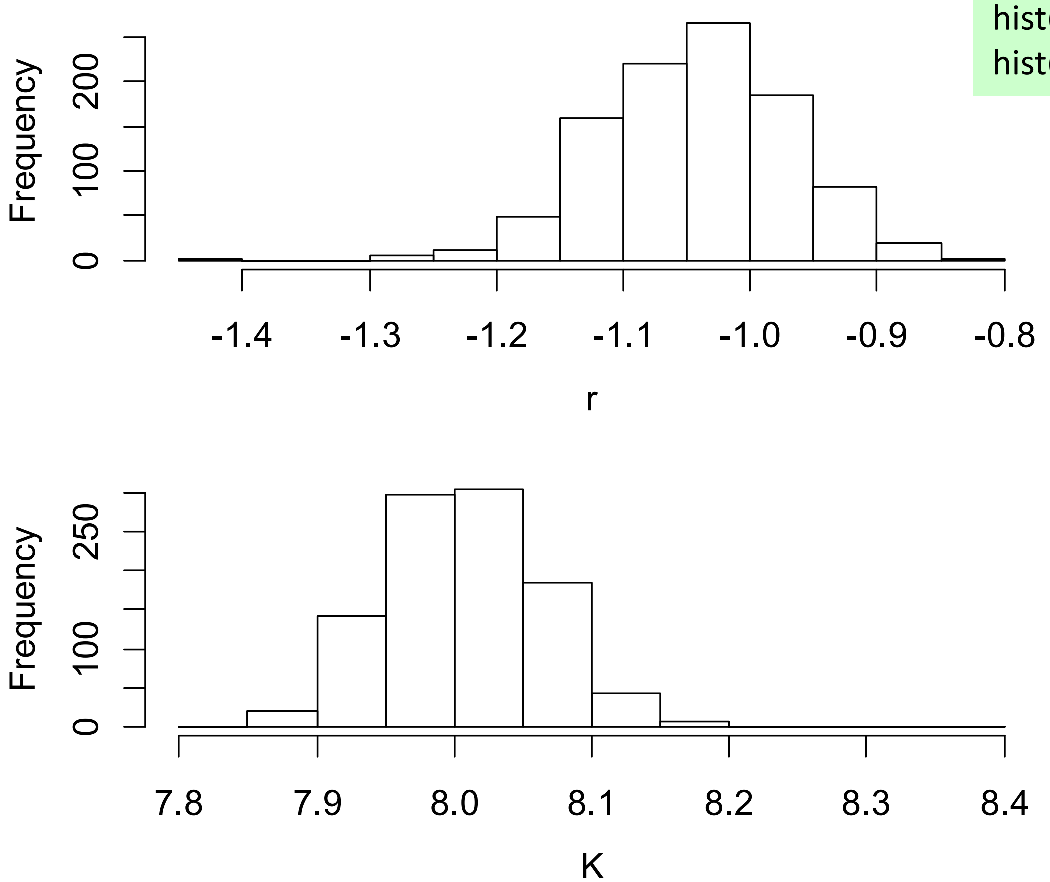


Parameter estimates are correlated

```
boo <- nlsBoot(spm.fit1)
par(
oma=c(0,0,0,0),
mar=c(2,2,1,1),
mgp=c(2.5,1,0)
)
plot(boo)
```

Bootstrap, *Bo=2K*

```
par(mfrow=c(2,1),mar=c(4,4,1,1),mgp=c(2.5,1,0))
hist(boo$coef[,2],xlab="r",main='')
hist(boo$coef[,3],xlab="K",main='')
```




```
options(digits=3)
> summary(boo)
------
Bootstrap statistics
      Estimate Std. error
logq    -8.01     0.0954
logr    -1.04     0.0733
logK     8.01     0.0589

------
Median of bootstrap estimates and
percentile confidence intervals
      Median  2.5%  97.5%
logq  -8.01 -8.20 -7.827
logr  -1.04 -1.18 -0.911
logK   8.01  7.90  8.127
```

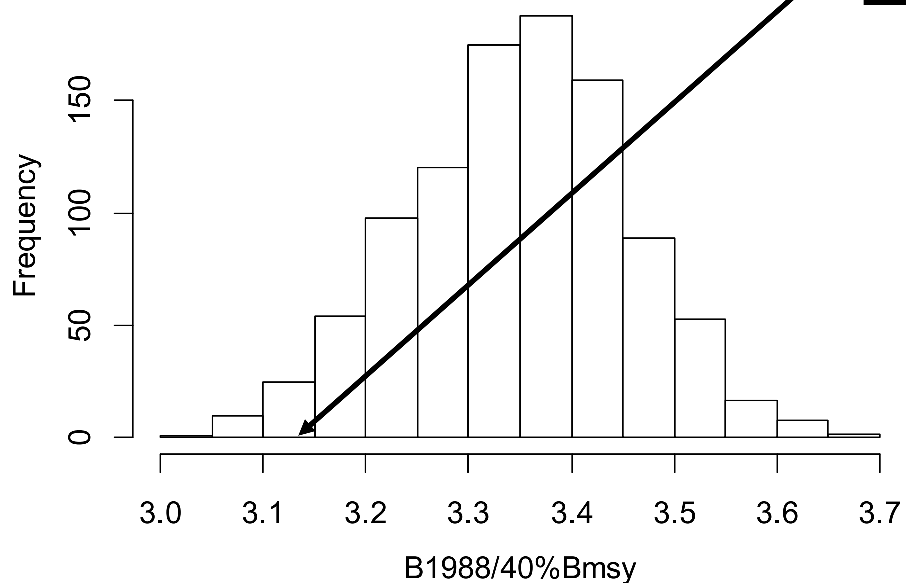
Current Stock Status relative to MSY

- A common question for a stock assessment is to evaluate current stock status in relation to Bmsy
- or relative to 40% of Bmsy, which is a limit reference point that fisheries managers want to avoid with high probability
- In the US, if the stock is less than 50% of Bmsy it is classified as over-fished

Current Stock Status relative to Bmsy

- For the Schaefer SPM, Bmsy = *K/2*,
- and 40%Bmsy = *20%K = K/5*.
- Want to get the bootstrap distribution of
- Bcurrent/40%Bmsy = 5Bcurrent/K
- For the hake example, this is $5B_{1988}/K$

Current Stock Status, *Bo=2K*



Very high prob that *B_{1988} > 40%Bmsy*

```
spm.wrap = function(parm,catch){
 r=exp(parm[1])
 K=exp(parm[2])
 B = spm(r,K,catch)
 stock.status =5*B[length(B)]/K
 return(stock.status)
}

boo.status = apply(boo$coef[,2:3],1,spm.wrap,
catch=hake.data$catch);

par(mar=c(3.5,3.5,1,1),mgp=c(2.5,1,0))
hist(boo.status,xlab="B1988/40%Bmsy",main='')
```

```
> quantile(boo.status,probs=c(0.5,0.025,0.975))
  50%  2.5% 97.5%
 3.35  3.13  3.56
```

Current Stock Status, *Bo=K*

50%	2.5%	97.5%
3.38	3.07	3.69

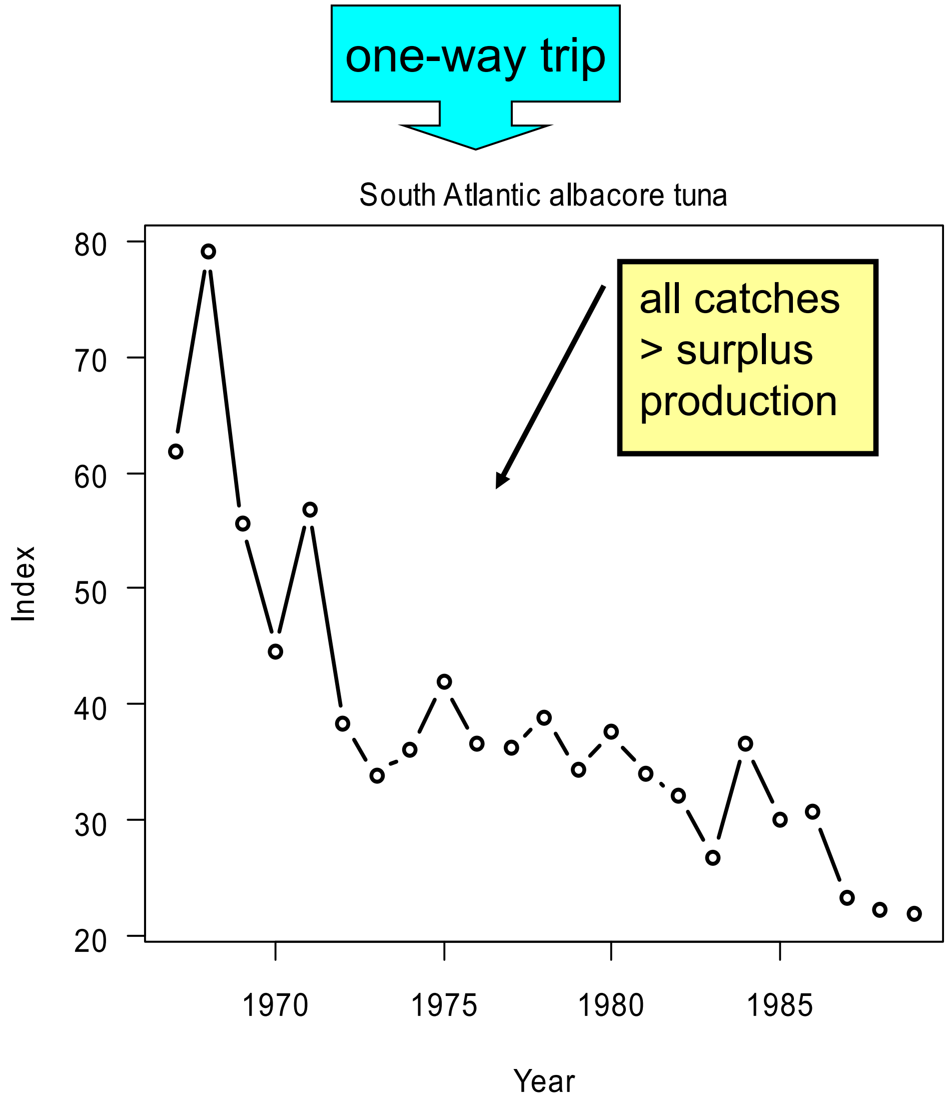
50%	2.5%	97.5%
3.35	3.13	3.56

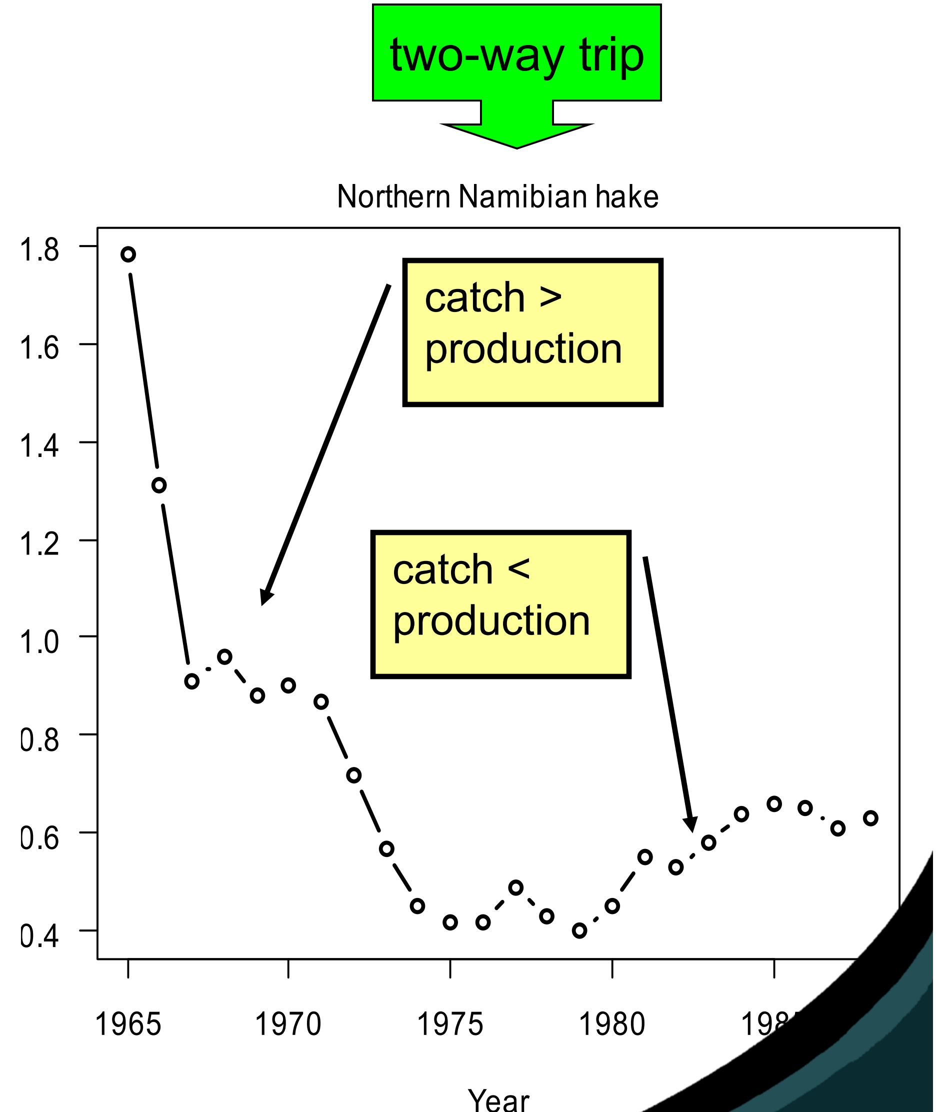
These results are similar to the results when *Bo=2K*
Hence, our conclusions about current stock status relative to 40% Bmsy are robust to the assumption about *Bo*

SPM estimation problems

- another example in Polachek et al (1993) involves southern albacore tuna
- It is a difficult example with poorly defined parameters
- This is because it is basically a “one-way trip”, with insufficient dynamic range in the catches and indices to produce reliable parameter estimates,
- You need a decline and recovery, or recovery and decline, to reliably estimate a SPM

SPM one-way trip





Surplus Production models

- It is a challenge to do a good stock assessment using production models because a fairly long time series with a fairly wide range of catch levels and abundance index levels is required to get reliable estimates
- They are not that precise for short term forecasts
- But they are commonly used to test the reliablity of more complex models

Process error estimation

- Another estimation approach assumes that the data are exact and that all the uncertainty is in the SPM

Not the same errors as the measurement errors in slide 6

- $B_{t+1} = \{B_t + g(B_t) - C_t\}exp(\varepsilon_{PE,t})$
- Process error (PE) surely exists, but so do observation errors, and research suggests that it is better to estimate with observations errors only than with process error only

Process error estimation

- Including both observation errors and process errors used to be difficult
- But is now fairly straight-forward using advanced software (We will do this in F6005!)
- Still the process error variance may be confounded with measurement variance
- There is an issue here – when there is process error then MSY, Bmsy, and Fmsy differ from the deterministic results

Stochastic MSY

- There is much literature dealing with harvesting in a stochastic environment.
- My overview is based on the Bousquet et al.

Bousquet, N., Duchesne, T. and Rivest, L.-P. 2008. Redefining the maximum sustainable yield for the Schaefer population model including multiplicative environmental noise. J. Theor. Biol. 254 65-75

Bordet, C. and Rivest, L.P., 2014. A stochastic Pella Tomlinson model and its maximum sustainable yield. *Journal of theoretical biology*, *360*, pp.46-53.

Complicated papers. You don't have to read these

Stochastic MSY

- They looked at the Schaefer surplus production model with a type of bounded multiplicative process error

$$\boxed{B_{t+1} = [(1-\phi+r)B_t - rB_t^2/K]\varepsilon_{t+1},}$$

Not the same errors as the measurement errors in slide 6

- Unbounded lognormal errors cannot lead to stationarity! ??

- They used a product of beta noise

$$\varepsilon_t = \frac{4\beta}{1+\alpha+\beta}U_tV_t. \qquad E[\varepsilon_t] = 1 \textit{ and } \mathrm{Var}[\varepsilon_t] = \sigma^2;$$

Not the same σ^2 as in slide 6. In future we denote this as σ^2_{PE}

Stochastic MSY

- The variance of the process error, σ_{PE}^2, should appear in the calculation of equilibrium reference points and can have important effects.
- Harvesting according to the deterministic MSY rule is an underoptimized strategy and can lead to strong decreases of the resource
- The deterministic Fmsy is incompatible with the assumption of equilibrium: on average, one cannot hope to harvest more than the stochastic MSY.
- Constant harvesting at the deterministic Fmsy will eventually lead to stock extinction.

Stochastic MSY

- The expected catch is optimized when

$$F_{MSY} = \frac{r}{2} - \frac{2(2-r)\sigma^2}{(4-r)^2} + o(\sigma^3) \qquad \lim_{x \to 0} \frac{o(x)}{x} = 0.$$

- At this fishing mortality rate

$$MSY = \frac{rK}{4}\left[1 - \frac{\sigma^2}{r(1-r/4)^2} + \frac{4\sigma^4}{r^2(4-r)^4}\left\{r^4 - 4r^3 - 12r^2 + 48r - 16\right\} + o(\sigma^5)\right]$$

- and

$$B_{MSY} = \frac{K}{2}\left[1 - \frac{8\sigma^2}{r(4-r)^2} - \frac{8\sigma^4}{r(4-r)^5}\left\{3r^3 - 18r^2 + 12r + 32\right\} + o(\sigma^5)\right]$$

σ^2_{PE}, etc

Stochastic MSY - Main conclusion

- You can’t fish as much or expect as much when there is process error.
- “Thus, our study has reinforced the conviction shared by numerous researchers that biological reference points calculated in a deterministic framework can be far from optimal in stochastic settings”

Miscellaneous

- Haddon frequently uses catch per unit effort (CPUE) as a stock size index
- $I_y = C_y/E_y$, where E_y is the fishery effort (hours fished, etc)
- Effort can be difficult to determine, and CPUE may not be a good index of stock size particularly when there is targeting of a schooling species (see Lecture 2)
- Effort may have more measurement error than catch!
- See lecture 2

Miscellaneous

- Haddon also discusses the problem when *q* is not constant over time
- of particular concern for CPUE indices because of changes in fishing power
- Much less concern for indices from standardized scientific surveys
- This is why survey indices are preferred
- *q*-drift is a tough problem

Bayesian

- SPM's are commonly estimated using Bayesian methods that involve the use of prior distributions for the parameters
- And some of these priors will be informative
- I am OK with this if the priors are based on additional information

Using demographic methods to construct Bayesian priors for the intrinsic rate of increase in the Schaefer model and implications for stock rebuilding

M.K. McAllister, E.K. Pikitch, and E.A. Babcock

Bayesian – I'm not saying much

Formal description of Bayesian inference [edit]

Definitions [edit]

- x, a data point in general. This may in fact be a vector of values.
- θ, the parameter of the data point's distribution, i.e., $x \sim p(x \mid \theta)$. This may in fact be a vector of parameters.
- α, the hyperparameter of the parameter distribution, i.e., $\theta \sim p(\theta \mid \alpha)$. This may in fact be a vector of hyperparameters.
- $\mathbf{X}$ is the sample, a set of n observed data points, i.e., $x_1, \ldots, x_n$.
- $\tilde{x}$, a new data point whose distribution is to be predicted.

Bayesian inference [edit]

- The prior distribution is the distribution of the parameter(s) before any data is observed, i.e. $p(\theta \mid \alpha)$.
- The prior distribution might not be easily determined. In this case, we can use the Jeffreys prior to obtain the posterior distribution before updating them with newer observations.
- The sampling distribution is the distribution of the observed data conditional on its parameters, i.e. $p(\mathbf{X} \mid \theta)$. This is also termed the likelihood, especially when viewed as a function of the parameter(s), sometimes written $\mathrm{L}(\theta \mid \mathbf{X}) = p(\mathbf{X} \mid \theta)$.
- The marginal likelihood (sometimes also termed the *evidence*) is the distribution of the observed data marginalized over the parameter(s), i.e.

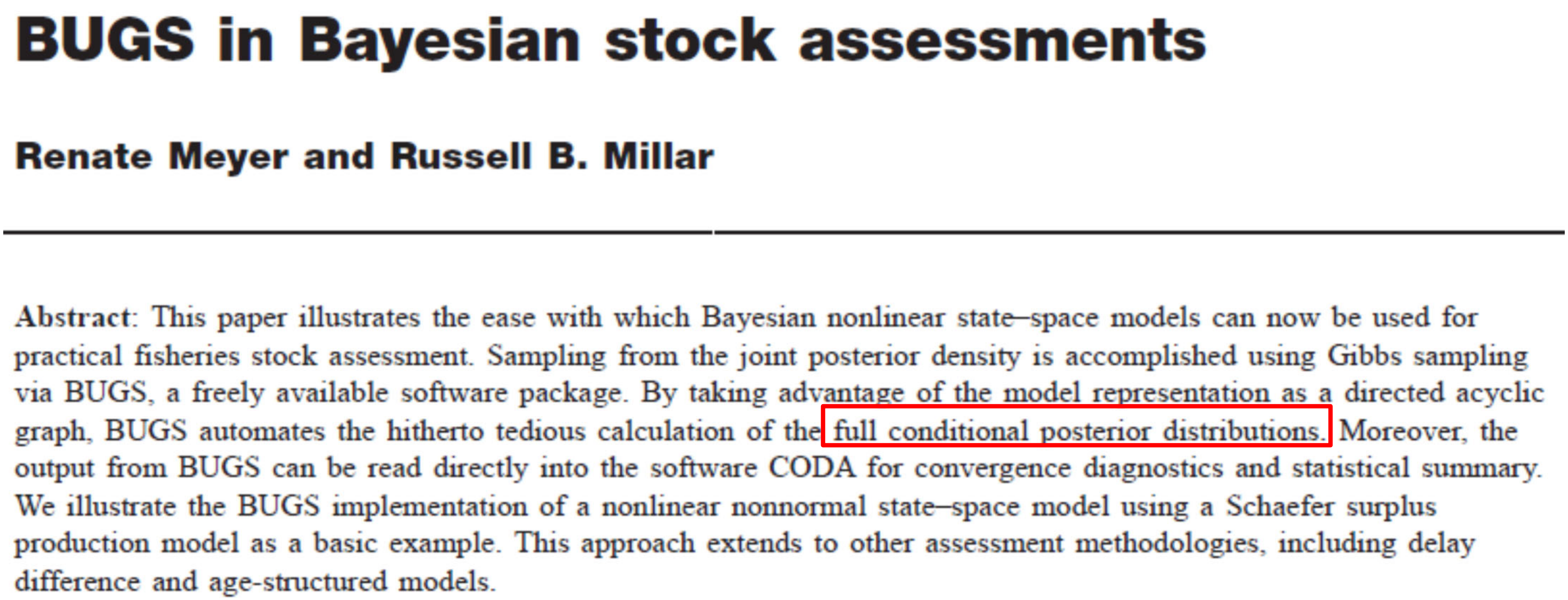
$$p(\mathbf{X} \mid \alpha) = \int_\theta p(\mathbf{X} \mid \theta) p(\theta \mid \alpha) \, \mathrm{d}\theta .$$

- The posterior distribution is the distribution of the parameter(s) after taking into account the observed data. This is determined by Bayes' rule, which forms the heart of Bayesian inference:

$$p(\theta \mid \mathbf{X}, \alpha) = \frac{p(\mathbf{X} \mid \theta) p(\theta \mid \alpha)}{p(\mathbf{X} \mid \alpha)} \propto p(\mathbf{X} \mid \theta) p(\theta \mid \alpha)$$

Note that this is expressed in words as "posterior is proportional to likelihood times prior", or sometimes as "posterior = likelihood times prior, over evidence"

Bayesian SPM

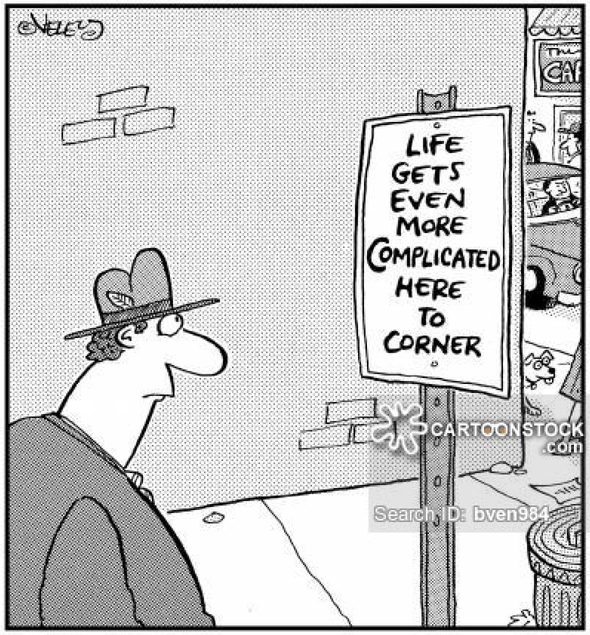

BUGS in Bayesian stock assessments

Renate Meyer and Russell B. Millar

Abstract: This paper illustrates the ease with which Bayesian nonlinear state–space models can now be used for practical fisheries stock assessment. Sampling from the joint posterior density is accomplished using Gibbs sampling via BUGS, a freely available software package. By taking advantage of the model representation as a directed acyclic graph, BUGS automates the hitherto tedious calculation of the full conditional posterior distributions. Moreover, the output from BUGS can be read directly into the software CODA for convergence diagnostics and statistical summary. We illustrate the BUGS implementation of a nonlinear nonnormal state–space model using a Schaefer surplus production model as a basic example. This approach extends to other assessment methodologies, including delay difference and age-structured models.

- If there is real prior information sitting around about some of the model parameters then I prefer to include that as a likelihood component in an integrated likelihood approach (F6005).
- This is straight-forward to do, and I do not include "subjective" or uninformative priors – the latter are pointless in this approach

A Real Life SPM



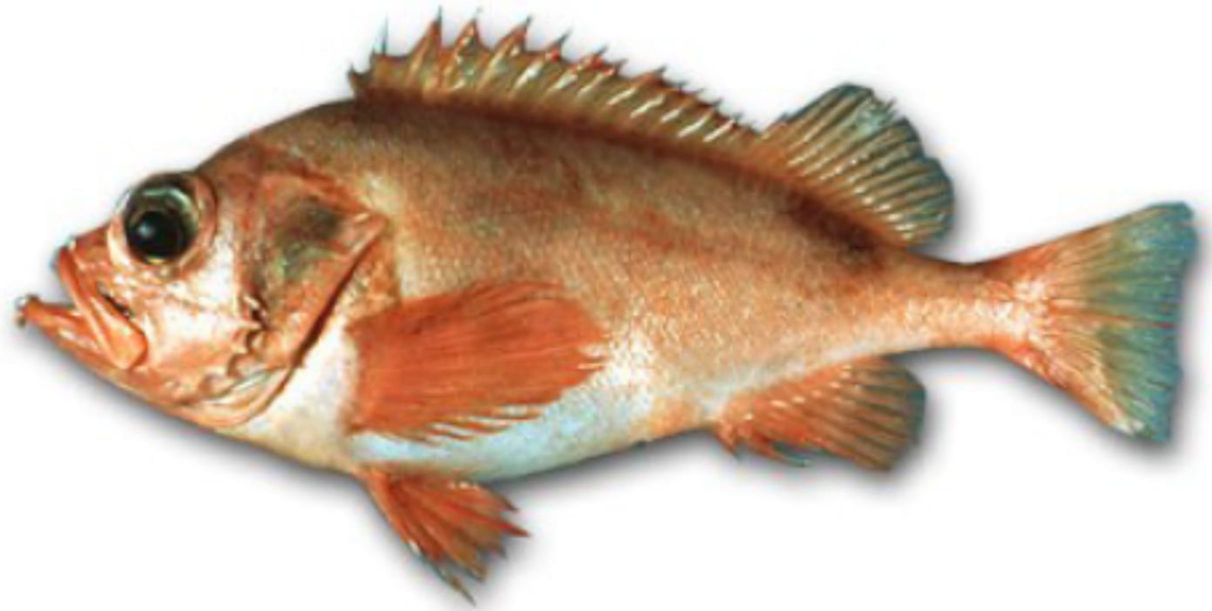


Figure 1. *Sebastes fasciatus* (Storer, 1856). Source: FAO species fact sheet[1].

3LN Redfish – A management success?

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Canada's first redfish fishery achieves MSC certification as sustainable

Canada's first redfish fishery achieves MSC certification as sustainable

May 23, 2017

The Marine Stewardship Council (MSC) and the Groundfish Enterprise Allocation Council (GEAC) are proud to announce Canada's first redfish fishery to meet the globally recognized MSC Fishery Standard. With this achievement, Acadian redfish (*Sebastes fasciatus*), also known as Atlantic redfish or ocean perch, caught in Northwest Atlantic Fisheries Organization (NAFO) Division 3LN, can now be sold as MSC certified by companies with MSC Chain of Custody certificates.

International collaboration toward successful rebuilding

MSC email updates
More information on email updates
More news about...
Fisheries in the program
More news from...
Canada

The Acadian redfish, also known as the Atlantic redfish, is marine deep-water fish belonging to the family of Sebastidae. The Northwest Atlantic redfish consists of a complex of three species identified as *Sebastes fasciatus, S. mentella*, and S. *marinus*, the last two occuring at much lower abundance. Their external characteristics are very similar, making them difficult to distinguish.

MSC Principles

MSC Fisheries Standard

Principle 1: Sustainable fish stocks

The fishing activity must be at a level which ensures it can continue indefinitely

Principle 2: Minimising environmental impact

Fishing operations must be managed to maintain the structure, productivity, function and diversity of the ecosystem

Principle 3: Effective management

The fishery must comply with relevant laws and have a management system that is responsive to changing circumstances

3LN Redfish

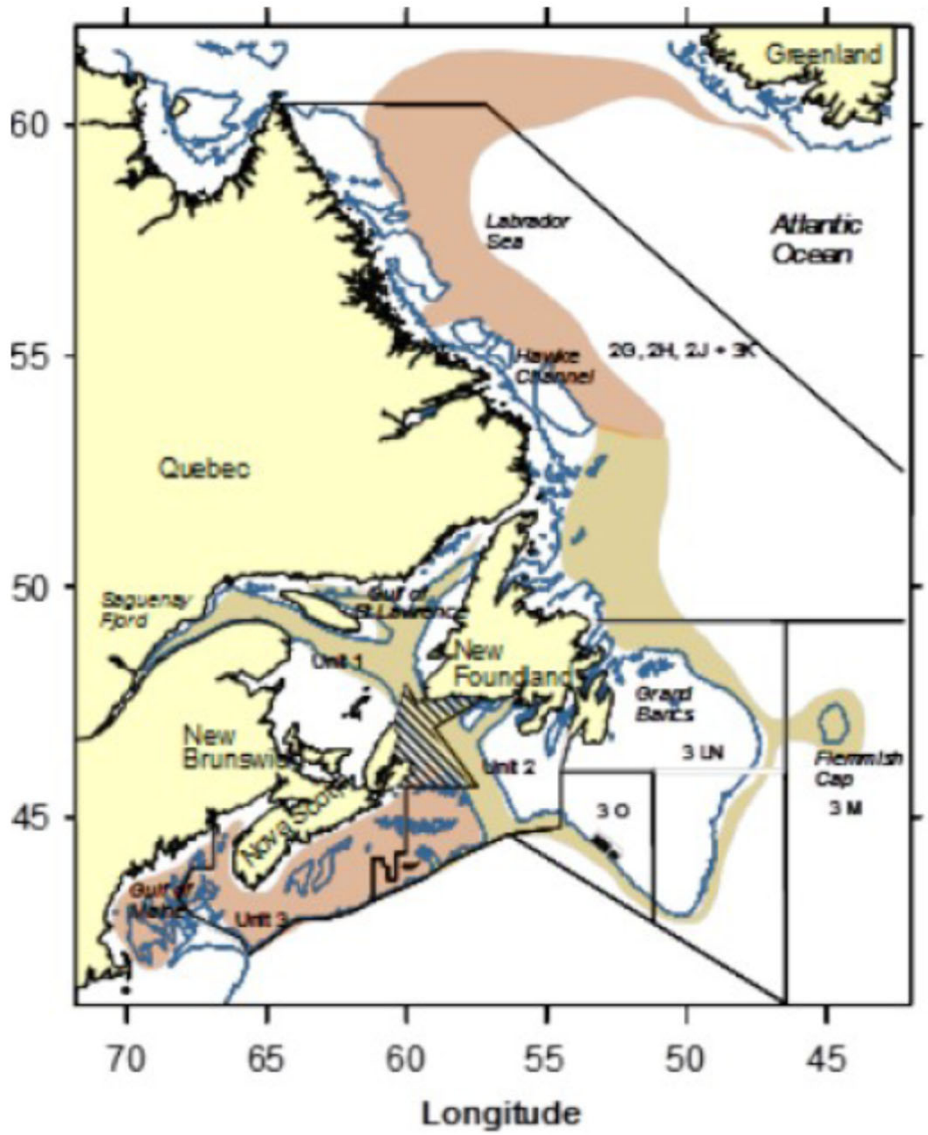
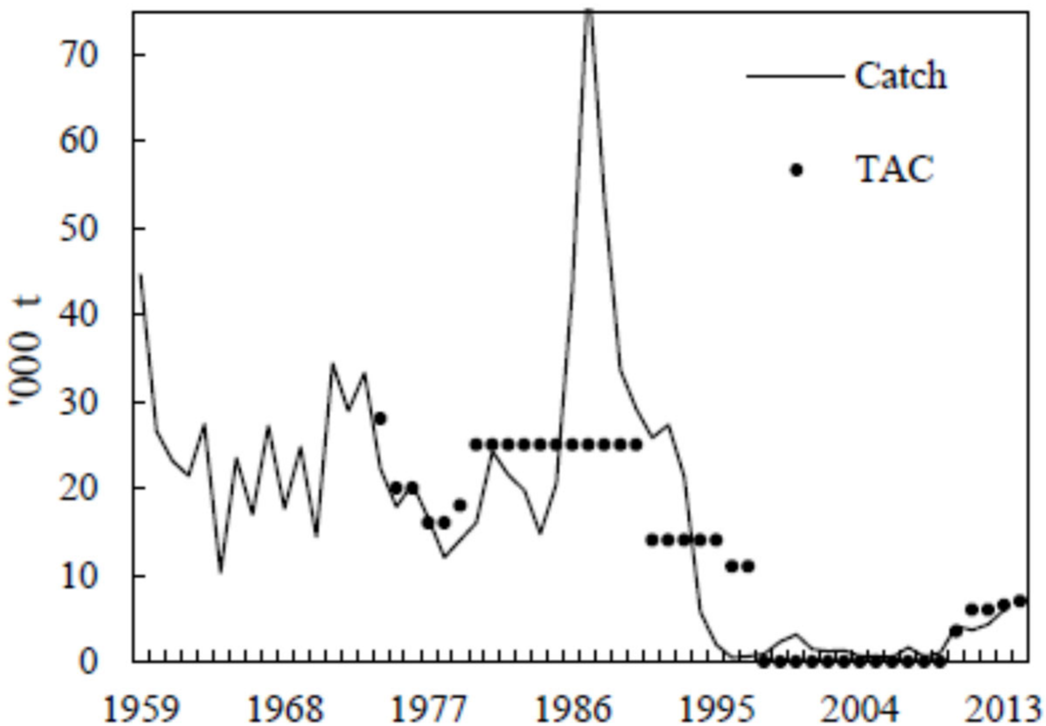


Figure 2. Map of the northwest Atlantic showing the distribution of redfish and boundaries of the management units. Source: DFO 2011.

Redfish inhabit deep cool waters throughout the Atlantic (3-8°C) along the slopes of fishing banks and deep channels. Redfish species are **bentopelagic** and show differential ecological preferences. *S. fasciatus* typically occurs in depths from 70 to 500 m.

Difficult to survey with a bottom trawl

3LN Redfish Fishery



Since 1994 most of the redfish catches in NAFO Divisions 3L and 3N were taken as by-catch of the Greenland halibut fishery

Moratorium on directed fishing in 1998

Lifted, with a TAC for 2010 of 3,500 t.

The fishing method is bottom and mid-water trawl. However, mid-water trawl has not been used recently.

	Overall TAC (t)	Canada's quota (t)	"GEAC's" allocation (t)
2012	6,000	2,556	2,479
2013	6,500	2,769	2,686
2014	7,000	2,982	2,892
2015	10,400	4,430	4,297

	2012	2013	2014	2015
GEAC catches (t)	1,213	2,428	1,443	4,443

3LN Redfish

4.3. Principle One: Target Species Background

As noted in section 4.1, the target species or stock for this full assessment is *S. fasciatus. S. mentella*, which is indistinguishable from *S. fasciatus* in commercial catches, is categorized in this assessment as an Inseparable/Practically Inseparable (IPI) species owing to its low relative abundance within the 3LN redfish complex. Its status and management is addressed in the P2 section. Therefore, while in this section focussing on P1, we refer to the stock as "redfish" or the "redfish complex" to be consistent with the NAFO management and assessment documents, we are referring to the status and management of *S. fasciatus* unless explicitly noted otherwise.

Nation	2012	2013	2014	2015
Canada	920	2,728	1,447	4,447
Cuba	134	-	-	-
Estonia	187	268	471	202
Faroe Islands	30	68	-	64
France (St. Pierre and Miquelon)	38	-	-	3
Lithuania	46	-	-	-
Portugal	1,242	1,191	1,327	2,100
Russia	1,588	1,695	2,062	2,972
Spain	309	282	388	170
Grand Total	**4,494**	**6,300**	**5,781**	**9,958**

3LN Redfish Assessment

The current assessment considers results from seven survey time series in addition to commercial CPUE to tune the population model; all are assumed to index the redfish complex and not the individual species (Figure 6). These include:

- Canadian 3LN spring survey (1991-2005, 2007-2015);
- Russian 3LN spring survey (1984-1991);
- Canadian 3L winter survey (1985-1986, 1990);
- Canadian 3L summer survey (1978-1979, 1981,1984-1985, 1990-1991, 1995);
- Canadian 3LN autumn survey (1991-2015);
- Spanish 3N spring survey (1995-2013);
- Spanish 3L summer survey (2006-2015).

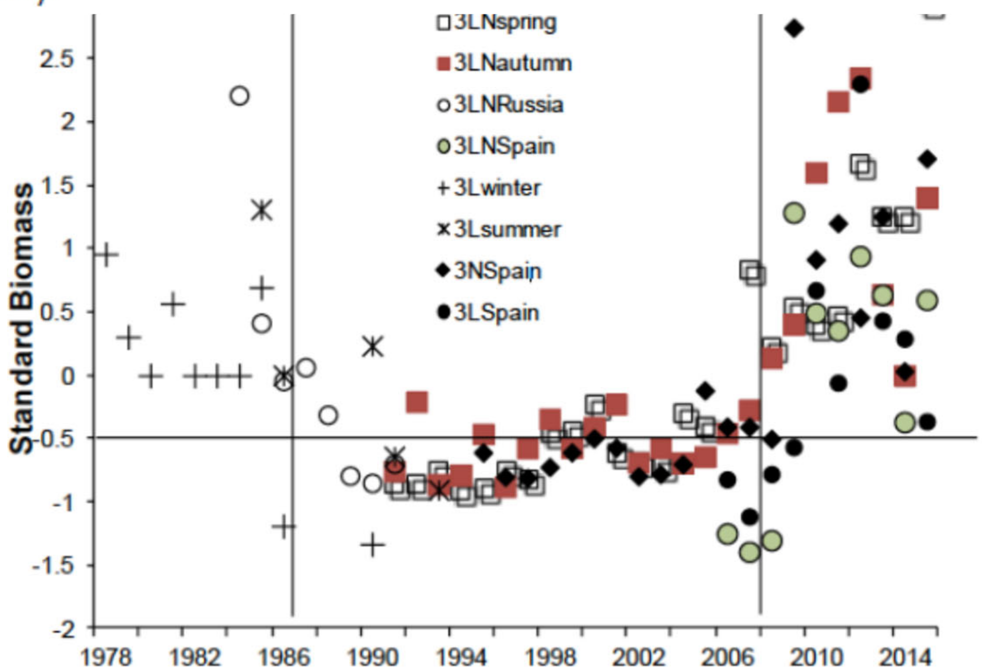


Figure 6. Standardized biomass from bottom trawl surveys included in the 2016 assessment. Source: Ávila de Melo *et al*. 2016.

3LN Redfish Assessment

4.3.1.2. Assessment model

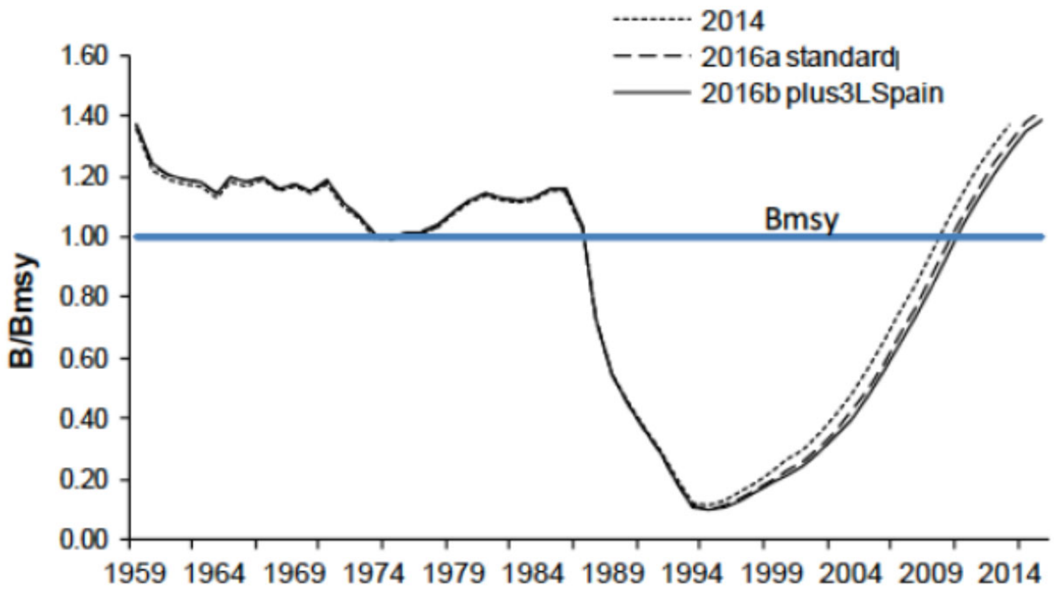
The 2016 assessment (Ávila de Melo *et al*. 2016) differs only modestly from the 2014 assessment (Ávila de Melo *et al*. 2014). The 2016 assessment again treats redfish in NAFO Div. 3LN as one complex because the commercial fish and surveys (prior to 2015) do not routinely identify them to species in the catches. The assessment uses a non-equilibrium surplus production model (current ASPIC model, Ver. 5.56). Principal input parameters were treated as:

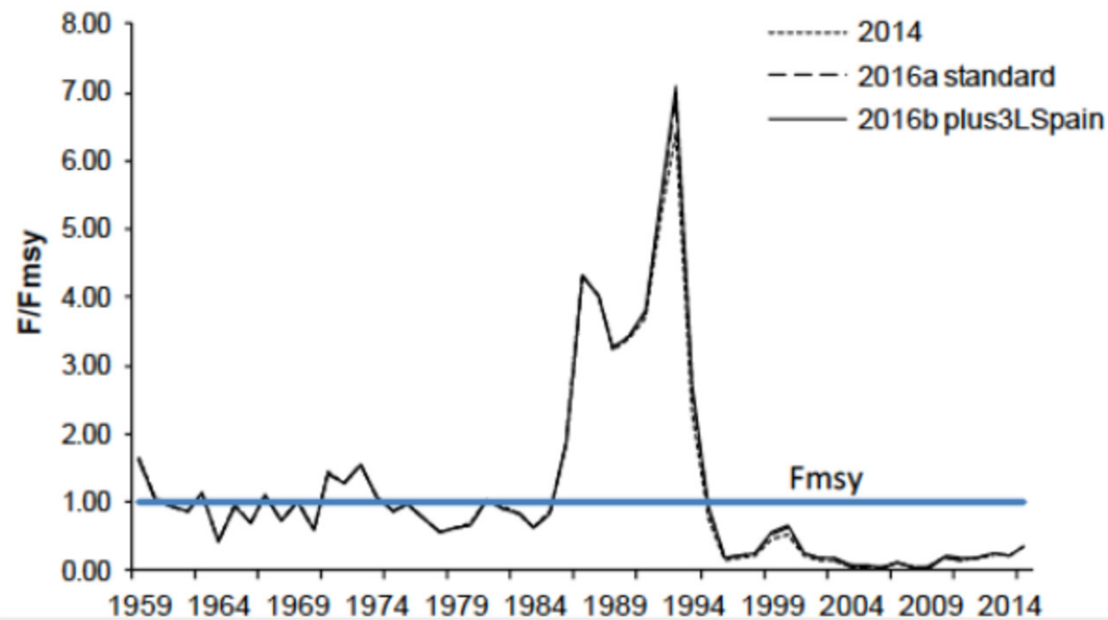
- $MSY = rK/4$;
- $B_{msy} = K/2$;
- $F_{msy} = r/2$.

The model fits the carrying capacity (K), and productivity (r) (note: $B_{msy} = rK/4$). All runs use a fixed estimate of *MSY* at 21,000, the average level of catch for the 1960-1985 interval, when the stock experienced an apparent stability. The 2014 assessment let the model fit MSY but results were viewed as implausible. The model is seeded with a starting guesses for B_1/K=0.5 and K=500,000 t. Biomass at year 1 was treated as being at B_{msy}. The model is allowed to fit the catchability of each survey independently but was assumed constant over time within each survey. Survey indices were given equal weighting in the model fitting although ASPIC includes an option for un-equal weighting in the fitting process. The model is fit to the catch, CPUE, and survey data.

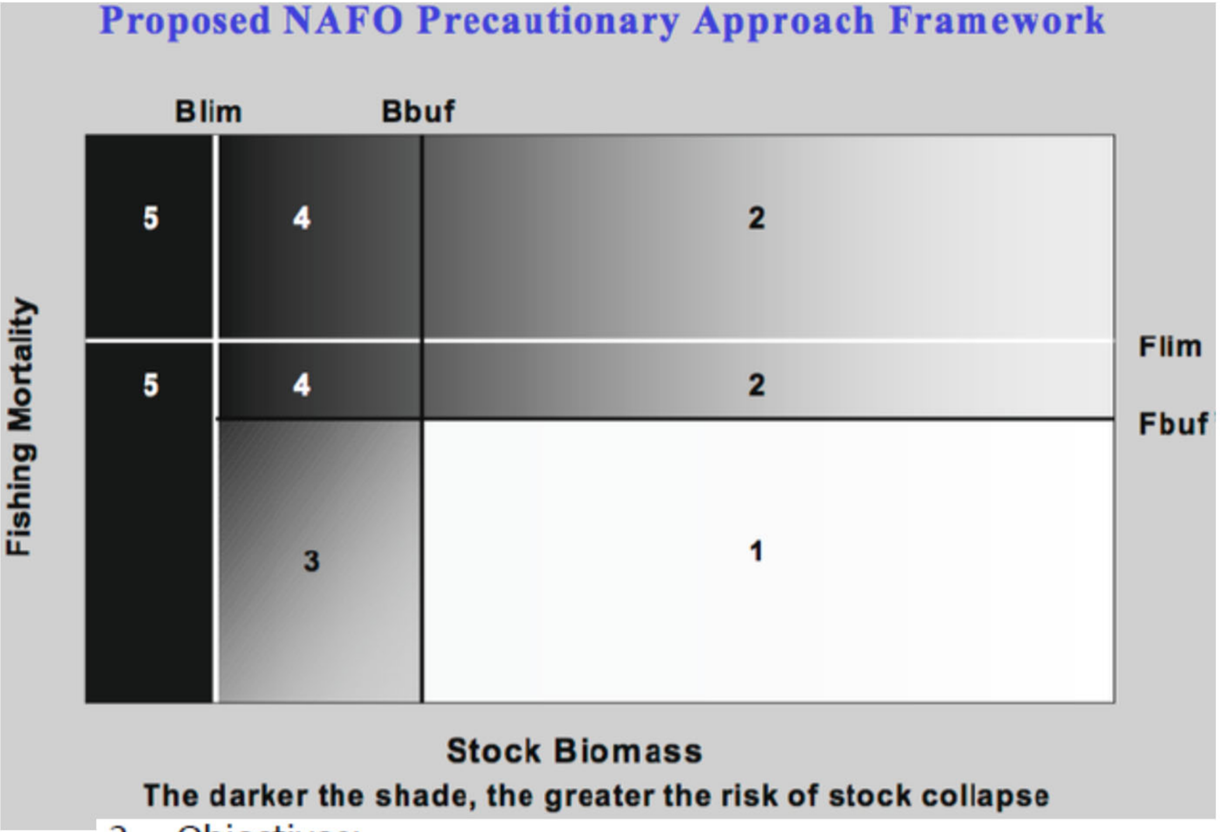
The assessment estimated the bias-corrected bootstrapped 80% confidence limits of the reconstruction of B/B_{msy} and F/F_{msy}. This version of ASPIC uses a frequentist as opposed to Bayesian approach to estimate uncertainty. In addition to estimating output uncertainty, the assessment

Assessment Results





Reference Points and Harvest Control Rule



2. Objectives:

   The long-term objective of this Conservation Plan is to maintain the biomass in the 'safe zone', as defined by the NAFO Precautionary Approach framework, and at or near B_{msy}.
3. Reference Points:
   a) Limit reference point for biomass (B_{lim}): 30% of B_{msy}
   b) Limit reference point for fishing mortality (F_{lim}): F_{msy}
4. Conditions to be satisfied when applying the Harvest Control Rules (Section 5 below):
   a) Very low (< 10%) probability of biomass declining below B_{lim}
   b) Less than 50% probability of declining below 80% of B_{msy} on or before 2021
   c) Low (< 30%) probability of fishing mortality $>F_{msy}$

MSC P1 Scoring

Table 19. Performance Indicators scoring assigned to the UoC 1 bottom trawl.

Principle	Wt (L1)	Component	Wt (L2)	PI No.	Performance Indicator (PI)	Wt (L3)	Weight in Principle	Score
One	1	Outcome	0.5	1.1.1	Stock status	0.5	0.25	90
				1.1.2	Reference points	0.5	0.25	90
				1.1.3	Stock rebuilding	0.333	0.1667	NS
		Management	0.5	1.2.1	Harvest strategy	0.25	0.125	100
				1.2.2	Harvest control rules & tools	0.25	0.125	100
				1.2.3	Information & monitoring	0.25	0.125	90
				1.2.4	Assessment of stock status	0.25	0.125	95

Table 20. Performance Indicators scoring assigned to the UoC 2 mid-water tra.

Principle	Wt (L1)	Component	Wt (L2)	PI No.	Performance Indicator (PI)	Wt (L3)	Weight in Principle	Score
One	1	Outcome	0.5	1.1.1	Stock status	0.5	0.25	90
				1.1.2	Reference points	0.5	0.25	90
				1.1.3	Stock rebuilding	0.333	0.1667	NS
		Management	0.5	1.2.1	Harvest strategy	0.25	0.125	100
				1.2.2	Harvest control rules & tools	0.25	0.125	100
				1.2.3	Information & monitoring	0.25	0.125	90
				1.2.4	Assessment of stock status	0.25	0.125	95

MSC P1 Scoring

Table 21. Summary of Conditions

Condition number	Condition	Performance Indicator	Related to previously raised condition? (Y/N/N/A)
1	The client must provide evidence that sufficient data continue to be collected to detect any increase in risk level to deep-water redfish.	2.1.3	NA
2	The client must provide documented evidence that short and long-term objectives for the 3LN Redfish fishery have been adopted which are consistent with achieving the outcomes expressed by MSC's Principles 1 and 2 and are explicit within the fishery's management system.	3.2.1	NA

No conditions on stock assessment – lets see if we agree

Setup SPM in R

```
> Cdat <- read.table("data\\catch.txt",header=TRUE, fill = FALSE)
> Cdat$imap = 1:nrow(Cdat);
> Cdat$catch = Cdat$catch/1000 ## units in Kilo tonnes
> head(Cdat)
  year catch imap
1 1959  44.6    1
2 1960  26.6    2
3 1961  23.2    3
4 1962  21.4    4
5 1963  27.4    5
6 1964  10.3    6
>
> Idat <- read.table("data\\indices.txt",header=TRUE, fill = FALSE)
> Idat$iq = as.numeric(as.factor(Idat$name))
> Idat$iyear = Cdat$imap[match(Idat$year,Cdat$year)]
> Idat$log_index = log(Idat$index)
> head(Idat)
  year index name iq iyear log_index
1 1959  1.43 CPUE  8     1     0.358
2 1960  1.60 CPUE  8     2     0.470
3 1961  1.70 CPUE  8     3     0.531
4 1962  1.63 CPUE  8     4     0.489
5 1963  1.63 CPUE  8     5     0.489
6 1964  1.81 CPUE  8     6     0.593
```

Map q parameters to indices

Map annual biomass to indices

We will fit to log(Index), so only take logs of data once here, and not within nls()

SPM R functions

```
spm = function(r,K,catch){
 n=length(catch)
 B=rep(NA,n);
 B[1]=K/2
 for (i in 2:n){
  B[i]=B[i-1]+r*B[i-1]*(1-B[i-1]/K)-catch[i-1]
  }
  B[B<0]=1e-10
return(B)
}

spm_fit = function(logq,logr,logK,log_index,iq,iyear){
  B = spm(exp(logr),exp(logK),Cdat$catch)
  log_EIndex = logq[iq] + log(B[iyear])
  resid = log_index - log_EIndex
  return(cbind(log_EIndex,resid))
}
```

Fixed Bo = Bmsy

Via data frame passed to nls()

A global object

Expansion operation

SPM fitting using nls()

```
n.index = length(unique(Idat$iq))

start.logq = aggregate(Idat$log_index,
list(name=Idat$iq),mean)$x - log(400)

sparm = list(logq=start.logq,logr=log(0.1),logK=log(800))

spm.fit <- nls(log_index ~ spm_fit(logq,logr,logK,log_index,iq,iyear)[,1],
  data = Idat,start = sparm,
  algorithm="port",control=list(maxiter=500),
  lower=c(rep(-Inf,n.index),log(0.01),log(100)),
  upper=c(rep(Inf,n.index),log(0.3),log(2000)))

HTMLStart(outdir=dname,file="myreport",
          extension="html", echo=FALSE, HTMLframe=TRUE)
summary(spm.fit)
HTMLStop()
```

Number of surveys and CPUE

Good starting values form log(q)

Based on MSY=21 and r=0.1

library(R2HTML)
Nicer output

3LN SPM parameter estimates

Formula: log_index ~ spm_fit(logq, logr, logK, log_index, iq, iyear)[, 1]

Parameters:

	Estimate	Std. Error	t value	Pr(>|t|)	
logq1	5.4217	0.3881	13.97	< 2e-16	***
logq2	6.9922	0.2457	28.45	< 2e-16	***
logq3	5.6041	0.3881	14.44	< 2e-16	***
logq4	7.1336	0.2476	28.81	< 2e-16	***
logq5	5.7648	0.2432	23.70	< 2e-16	***
logq6	6.4567	0.2482	26.02	< 2e-16	***
logq7	6.5146	0.2750	23.69	< 2e-16	***
logq8	-4.6090	0.1457	-31.62	< 2e-16	***
logr	-1.3318	0.1565	-8.51	8.79e-14	***
logK	5.8617	0.1325	44.23	< 2e-16	***

--- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: **0.665** on **112** degrees of freedom

3LN SPM parameter estimates

Parameter Estimates (natural scale)

	parm.est	2.5 %	97.5 %
q 3L_FALL	226.2632	105.7538	484.0961
q 3L_SUMR	1,088.0600	672.1669	1,761.2810
q 3L_WNTR	271.5444	126.9180	580.9766
q 3LN_FALL	1,253.3570	771.4487	2,036.3030
q 3LN_RSSN	318.8695	197.9740	513.5917
q 3LN_SPRG	636.9745	391.6336	1,036.0100
q 3N_SPNH	674.9150	393.7363	1,156.8920
q CPUE	0.0100	0.0075	0.0133
r	0.2640	0.1943	0.3588
K	351.3074	270.9495	455.4978

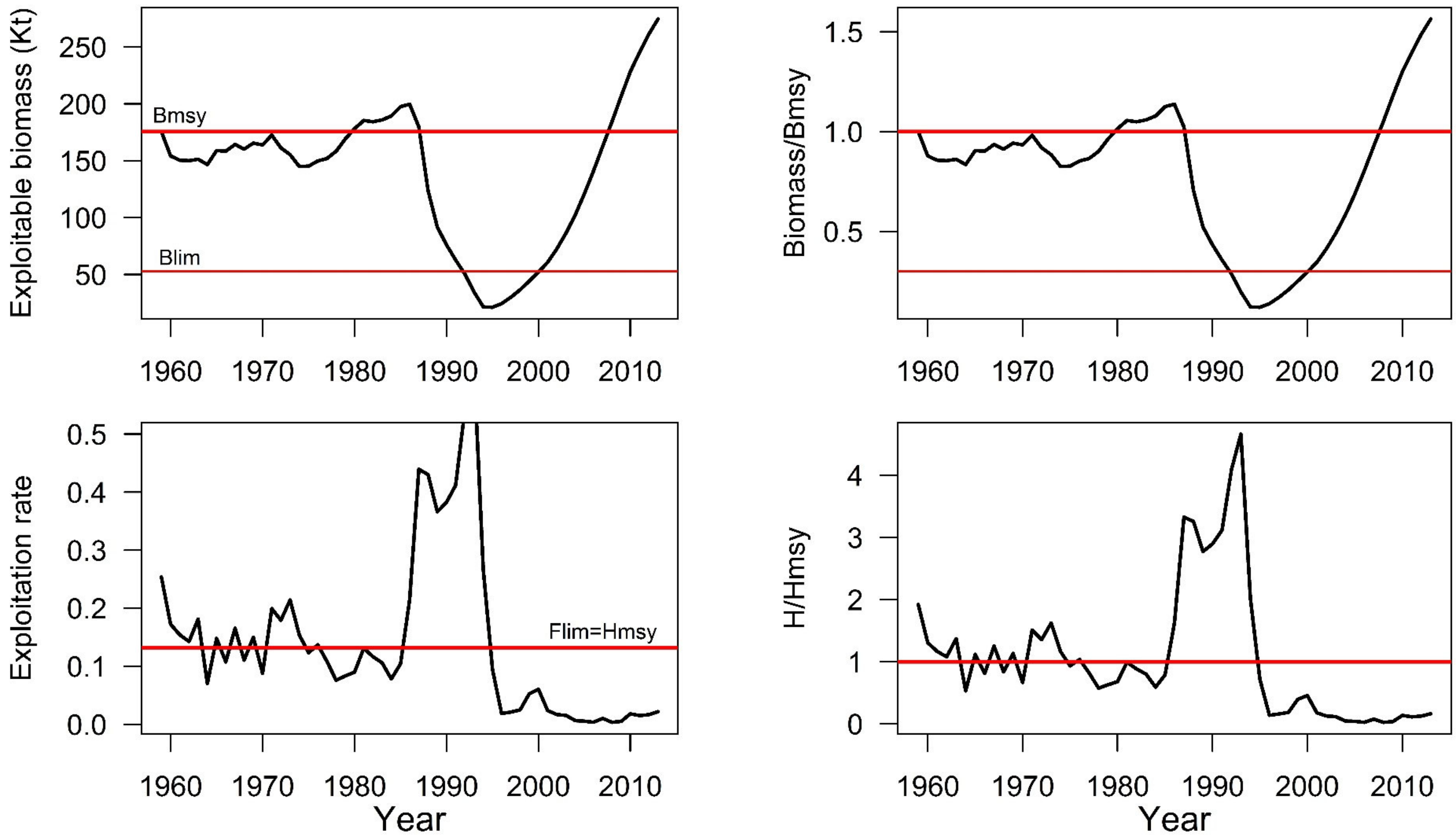
McAllister and Duplisea (2012) computed a prior probability distribution for *S. fasciatus* using a stochastic simulation demographic analysis based on life history information for the species. The prior median of r from their analysis was 0.15, with a standard deviation of 0.069.

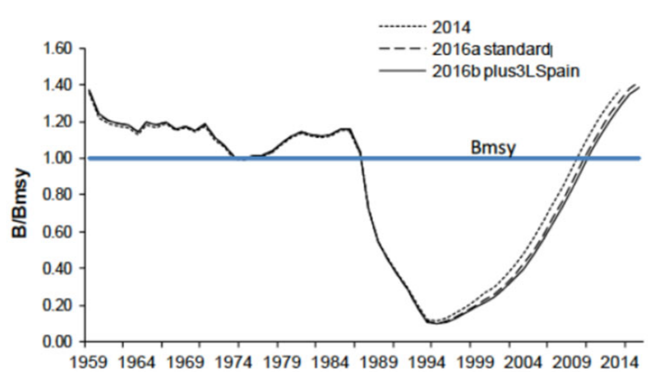
Seems too high?

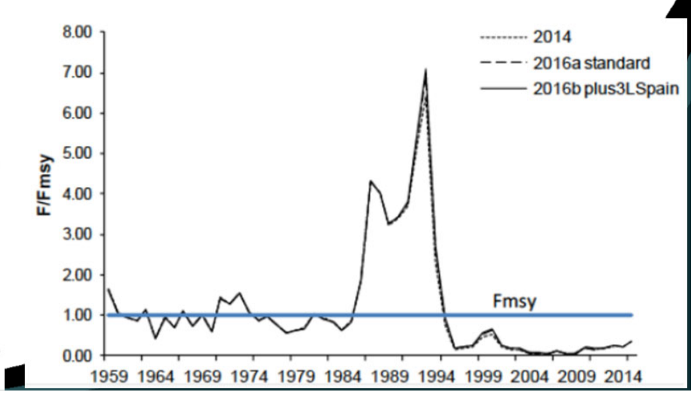
carrying capacity (*K*) of 376,500 t.

From MSC report

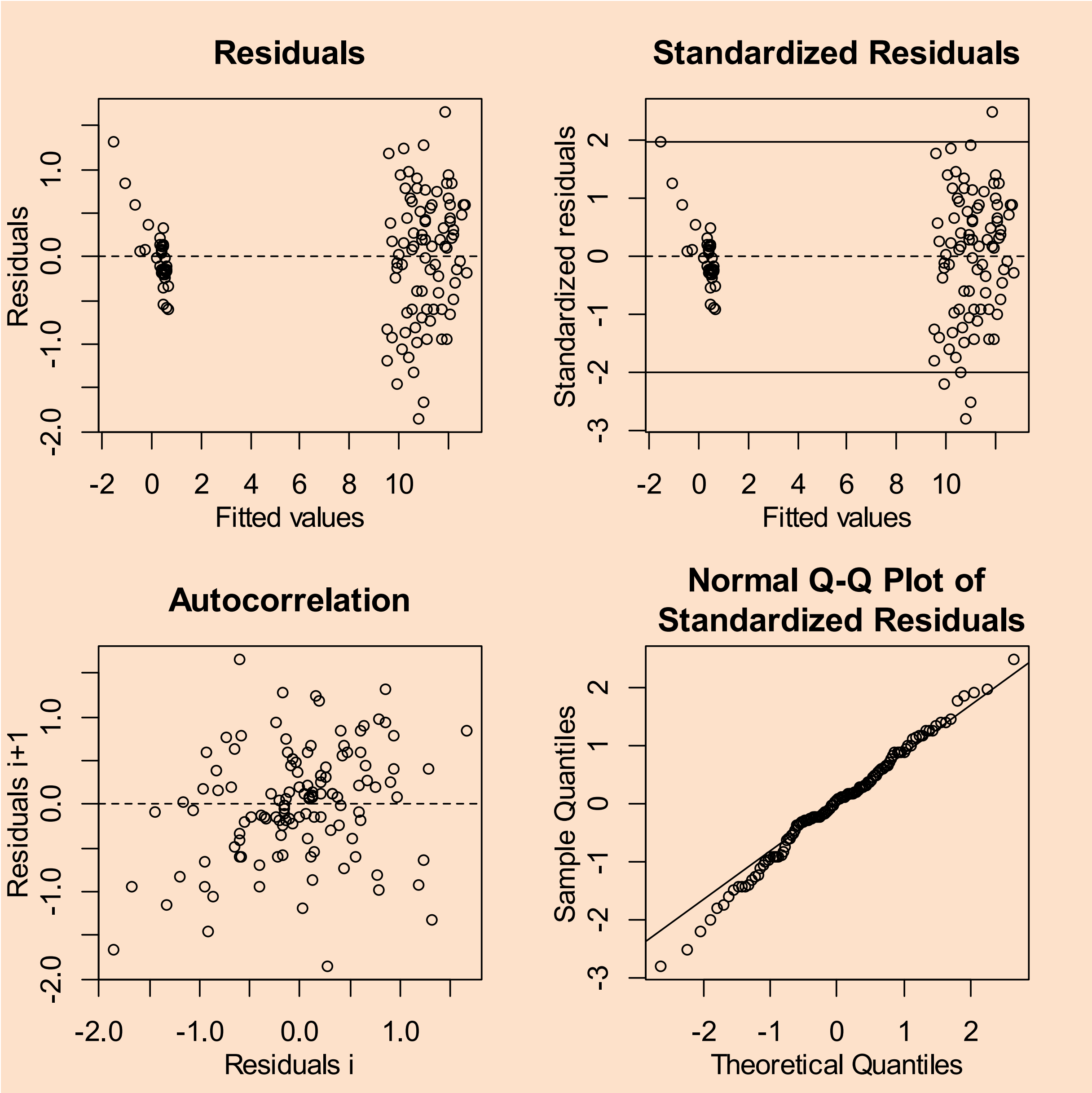
3LN Redfish Stock Size



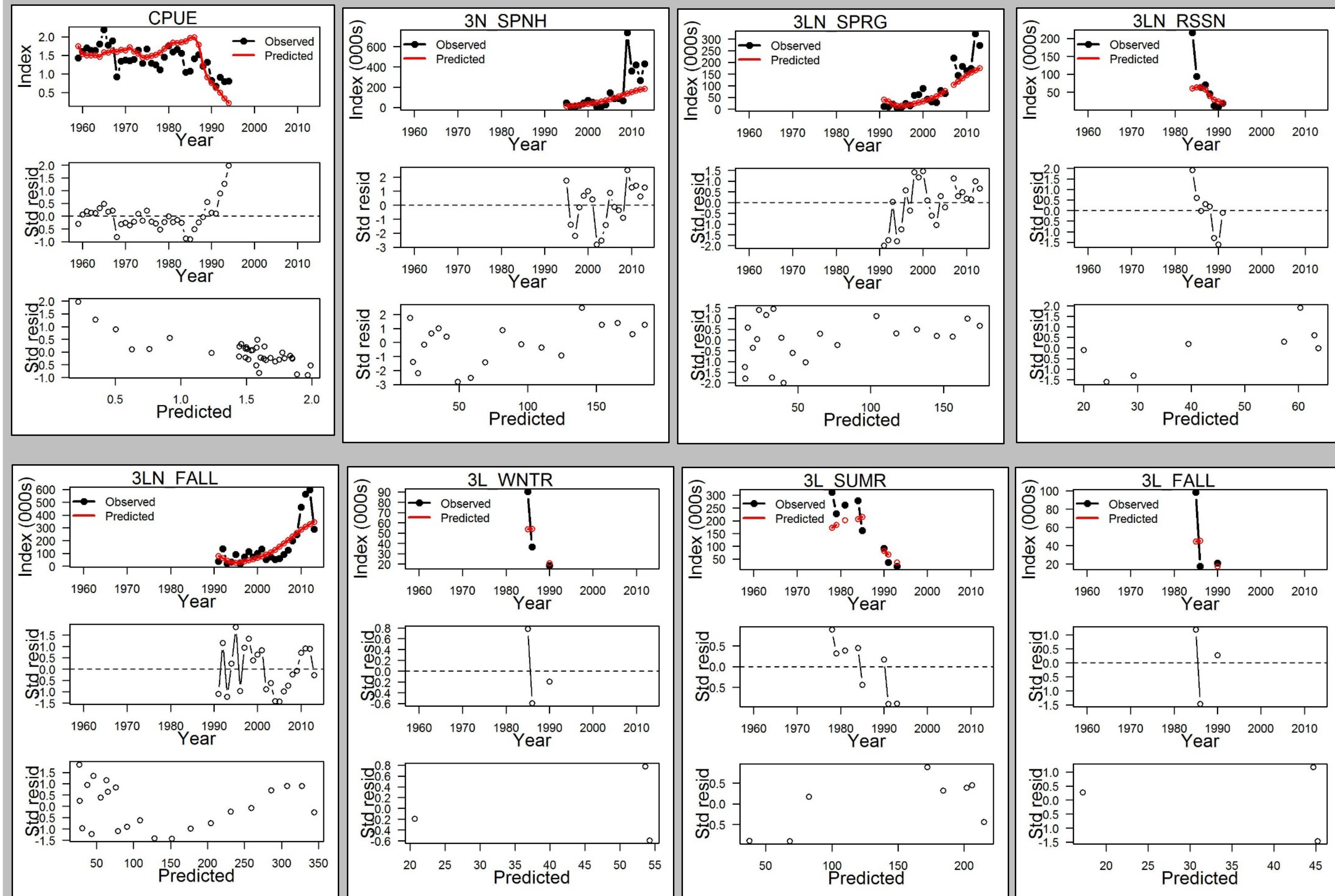




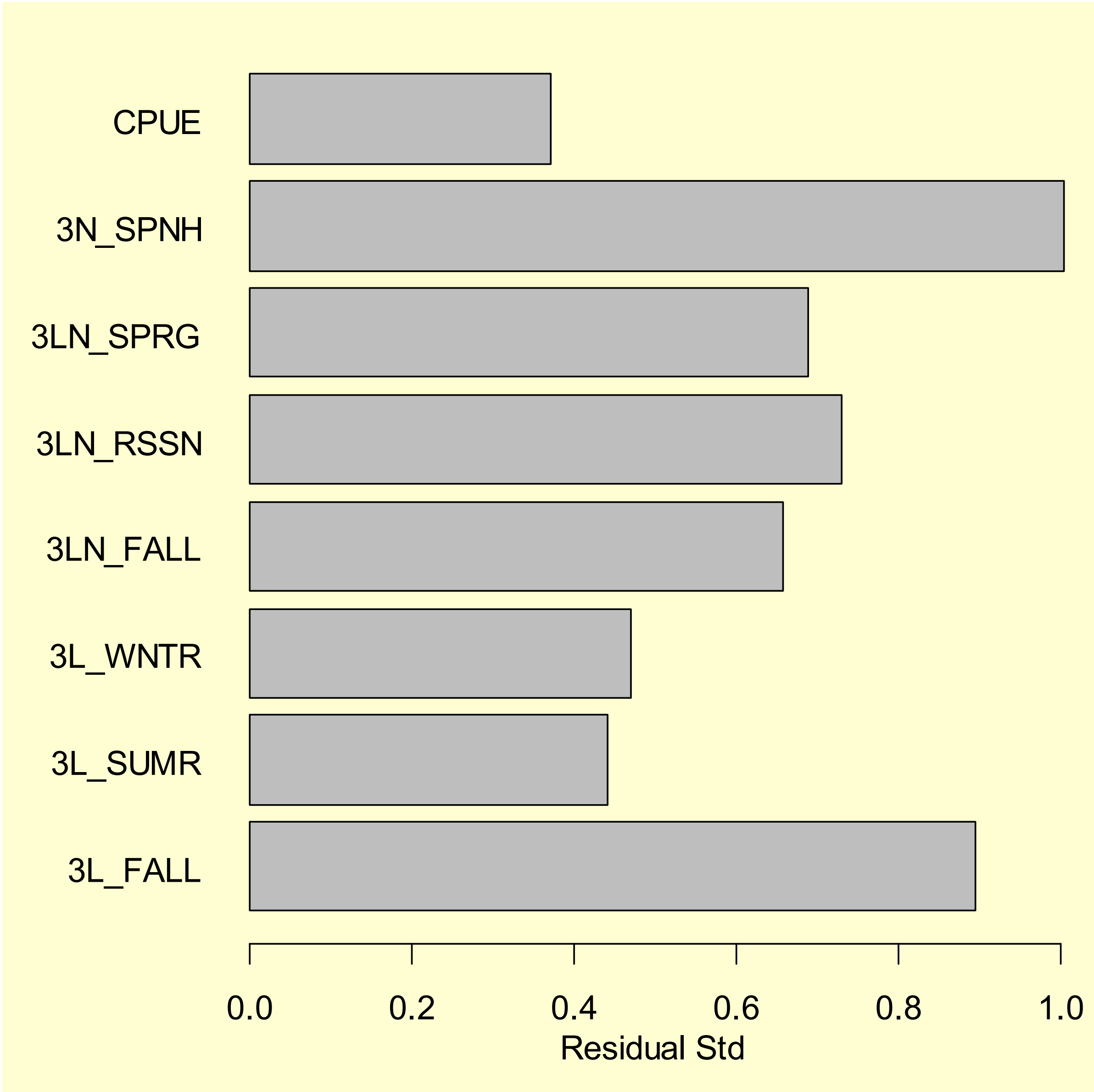
Residuals


Residuals
Standardized Residuals
Residuals
Fitted values
Standardized residuals
Autocorrelation
Normal Q-Q Plot of Standardized Residuals
Residuals i+1
Residuals i
Sample Quantiles
Theoretical Quantiles

Residuals


CPUE
3N_SPNH
3LN_SPRG
3LN_RSSN
3LN_FALL
3L_WNTR
3L_SUMR
3L_FALL
Observed
Predicted
Index
Index (000s)
Year
Std resid
Predicted

Residual Standard Deviations



Issues??

- Bo?
- How can we fix MSY, and should we?
- Accuracy of catches
- Accuracy of surveys
- An episodic spawner with occasional recruitment
  1. Not a stock for which SPM assumptions are appropriate
  2. How do you sustainably (i.e. MSY) manage something like redfish
- Is MSC correct that 3LN redfish is sustainably managed?