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Exploration of priors used in surplus production model in a Bayesian framework applied to witch flounder in NAFO Div. 3NO

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Abstract

In 2018 STACFIS recommended that the prior distributions for the surplus production model for witch flounder in Div. 3NO be further explored. This recommendation was mainly based on a concern about the relatively narrow prior for carrying capacity, K. This paper briefly outlines the previous work done on this issue and presents some explorations of priors included in the currently accepted model formulation. The new priors explored were priors on K with 100% and 1000% CV, prior on r with 120% CV and a wider prior on initial population size (Pin). A comparison of Bratio from the different formulations shows very little difference except for the model with the broader prior on Pin. This model formulation had a higher population size at the beginning of the time series. Once the survey time series start, this formulation has very similar results to the others. This type of response is not uncommon for production models where there is only catch information at the beginning of the time series. Process error for all formulations was very similar with essentially no difference in the medians from the different models. The main parameters had large overlap in credible intervals and model runs with the new priors tested here tended to have wider credible intervals than the current accepted model. The model results are robust to the tested variation in the priors.

Key words: Bayesian surplus production model, Div. 3NO witch flounder, priors

Introduction

In 2018 STACFIS recommended that the prior distributions be further explored for the surplus production model for witch flounder in Div. 3NO. This recommendation was mainly based on a concern about the relatively narrow prior for carrying capacity K. During the development of this model a number of formulations using different data series and different priors were explored. However, in 2018 there was a change in model formulation (Morgan and Lee, 2018) and so further exploration of priors is warranted.

This paper briefly outlines the previous work done on this issue and presents explorations of the priors included in the currently accepted model formulation.

First explorations presented in 2014

The inclusion/exclusion of various data series as well as various priors, were explored in 46 different model formulations presented to Scientific Council at that time. These preliminary analyses resulted in the set of surveys used in the current accepted model and the use of gamma distribution for the priors for q.

The model was not accepted in 2014 and these analyses were not reported in any published document. The results of these analyses are given in an annex to this paper.

Model formulations presented in 2015

In 2015 there were 11 more model formulations presented (Morgan et al 2015). These explorations mainly were focused on q and observation error but there was an exploration of both r and K. This resulted in an accepted model formulation with r informed by the work of Swain (2012) on witch flounder and with the prior for K based on the results of ecosystem production potential modelling. Since the derivation of the prior used for K has not been previously described in detail we discuss this here.

Derivation of the prior for K

Ecosystem Production Potential (EPP) models aim at estimating ecosystem productivity based on primary production and a generalized food web structure (Fogarty et al., 2016; Koen-Alonso et al., 2013; Rosenberg et al., 2014). Since 2013, NAFO SC has been developing EPP models to inform guidelines for total catches at the ecosystem level as part of the NAFO Roadmap for an Ecosystem Approach to Fisheries (Koen-Alonso et al., 2019; NAFO, 2015). These models are implemented at the Ecosystem Production Unit (EPU) scale (e.g. 2J3K, 3LNO, 3M) (NAFO, 2015; NAFO, 2018).

EPP models are invariant in time (i.e. they only track the flow of energy through the food web, but not the ecosystem dynamics) and render estimates of ecosystem productivity by functional guilds under the assumption that the ecosystem is fully functional (Koen-Alonso et al., 2013). These features of the EPP model are conceptual analogs to the idea of carrying capacity (K) in stock-production models; a potential maximum level that the stock can sustain when the proper ecosystem conditions are met (e.g. a fully functional ecosystem). Therefore, an approximation for K can be derived by considering the fraction of EPP that corresponds to witch flounder, and estimating the stock biomass that would be associated to that level of production.

Following this rationale, a plausible ecosystem-informed K value for witch flounder was derived as follows: a) selection of a set of plausible working version of the EPP model for 3LNO and gather the EPP estimates corresponding to the functional guild in the model that contains witch flounder (i.e. the benthivore box in EPP model), b) for each EPP estimate, calculate the fraction associated to the 3NO area, c) use the fraction of witch flounder in the RV biomass of the relevant fish functional groups (i.e. small, medium and large benthivores) to approximate the fraction of the EPP that would correspond to witch flounder, and d) use the production/biomass ratio to estimate the biomass associated to the approximated witch flounder production; this biomass would be an approximation to K. Since this process is performed for multiple plausible working versions of the EPP model, the mean and coefficient of variation (CV) of these estimates would be the mean and CV for K to be used as informed prior in the Bayesian stock-production assessment model.

Four plausible working EPP models were selected for this exercise. These models were the original EPP model version 1, and three configurations of the version 2 of the model corresponding to the following values for the *Xnan* model parameter: fixed values at 80% and 90%, and a uniform distribution between 50-90% (NAFO, 2015). The *Xnan* parameter in the EPP v2 model controls the fraction of bacterial production available to deposit feeding benthos (1-*Xnan*), which effectively defines the strength of the bentho-pelagic coupling, and consequently, impacts productivity of benthivores (the functional guild in the model that includes witch flounder). The median benthivore productivities for 3LNO from these models were 765.44, 1356.65, 851.67, and 1507.98 thousand tonnes/yr for the EPP v1 model, and the EPP v2 models with *Xnan* values of 80%, 90%, and uniform 50-90% respectively. These productivities were then scaled down to 3NO by applying a factor of 0.444, which corresponds to the 3NO area within the 3LNO domain used in the EPP models.

The 6% of the 3NO benthivore production was assumed as witch flounder production. This percentage corresponds to the maximum fraction of witch flounder in the RV fall biomass of small, medium and large benthivore functional groups in 3NO during the 1995-2013 period. The use of the maximum is based on the idea that K would be the maximum biomass that the stock could achieve, and that would be linked to the highest possible witch flounder fraction among benthivores.

The biomass corresponding to the estimated 3NO witch flounder production was derived by assuming a constant Production/Biomass ratio (PB Ratio) of 0.288. This PB ratio was estimated as the mean between the estimates obtained from using the pooled equation in Randall et al. (1995) (PB ratio=0.248) and the pooled equation from Randall (2002) (PB ratio=0.327). Both equations are allometric-based and fitted to freshwater fish data, but considered to provide an acceptable approximation for fishes in general. An individual witch flounder mean weight of 385.65g was used as input for these calculations. This mean weight was obtained as the average of witch flounder RV biomass/RV abundance for the 1995-2015 period.

The results from these steps rendered the following biomass estimates: 70.946, 125.744, 78.938, and 139.770 thousand tonnes associated to the EPP v1 model, and the EPP v2 models with *Xnan* values of 80%, 90%, and uniform 50-90% respectively. The average of these estimates is 103.850 thousand tonnes with a coefficient of variation (CV) of 32.76%. Based on these results, an approximate mean of 100 thousand tonnes with a CV of 30% was used as a reasonable informed prior for K in the witch flounder Bayesian stock-production assessment model.

Explorations in 2017

In 2017 there was some concern that the posteriors for K and r were similar to their priors. To explore if there was information in the data to allow the estimation of r and K, a run with a different prior on r was conducted. This run had a prior for r with mean of 0.3 and standard deviation of 0.12. The use of a different prior on r resulted in more difference between the priors and posteriors for both r and K, with posteriors being very similar to the run with r with mean of 0.2 and standard deviation of 0.12.

Methods

The current accepted formulation is the Schaefer (1954) form of a surplus production model:

$$P_t=[P_{t-1}+ r\cdot P_{t-1} (1 - P_{t-1})- C_{t-1}/K]\cdot\eta_t$$

where P_{t-1} and C_{t-1} denote exploitable biomass (as a proportion of carrying capacity) and catch, respectively, for year t-1 (Meyer and Millar, 1999a, 1999b). Carrying capacity, K, is the level of stock biomass at equilibrium prior to commencement of a fishery, r is the intrinsic rate of population growth, and η_t is a random variable describing stochasticity in the population dynamics (process error). The model utilizes biomass proportional to an estimate of K in order to aid mixing of the Markov Chain Monte Carlo (MCMC) samples and to help minimize autocorrelation between each state and K (Meyer and Millar, 1999a, 1999b).

An observation equation is used to relate the unobserved biomass, P_t, to the research vessel survey indices:

$$I_t=q\cdot P_t \cdot\varepsilon_t$$

where q is the catchability parameter, Pt is an estimate of the biomass proportional to K at time t, and εt is observation error.

The prior on r was informed by that derived by Swain (2012) for witch flounder in the southern Gulf of St. Lawrence. The prior used here allowed for a higher r than derived by Swain (2012) as some of the morphometric methods explored indicated a higher r. Therefore the mean (0.17) derived by Swain (2012) was used as the central tendency (i.e. the median) but with a larger standard deviation.

A mean of 0.2 and standard deviation of 0.12 gives a median of 0.17 on the log normal scale. The prior used therefore was:

R~(-1.763,3.252)

The prior for K was based on Ecosystem Production Potential modelling (NAFO 2014). This modelling indicated that a reasonable distribution for K would have a mean of 100 and a standard deviation of 30.

K~dlnorm(4.562,11.6)

The priors on survey q and observation error were:

pq ~dgamma(1,1)
q <-1/pq

tau ~dgamma(1,1)
itau2 <- 1/tau

For process error:

sigma ~ dunif(0,10)

The results of the 2017 assessment indicated that over 2014-2016 the survey indices were declining faster than can be explained by the process being modelled. To account for this a change was made to allow the process error to increase in 2014, 2015 and 2016 compared to the rest of the years (the sigma parameter was increased by 1 in those years).

Prior exploration

The main concern in 2018 was around the informative nature of the prior on K. Therefore the explorations presented here focus on that issue. The accepted formulation has a CV of 30% on the prior for K. Two model formulations were conducted with larger CV on K

Run 1

The CV was increased to 100% giving a mean of 100 and a standard deviation of 100.

K~dlnorm(4.259,1.44)

Run 2

The CV was increased CV to 1000% giving a mean 100 and standard deviation of 1000

K~dlnorm(2.298,0.217)

Run 3

The accepted formulation has a prior on r with a mean of 0.2 and standard deviation of 0.12 for CV of 60%. Run 3 increases the CV on r but is other wise the same as the accepted formulation. The mean of the r prior comes from a production model fit to a different witch flounder population. There is information that in general r will not be overly large, particularly for flatfish, so there is a limit on the likely distribution. Because of this I did not test CV of 1000 (which would have potentially allowed r's of more than 2.5) but did double the CV to 120% giving a mean of 0.2 and a standard deviation of 0.24.

R~dlnorm(-2.055,1.121)

Run 4

The prior on the initial population size as a proportion of K (Pin) has had very little exploration so one run with a different prior on this parameter was explored. The prior on Pin in the accepted model is a uniform distribution from 0.5 to 1. An exploratory run was conducted with a wider uniform prior, ranging from 0.5 to 1.5.

Pin~dunif(0.5, 1.5)

Results and Discussion

A comparison of the posteriors for some of the main parameters for each run are given in Table 1. In all cases there was large overlap in the credible intervals of the parameters. There was very little difference in process error across the various formulations. MSY varied from 7% less than to 2% more than the median MSY estimated in the accepted formulation. Increases in the CV on the prior for K resulted in posteriors with wider credible intervals, and a 7.5% difference in the median of K.

The biggest differences in MSY and process error were for the run with the different prior on Pin. This run also resulted in a different posterior with substantially wider credible intervals for Pin (0.527-0.815-0.992 for the accepted formulation and 0.571-1.137-1.482 for the different prior).

A comparison of deviance information criteria shows very little difference in model fit:

Model	DIC
Accepted	354.9
CV K 100	354.1
CV K 1000	353.4
CV r 120	355.0
Pin 0.5-1.5	355.0

A comparison of Bratio from the different formulations shows very little difference except for the model with the broader prior on Pin (Figure 1). This model formulation had a higher population size at the beginning of the time series. Once the survey time series start, this formulation has very similar results to the others. This type of response is not uncommon for production models where there is only catch information at the beginning of the time series. A comparison of the credible intervals of Bratio from the various formulations clearly shows their similarity (Figure 2). The 10th and 90th credible intervals are virtually identical except for the formulation where the prior on Pin is changed.

Process error for all formulations was very similar (Figure 3) with essentially no difference in the medians from the different models.

These analyses show that the model results are robust to these changes to the priors.

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Table 1. Median and 95% Credible Intervals for various parameters estimated in the different model formulations. Accepted is the model currently accepted as the basis of the assessment.

	r	K	MSY	FMSY	Process error
Accepted	0.081-0.126-0.235	75.82-119.8-163.8	2.516-3.774-5.686	0.041-0.063-0.117	0.003-0.067-0.250
CV K 100	0.074-0.120-0.247	71.61-127.1-196.8	2.537-3.819-6.094	0.037-0.060-0.123	0.002-0.064-0.252
CV K 1000	0.072-0.119-0.249	69.39-128.8-210.8	2.554-3.839-6.396	0.036-0.059-0.125	0.003-0.064-0.262
CV r 120	0.067-0.120-0.234	76.75-121.9-169.9	2.14-3.677-5.62	0.033-0.060-0.117	0.003-0.064-0.248
Pin 0.5-1.5	0.078-0.124-0.225	76.18-112.7-154.3	2.306-3.514-5.35	0.039-0.062-0.113	0.003-0.061-0.236

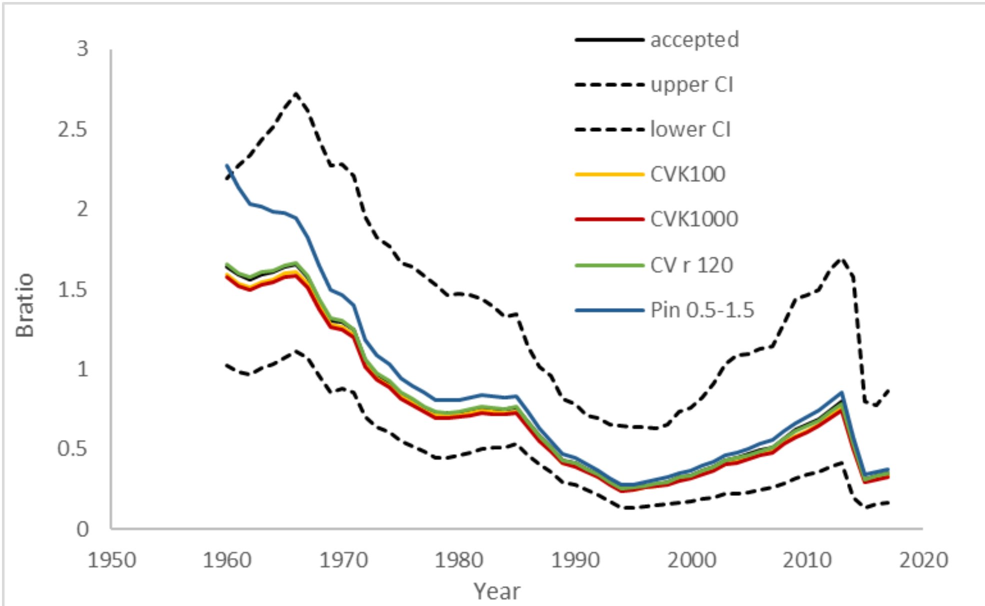


Figure 1. Bratio from various model formulations. The dashed lines are the 95% credible intervals from the accepted model.

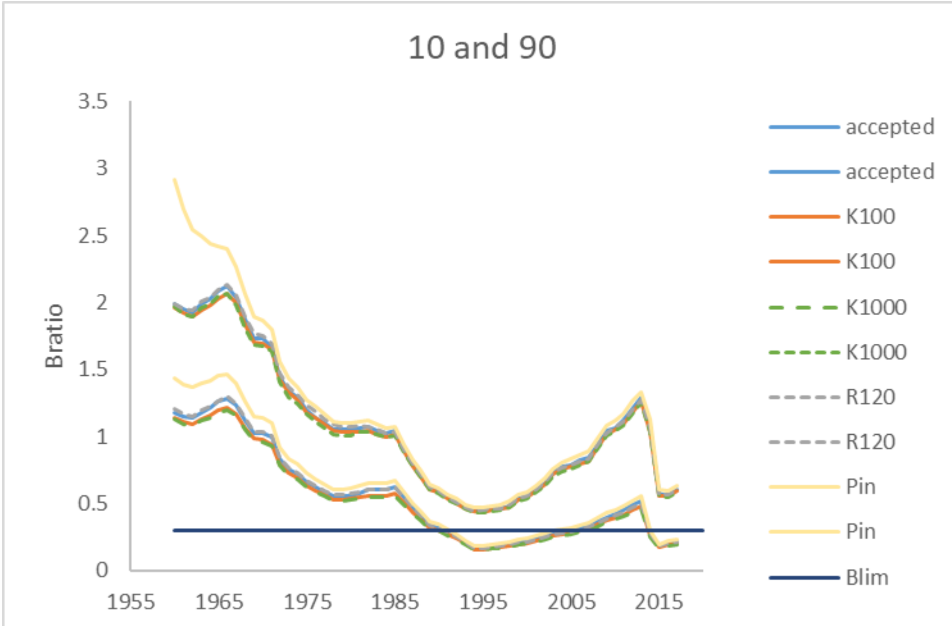


Figure 2 Credible intervals (10th and 90th) of Bratio from the various model formulations. Blim (the horizontal line) is also show in each plot. The different formulations are as described in the text.

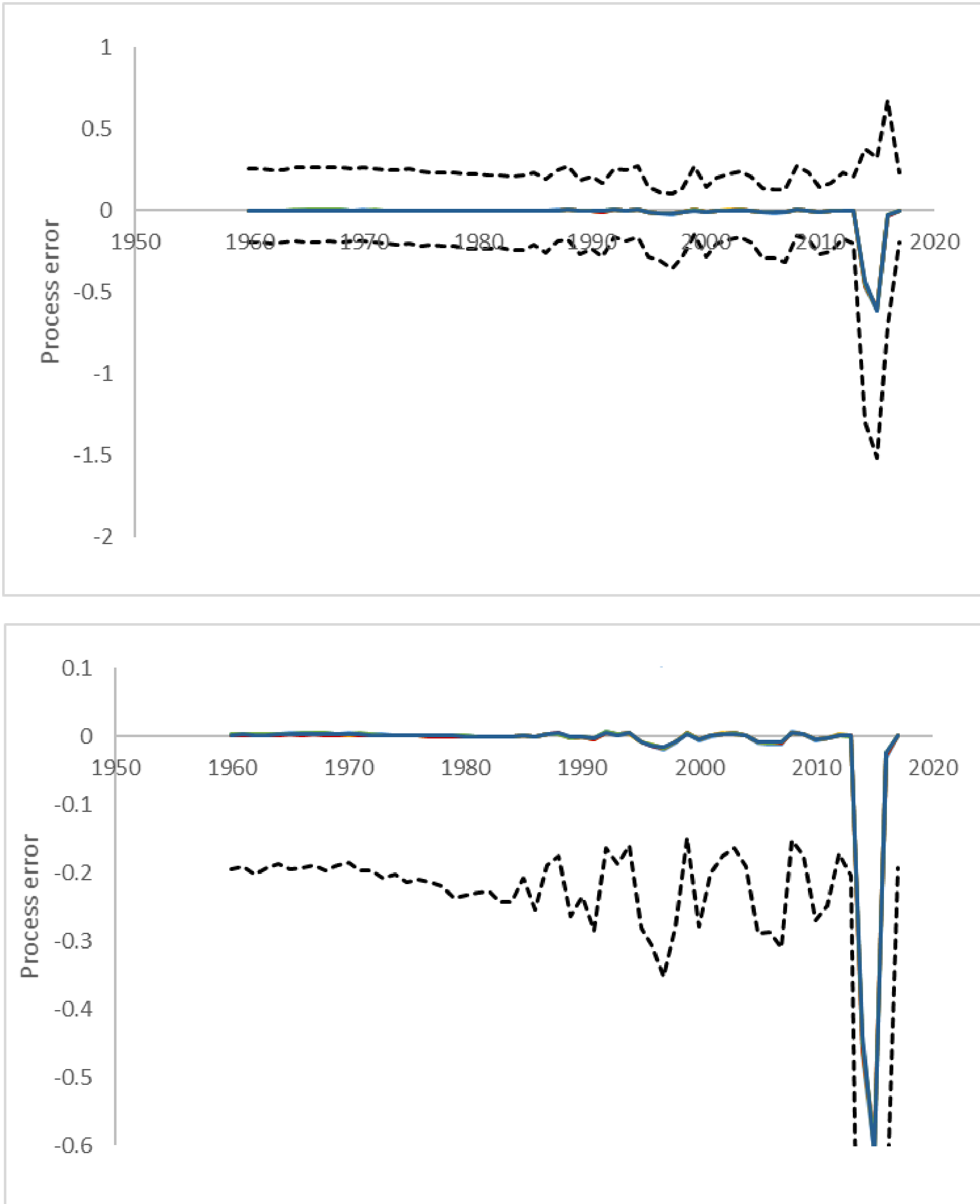


Figure 3. Process error for the various model formulations. The dashed lines are the 95% Credible Intervals from the accepted model. Top panel shows the full vertical range while the bottom panel shows the range of the median.

Appendix 1

Formulations presented at the 2014 Scientific Council meeting

Non-informative or vague priors were used for all parameters as the initial prior distributions. Priors on the catchability (q), observation error and process error were uniform and broad.

Often, K is set to the stock biomass in the year prior to the onset of fishing (P0; see Meyer and Millar, 1999a). However, in the models used here, initial stock biomass was not assumed to be the virgin biomass as fishing began on these stocks prior to 1960. P0 was allowed to vary between 0.5 and 1 (i.e. initial biomass was allowed to vary between K/2 and K). A lognormal distribution for K was specified here with a mean of 900 ('000t) and a standard deviation of 1000 ('000t).

The prior for r was based on plaice but with slightly lower mean as witch are some what longer lived and have a lower body weight. The prior was lognormal with a mean of 0.1 and a standard deviation of 2.

Data explored were as follows: (TABLE A1.1)

(1) Landings – 1960-2012

(2) Canadian RV spring Survey Indices: ATC – 1975-1984

(3) Canadian RV spring Survey Indices: Engel trawl – 1984-1995

(4) Canadian RV spring Survey Indices: early series with shallow coverage converted to Campelen– 1984-1990

(5) Canadian RV spring Survey Indices: early series adjusted for lack of deep coverage converted to Campelen– 1984-1990

(6) Canadian RV spring Survey Indices: later part of series in Campelen or equivalents– 1991-2012

(7) Canadian RV fall survey indices: Campelen Trawl or equivalent – 1990-2012

(8) EU RV Survey Indices: Pedreira trawl -1995-2000 (2001 not used)

(9) EU RV Survey Indices: Campelen trawl -2001-2012

(10) Russian/USSR Survey Indices – 1980-1993

(11) Canadian commercial CPUE – 1974-1993

In addition the Canadian Spring (1996-2012) and Fall series (1995-2012) using the Campelen trawl were also used without the converted portions of the series. Some series are not independent (e.g. Series 5 is converted from Series 4) but these were never used in the same model, that is no data was used more than once in any given model. Landings were used in all models.

Model testing began using series 2, 5, 6 (with 5 and 6 as one combined series), 7, 8, 9 and 10. Then various combinations of series were used based on model diagnostics including examination of residuals and posteriors relative to priors and the estimated parameters. For example, in this first model formulation the following were noted: Spain1 5 of 7 residuals were positive; Spain2 all residuals negative; Spain1 data have a large increase in biomass in year 4 and years 4-7 have much more biomass than years 1-3. Spain1 and Spain2 only cover a very small portion of 3O where most of the population is: conclusion, next formulation did not include Spain1 or Spain2 (although some other tests did include Spain2). More than 30 different model formulations with differing tuning series and/or priors were tested in this way.

Run 1

This was the starting point and all other model formulations built from this. Therefore this run is described in more detail. Results for parameter estimates for selected runs are given in Table 3.

Data:

ATC 1973-1982 (no 1974 or 1981)

Canadian spring adjusted 1984-2012 (no 2006) this is campelen or equivalent with the 1984-1990 adjusted to account for survey coverage in strata between 366 and 731 m in depth, which began in 1991 by multiplying by 1.2452 based on the average proportion of biomass in the deeper strata from 1991 to 1995 (as done by SC in 2013, ATC was not adjusted).

Spain1 1996-2001 (1995 much shallower so not included)

Spain2 2001-2012

Russia 1980-1993 (no 1992)

Priors:

R prior based on plaice but with slightly lower mean as witch are somewhat longer lived and have a lower body weight so might be expected to have a lower R. So used lognormal with mean 0.1 standard deviation of 2. *(-5.3,0.167)*

All q given the same prior except for ATC which was given a q with mean of 1/2 of the others as it does not cover deeper strata. *Uniform 0,2 ATC 0,1,.* In the run using the CPUE the prior for that was uniform [-1,2].

Prior for K: the two highest survey points in the spring survey were in the mid 1980s, highest survey*2 is about 60000. Used lognormal with 100000 as mean with SD of 50000 in 1000's *[4.49,4.48]*

Process error same as plaice *dunif(0,10)*

Observation error probably larger than plaice so used uniform [0,10]

Result Run 1

Spain1 5 of 7 residuals positive. Spain2 all residuals negative. The Spain1 data has a large increase in biomass in year 4 and years 4-7 have much more biomass than years 1-3. The Spanish survey only covers a very small portion of 3O where most of the population is. R estimated to be 0.8 which seems too high for witch and MSY estimated to be 24.6 000t which seems too high for this population.

Run 2

All survey indices except Spain 1 and Spain 2. All priors the same as Run 1.

MSY 11.2 r=0.37 (somewhat high compared to the 0.18 of plaice)

All ATC residuals negative, 12 of 14 Russian residuals negative

Error on Russian (1.2) and on ATC (1.4) very high.

Run 3

Canadian spring adjusted and fall only, all priors the same as Run 1.

R=0.1853 MSY=5.482

A lot of negative residuals in the spring adjusted.

(3.2) K seem to be hitting the lower bound of 100 so adjusted to I(50,3000)

(3.3) Much better so changed lower bound to 10 I(10,3000) and this better still

R does not look to be affected by the prior or bounds

Q for fall not too bad but q for spring adjusted seems to be hitting lower bound

'Process error' relatively small and without trend

(3.4) Prior for springadjusted and fall broadened [-4,2] .

This looks better in terms of the posterior for q hitting the bounds however, stock size is well above BMSY and MSY is only 1.5 ktons

(3.5) Prior spring adjusted [-4,2] and kept fall [0,2] spring posterior q looks good, fall looks close to bounds, results make more sense.

(3.6) Prior spring adjusted [-4,2] and fall [-1,2]. Q for fall shifts further left and results are sensitive to this. When q for fall goes down the Bratio goes up and MSY goes down.

Run 4

Only 1 survey index: spring adjusted with prior of [-4,2]. This results in r posterior being very similar to prior and the q is skewed towards the lower end of the prior.

Run 5

Used spring adjusted with prior [-4,2] fall [0,2] and atc [-4,2] results show no major issues

(5.2) Another run with all the same but fall prior [-1,2]. R becomes bimodal and logq fall shifts, so still affected by prior, bratio probably too high.

(5.3) Same as 5 but with different K [200,50] K is somewhat affected and r a bit different and is slightly bimodal, more iterations might fix this. Observation and process error very similar to 5.

Run 6

This formulation was the same as 5 but with the addition of a shape parameter. It is not unusual for the yield curve for groundfish to be skewed so a form of the Pella Tomlinson production model was also applied:

```
Pt<- log(max(P[t-1] + r*P[t-1]*(1-pow(P[t-1],shape)) - (L[t-1]/K), 0.0001))
```

The symbols are as described above and the shape parameter allows the production curve to be non-symmetrical. The prior on the shape parameter was uniform [1,4]

The estimated shape parameter is not significantly different from 2 but productivity is much lower and not reasonable for the stock. No further Pella Tomlinson formulations were attempted.

Run 7

All the same as run5 but no fall: results have current biomass above bmsy and f at 5 times fmsy with an MSY of only 1000 t.

Run 8

Split the spring series into an early unadjusted and a late series with different q's . Results are essentially the same as Run 5. There is a slight bimodality in r which would probably go away with more iterations.

(8.2) Same as 8 but with q on fall [-1,2]. Results are still affected (particularly bratio which seems too high currently) but effect of changing prior on fall q not as bad as in previous attempts.

Further comparison of 8 and 8.2 indicates that although DIC for 8.2 is smaller, the parameters in 8 are actually better estimated (narrower confidence limits, r doesn't move much from prior in 8.2).

Run 9

Same as Run 1 but with prior on logq fall [-1,2]. This is an attempt to see how much this affects this formulaton. Results were similar to Run 1.

Run 10

Same as Run 1 but no Russia, no spain1. Posterior for K looks truncated at lower bound

Run 10.2 - lower bound of 10 then K posterior unaffected by lower bound

Run 10.3 set lower bound to 0 and nothing shifts further.

Run 11

All surveys, spring split, K with lower bound= 0: r seems high (0.78) and bratio maybe low (0.12) spain2 all negative residuals, there is pattern in the process error with all but 1 of the residuals back to about 1995 being negative. Q on fall becomes very large, although does not seem to be as skewed.

Run 12

ATC, Russia, spring late, fall bratio and msy somewhat high, r high, most of recent process error negative.

Run 13

More runs were done exploring the prior on the fall survey q. The biggest difference in residuals seems to be in the early part of the time series. 1990-1992 didn't have very deep coverage so eliminated those years and reran with original narrower prior (**13**) and the wider prior (**13.2**). There is still a large difference in posterior q on fall. R is bimodal even after going to 3 chains and more iterations and thinning (**13.3**).

Run 14

Removed spring early and used ATC, spring late, fall (narrow prior [0,2]) and compared to ATC, spring late, fall (broad prior [-1,2]) **14.2** There is still an effect of prior on fall with the results the same as previous runs looking at this.

8 compared to 14, less patterning in process error in 8. Fratio and Bratio more poorly estimated in 14.

Run 15

All early survey data were eliminated in an attempt to see if the early data are causing the bimodal pattern in r in some formulations. This formulation used spring Campelen, fall and spain2. Prior on q for fall Campelen is the wider prior.

R was not bimodal, but the Bratio in the most recent year was very low at 0.06.

Run 16

In 15 there is a small bump in r near zero so checked if this is being caused by the constraints. Reran 13 without constraint but r is still bimodal with a smaller mode very near zero. Overall results were very similar to model with the bounds.

Run 17

Same as 15 but with addition of CPUE. Results similar to 15.

Run 18

Spring campelen, fall campelen, spain2, spring engel gave a very low bratio.

Run 19

Spring campelen, fall campelen, (with prior on fall q [-1,2]) spring engel , q's truncated.

19.1 same as 19 but with wider standard deviation on r, this improves the r posterior relative to the prior.

19.2 same as 19.1 but with narrow q on fall and in this case the results same as 19.1

19.3 broader prior on log q fall. Similar results as others.

19.4 broader priors on all q. r truncated.

19.5 same as 19.4 plus broader prior on r, same result as 19.4. Fmsy very poorly estimated.

Run 20

Only spring and fall Campelen, r very bimodal.

Run 21

Same data as 19 but with a lognormal prior on logq instead of uniform. Parameter estimates OK but logq on the two spring surveys still skewed to the lower bound of the prior, fall seems OK…prior the same for all of them.

Run 22

Went right back to run 2 and made a lower bound on K since it seemed to be hitting the bound.

Several of the surveys posterior logq were hitting the bounds of the priors. Increased the width of the prior. Had to increase it (on the negative side) a lot for Russia. At that point the bratio became very poorly estimated.

Removed Russia. Bratio still poorly estimated

Diagnostics and results of Run 19.1

Taking all of the runs into consideration it was concluded that run 19.1 was the best formulation. Detailed diagnostics and results for this run are presented here.

The priors for all of the estimated parameters were updated by the data so that the posteriors differed from the priors (Figures A1.1-A1.3).

Process error showed no major trend (Figure A1.4) and was small (0.13) compared to the observation error which was 0.63 for the Engel series, 0.44 for the fall Campelen and 0.41 for the spring Campelen.

Model fit to the observed indices was generally good with small residuals (Figure A1.5-A1.7). In the most recent years there was some patterning with the last 7 spring residuals being negative (although only 1 is outside of the 95% credible intervals) and 6 of the last 8 fall residuals being positive. This is the result of the more rapid increase in the fall survey in recent years relative to the spring survey. For both surveys the last predicted point (2012) is very close to the observed.

A variety of convergence diagnostics were examined, focusing on the main parameters of r, K and sigma.

In a converged model the MC error should be small relative to the standard deviation for each chain. This is the case for Run 19.1.

R

Chain: witchchain1

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.166	0.057	0.002	0.002	0.002	0.091	0.054	0.1591	0.291

Chain: witchchain2

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.161	0.055	0.002	0.002	0.002	-0.400	0.043	0.1596	0.275

K

Chain: witchchain1

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
109.8	30.1	1.10	1.39	1.189521	0.008	65.60	106.25	178.81

Chain: witchchain2

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
112.2	30.2	1.10	1.40	1.26	-0.07	68.50	106.85	187.73

Sigma

Chain: witchchain1

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.147	0.107	0.004	0.007	0.009	0.509	0.001	0.132	0.415

Chain: witchchain2

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.151	0.107	0.004	0.006	0.007	-0.060	0.003	0.134	0.393

Figure A1.8 shows the posterior densities for the two chains. They should be similar if the model has converged. The two chains are quite similar for each of the parameters but may indicate that further iterations and/or thinning may be warranted.

Gelman-Rubin shrink factors should be near 1 in a converged model and this was the case for Run 19.1 (Figure A1.9) with an estimate of 0.999 for r, 1.02 for K and 1.03 for sigma.

The estimates from the different chains should become very similar in a model that has converged. This is shown by the sampler running mean in Figure A1.10 and Run 19.2 meets this criteria for the three main parameters.

If a model has converged the autocorrelation should become very small as lag increases and should be small at quite short lags. The autocorrelation plots show this to be the case (Figure A1.11).

The final convergence diagnostic examined was the Geweke where the estimate should be between 2 and -2.

R

Chain: witchchain1

	x
Z-Score	0.9580814
p-value	0.3380217

Chain: witchchain2

x

Z-Score -0.3327973

p-value 0.7392873

K Chain: witchchain1

x

Z-Score 0.3439028

p-value 0.7309194

Chain: witchchain2

x

Z-Score -1.253681

p-value 0.209958

Sigma

Chain: witchchain1

x

Z-Score 0.6904305

p-value 0.4899235

Chain: witchchain2

x

Z-Score -2.694811953

p-value 0.007042837

Chain 2 for sigma was outside of this bound which could mean that more iterations are required.

Table A1.1. Data used in the Bayesian Surplus Production models. All values are research vessel survey indices in thousands of tons except CPUE which is estimated from the Canadian commercial fishery and is in tons per hour. See text for description.

Year	Landings	atc	spring engel	spring early	spring adjusted	spring late	fall	spain1	spain2	russia	cpue
1960	5.80										
1961	4.63										
1962	1.23										
1963	2.18										
1964	1.07										
1965	2.18										
1966	7.52										
1967	11.50										
1968	10.60										
1969	4.70										
1970	6.76										
1971	14.97										
1972	9.18										
1973	6.69	5.65									
1974	8.05										0.33
1975	6.17	2.83									0.28
1976	6.04	10.70									0.25
1977	5.76	3.59									0.35
1978	3.47	3.73									0.23
1979	3.08	2.59									
1980	2.42	4.88								6.03	
1981	2.43									2.35	0.32
1982	3.73	10.91								8.25	0.73
1983	3.62									1.90	0.36
1984	2.80		7.45	14.31	17.82					3.88	0.27
1985	8.77		14.19	24.58	30.61					8.89	0.52
1986	9.13		5.32	9.21	11.47					6.45	0.46
1987	7.60		6.95	11.20	13.95					5.11	0.39
1988	7.33		13.41	24.66	30.70					7.87	0.29
1989	3.69		5.55	8.99	11.19					3.27	0.37
1990	4.18		6.15	10.76	13.40		15.37			3.34	0.64
1991	4.85		3.74			7.07	5.48			12.12	0.19
1992	4.96		4.11			8.22	9.12				0.24
1993	4.41		2.00			4.23	9.47			3.43	0.16
1994	1.12		7.37			16.28	7.82				
1995	0.30		2.00			4.06	11.74	3.59			
1996	0.36					4.09	12.28	9.42			
1997	0.51					7.13	4.69	6.15			
1998	0.61					2.69	6.69	13.10			
1999	0.76					8.94	13.33	17.00			
2000	0.55					5.49	7.64	30.84			
2001	0.69					9.42	7.02	27.39	2.82		
2002	0.45					7.56	11.13		1.78		
2003	1.54					15.86	10.32		3.15		
2004	0.63					11.83	18.63		3.35		
2005	0.26					6.87	18.13		2.63		
2006	0.48						14.61		2.57		
2007	0.22					7.19	7.72		1.48		
2008	0.26					8.83	22.74		2.12		
2009	0.38					9.18	37.71		1.87		
2010	0.42					6.64	27.04		3.24		
2011	0.35					9.75	17.94		1.43		
2012	0.31					12.84	27.03		2.76		

Table A1.2. Priors for parameters used in initial surplus production model for Div. 3NO witch flounder

Parameter	Description	Prior Distribution
K	Carrying Capacity	lognormal(u=100kt,std=50kt)
r	Intrinsic rate of increase	lognormal (u=0.1, sdt=3)
logq.eng	Catchability, Engels	U(-1,2)
logq.cams	Catchability spring Campelen	U(0,2)
logq.camf	Catchability fall Campelen	U(-1,2)
sigma	Process error	U(0,10)
tau.eng	Observation error Engel	U(0,10)
tau.cams	Observation error Campelen spring	U(0,10)
tau.camf	Observation error Campelen fall	U(0,10)

Table A1.3. Results of selected formulations of surplus production models for Div. 3NO witch flounder. See text for more detailed description.

RUN	1 (all data)	5 (atc, springadj, fall)	5.2 (prior q fall [-1,2])	5.3 (prior K x=200,sd=50)	8 (atc, spring early and late, fall)	8.2 (prior q fall [-1,2])
R	0.35 0.80 1.31	0.06 0.14 0.26	8.3E-4 0.09 0.19	0.03 0.11 0.19	0.05 0.14 0.28	0.003 0.10 0.26
K	100.7 119.6 215.1	68.83 116.3 186.7	73.6 135.7 236.3	109.1 153.0 254.0	64.94 113.0 179.6	66.8 133.3 218.4
MSY	10.45 24.64 50.99	1.835 4.009 6.59	0.03 3.03 5.26	1.41 4.22 8.21	1.43 3.95 6.69	0.08 3.47 5.86
Bratio	0.03 0.07 0.22	0.20 0.39 0.72	0.29 0.59 1.39	0.14 0.28 0.48	0.20 0.39 0.77	0.35 0.71 1.68
Process error	0.34 0.57 0.87	0.003 0.09 0.32	0.005 0.10 0.31	0.003 0.09 0.31	0.004 0.096 0.36	0.003 0.08 0.30
Obs err springadj	0.31 0.46 0.67	0.35 0.46 0.64	0.34 0.45 0.63	0.35 0.46 0.63	NA	NA
Obs err fall	0.37 0.59 0.90	0.33 0.47 0.69	0.30 0.43 0.63	0.34 0.49 0.72	0.33 0.47 0.69	0.30 0.42 0.61
Obs err ATC	0.36 0.83 2.28	0.36 0.62 1.32	0.36 0.62 1.3	0.37 0.63 1.35	0.36 0.62 1.3	0.37 0.62 1.31
Obs err Spain1	0.34 0.72 1.68	NA	NA	NA	NA	NA
Obserr Spain2	0.05 0.48 1.71	NA	NA	NA	NA	NA
Obserr Russia	0.36 0.63 1.35	NA	NA	NA	NA	NA
Obserr spring early	NA	NA	NA	NA	0.29 0.52 1.20	0.28 0.49 1.13
Obserr spring late	NA	NA	NA	NA	0.34 0.48 0.71	0.33 0.46 0.68
Obserr spring engels	NA	NA	NA	NA	NA	NA
Obserr spring campelen	NA	NA	NA	NA	NA	NA
Obserr fall camp	NA	NA	NA	NA	NA	NA

RUN	9 as 1 but prior q fall [-1,2] lower bound K 100	10 no Russia or spain1 lower bound K 100	10.2 as 10 but lower bound K 10	15 spring late and fall camp, spain2 prior fall q [-1,2]	19.1 Spring fall camp, spring engel prior fall q [-1,2],	19.2 Spring fall camp, spring engel prior fall q [0,2]

					prior r dlnorm(-5.70,0.147)	
R	0.35 0.80 1.3	0.13 0.25 0.58	0.15 0.31 0.69	0.06 0.28 0.50	0.05 0.16 0.29	0.03 0.16 0.29
K	100.8 120.5 220.8	100.6 116.8 195.7	44.1 81.15 161.3	52.06 92.1 207.8	66.41 106.7 185.3	64.2 105.6 180.3
MSY	10.45 25.0 52.03	3.96 7.59 19.31	3.42 6.11 14.52	1.61 6.23 14.51	1.45 4.30 7.89	0.86 4.31 7.60
Bratio	0.03 0.07 0.22	0.08 0.20 0.37	0.11 0.30 0.67	0.03 0.06 0.14	0.10 0.22 0.41	0.10 0.22 0.43
Process error	0.33 0.58 0.87	0.06 0.27 0.57	0.07 0.29 0.56	0.15 0.36 0.64	0.002 0.13 0.40	0.01 0.14 0.41
Obs err springadj	0.31 0.46 0.68	0.33 0.47 0.68	0.32 0.47 0.67	NA	NA	NA
Obs err fall	0.39 0.59 0.91	0.32 0.50 0.75	0.31 0.48 0.74	NA	NA	NA
Obs err ATC	0.36 0.84 2.29	0.81 1.97 4.49	0.71 1.80 4.11	NA	NA	NA
Obs err Spain1	0.34 0.72 1.7	NA	NA	NA	NA	NA
Obserr Spain2	0.04 0.47 1.7	0.78 1.53 2.8	0.73 1.52 2.80	0.13 0.31 0.68	NA	NA
Obserr Russia	0.35 0.63 1.33	NA	NA	NA	NA	NA
Obserr spring early	NA	NA	NA	NA	NA	NA
Obserr spring late	NA	NA	NA	0.20 0.33 0.55	NA	NA
Obserr spring engels	NA	NA	NA	NA	0.40 0.63 1.13	0.40 0.63 1.12
Obserr spring Campelen	NA	NA	NA	NA	0.26 0.41 0.68	0.25 0.40 0.66
Obserr fall camp	NA	NA	NA	0.33 0.50 0.77	0.28 0.44 0.70	0.28 0.43 0.68

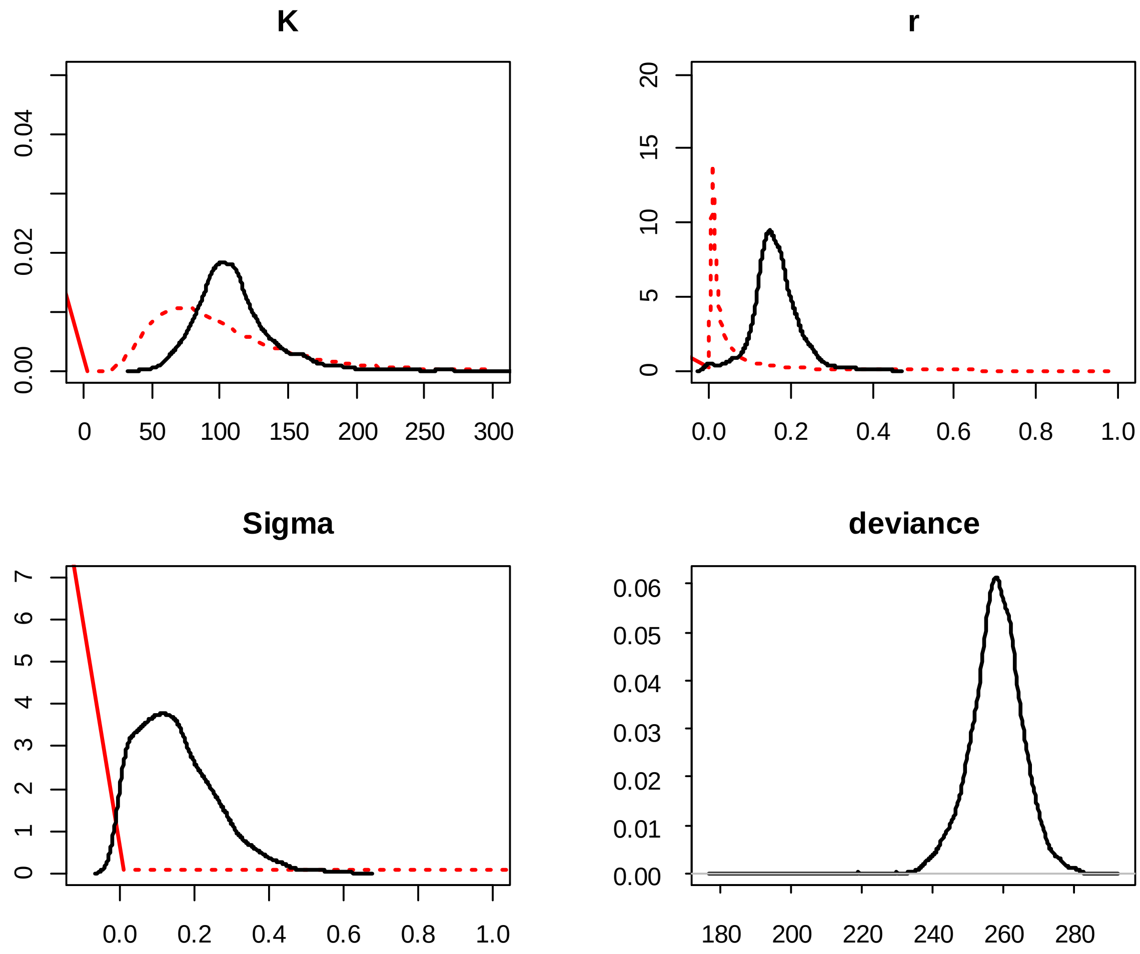


Figure A1.1. Priors (dotted lines) and posteriors (solid lines) for K, r and sigma (process error) as well as the posterior distribution of the deviance from a surplus production model for Div. 3NO witch flounder.

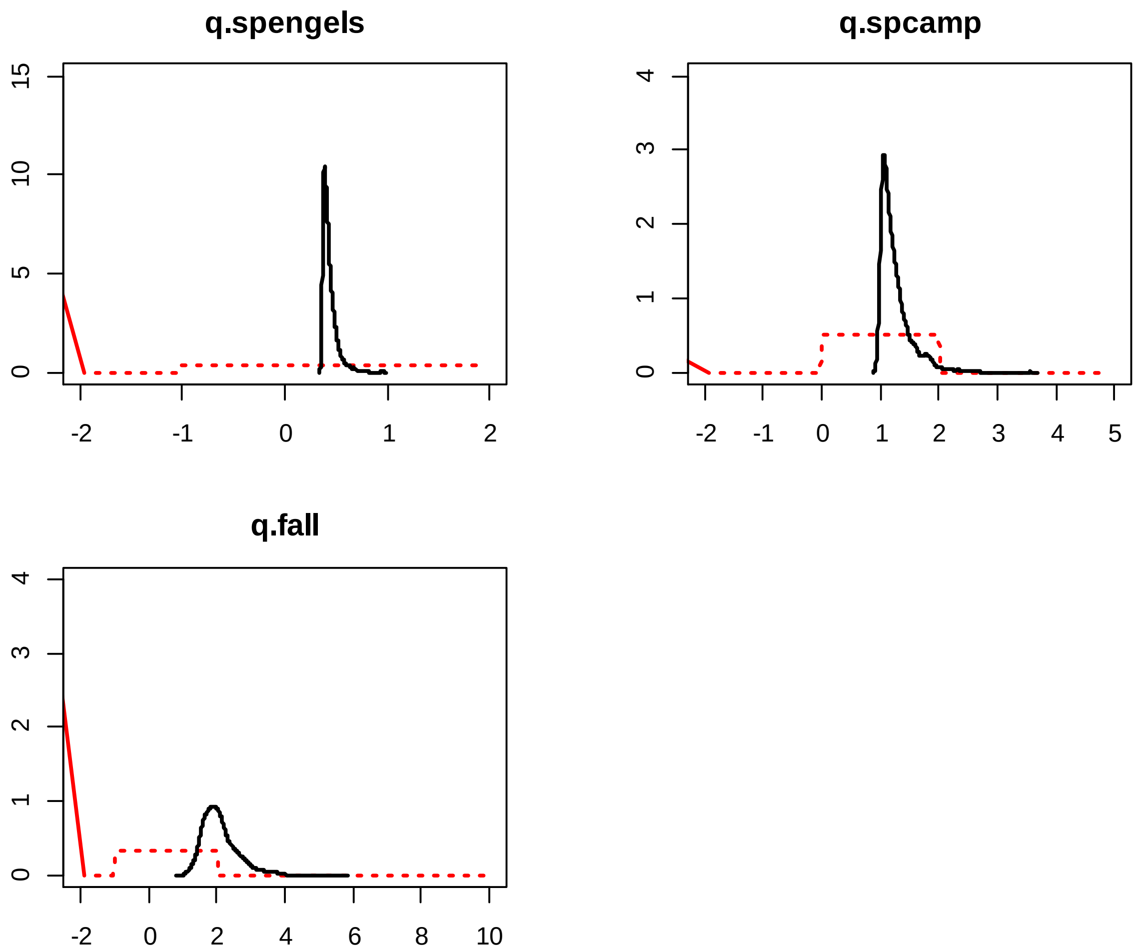


Figure A1.2. Priors (dotted lines) and posteriors (solid lines) for the catchabilities for the surveys used in the surplus production model for Div. 3NO witch flounder. Spengels is the Engel series, spcam is the spring Campelen series and fall is the fall Campelen series.

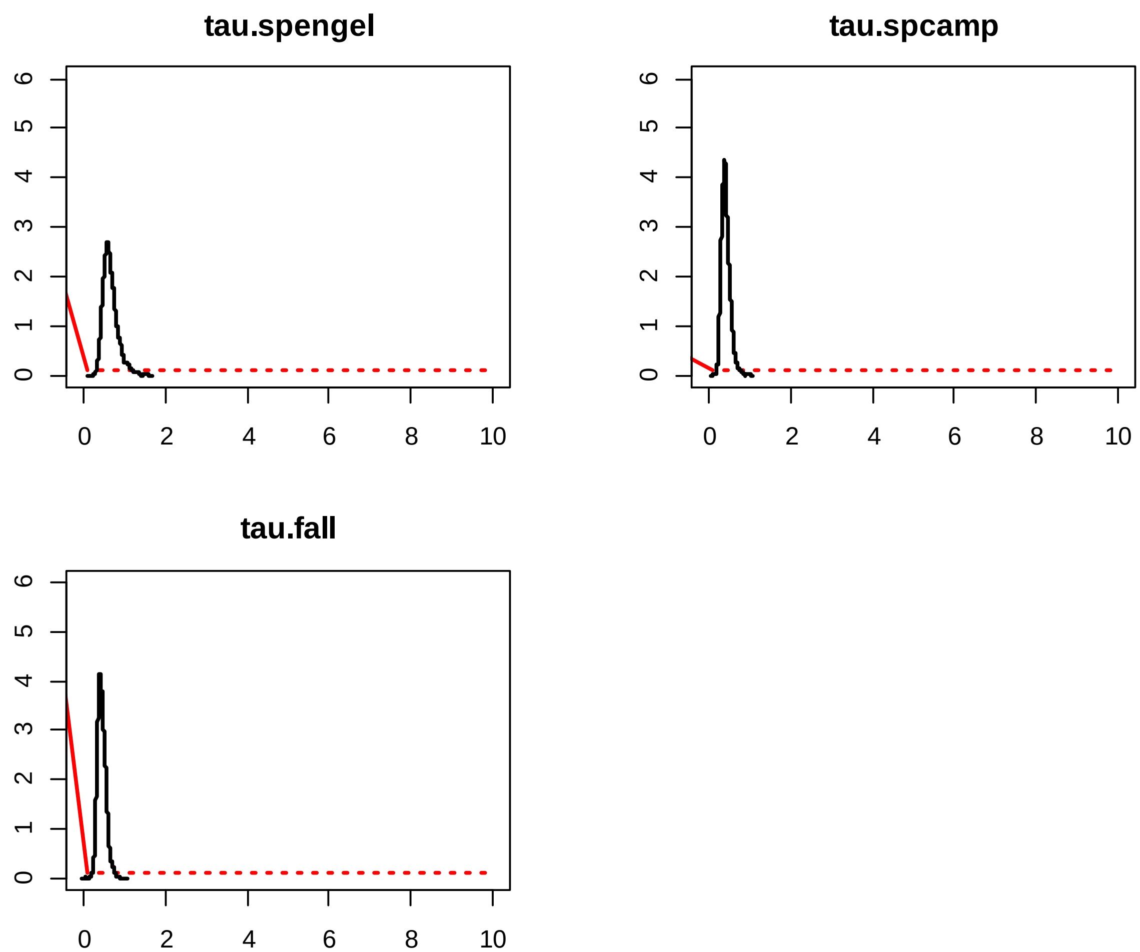


Figure A1.3. Priors (dotted lines) and posteriors (solid lines) for the observation error for the surveys used in the surplus production model for Div. 3NO witch flounder. Spengels is the Engel series, spcam is the spring Campelen series and fall is the fall Campelen series.

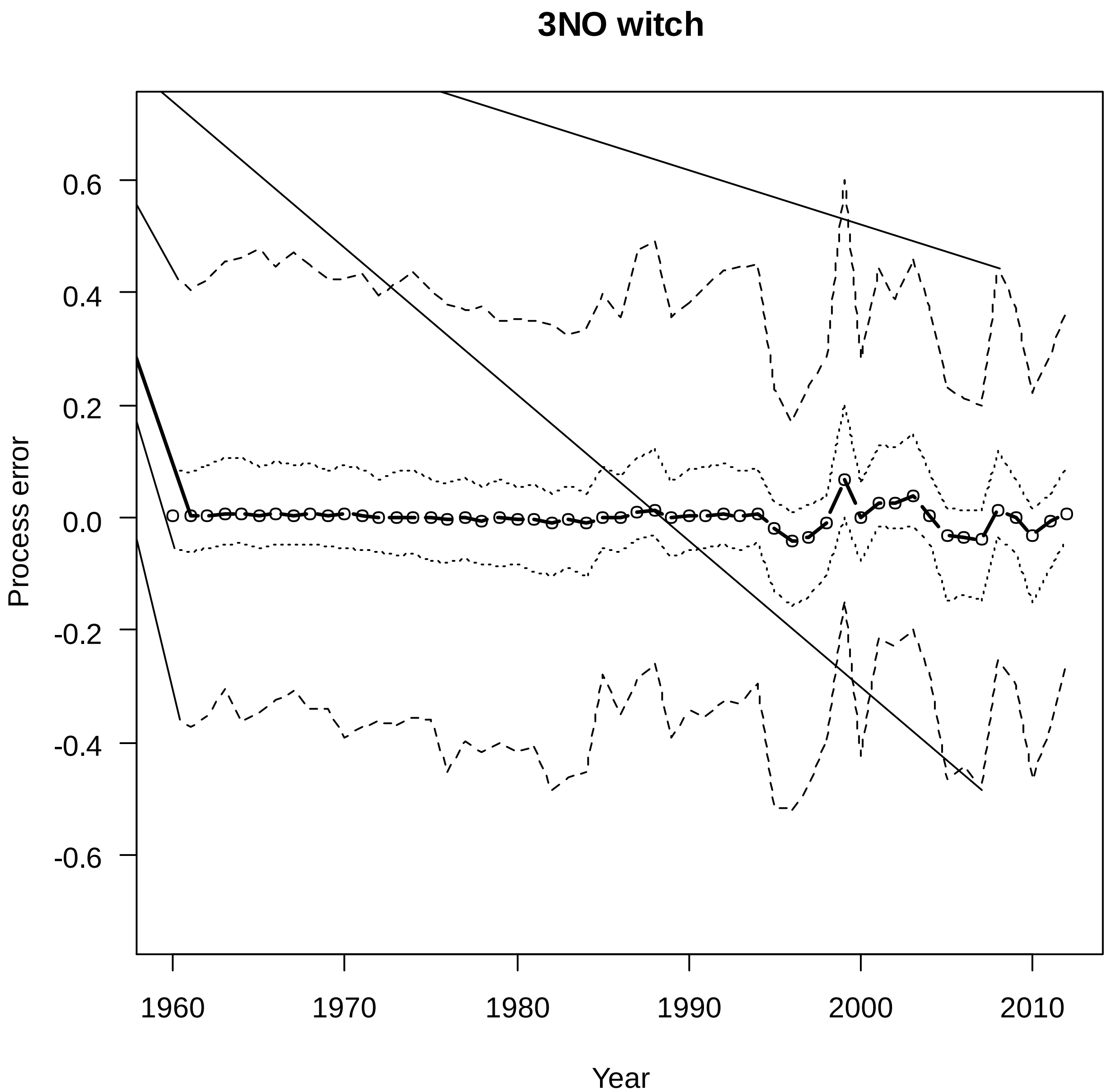


Figure A1.4. Process error from the surplus production model for Div. 3NO witch flounder. The median (heavy line with circles), 50% (dotted line) and 95% (dashed line) credible intervals are shown.

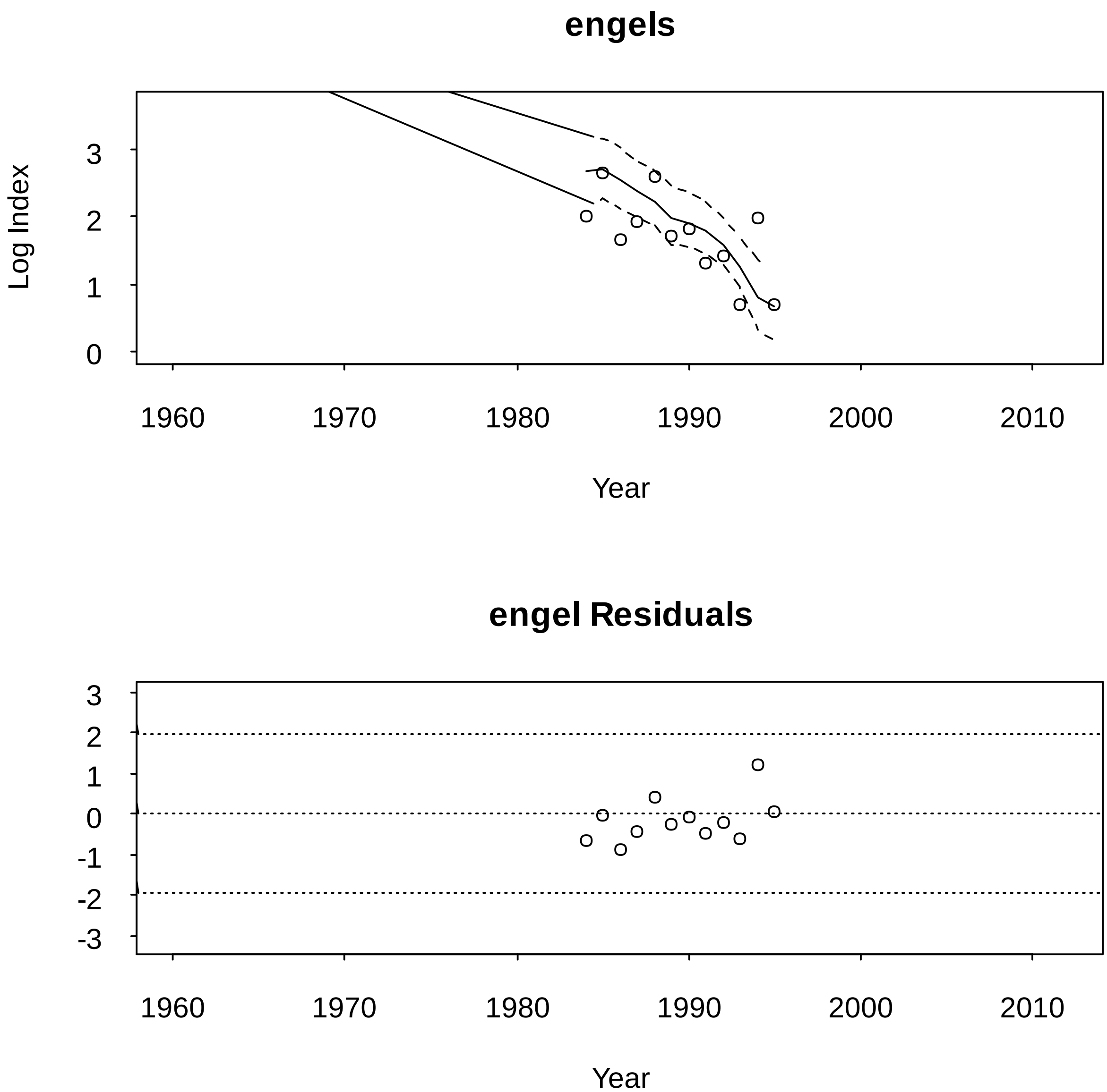


Figure A1.5. Observed (dots) and predicted (line, median with 95% credible intervals) log survey index for the Engel series (top) from the surplus production model for Div. 3NO witch flounder. The standardized residuals are shown in the bottom panel.

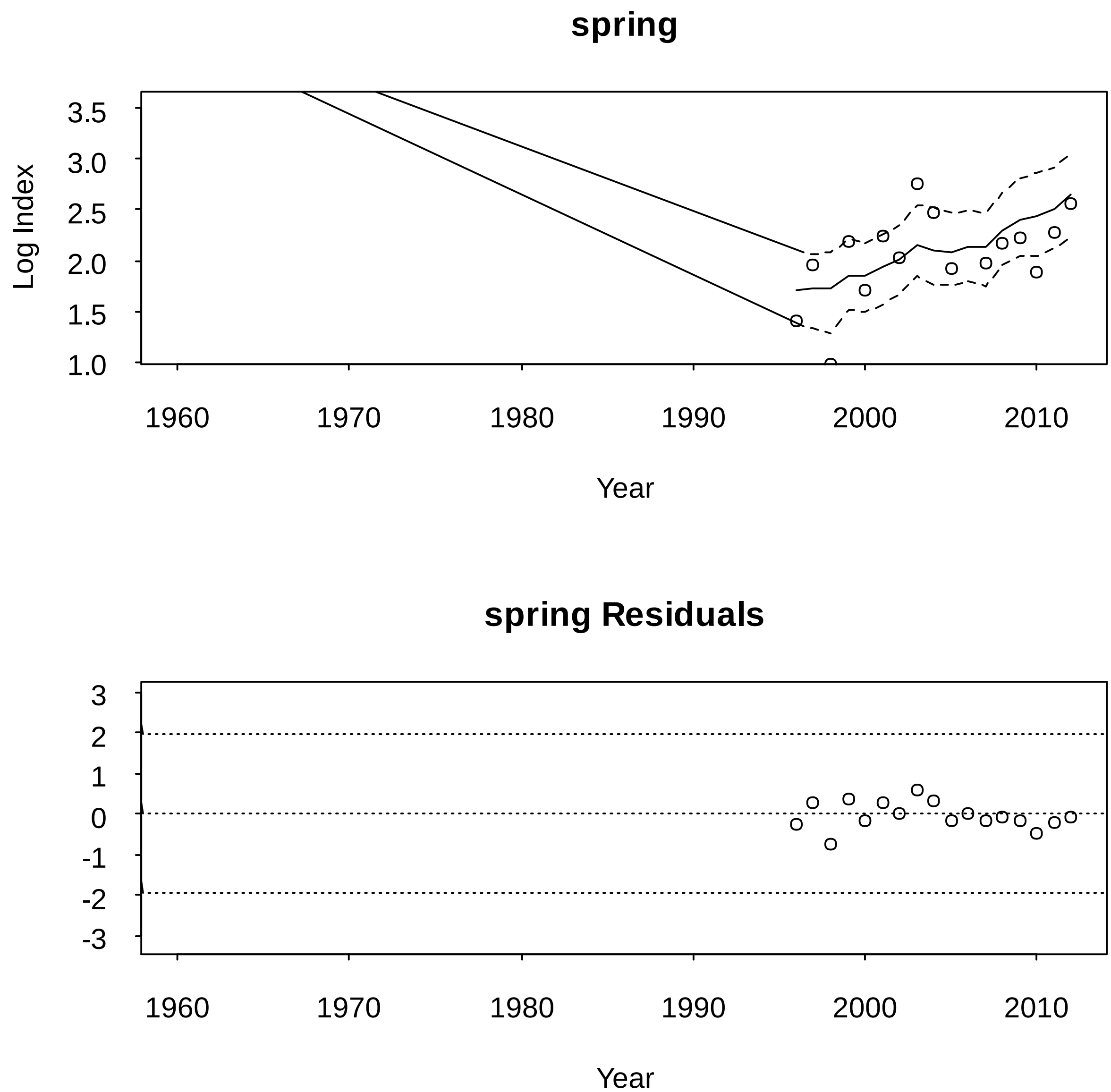


Figure A1.6. Observed (dots) and predicted (line, median with 95% credible intervals) log survey index for the spring Campelen series (top) from the surplus production model for Div. 3NO witch flounder. The standardized residuals are shown in the bottom panel.

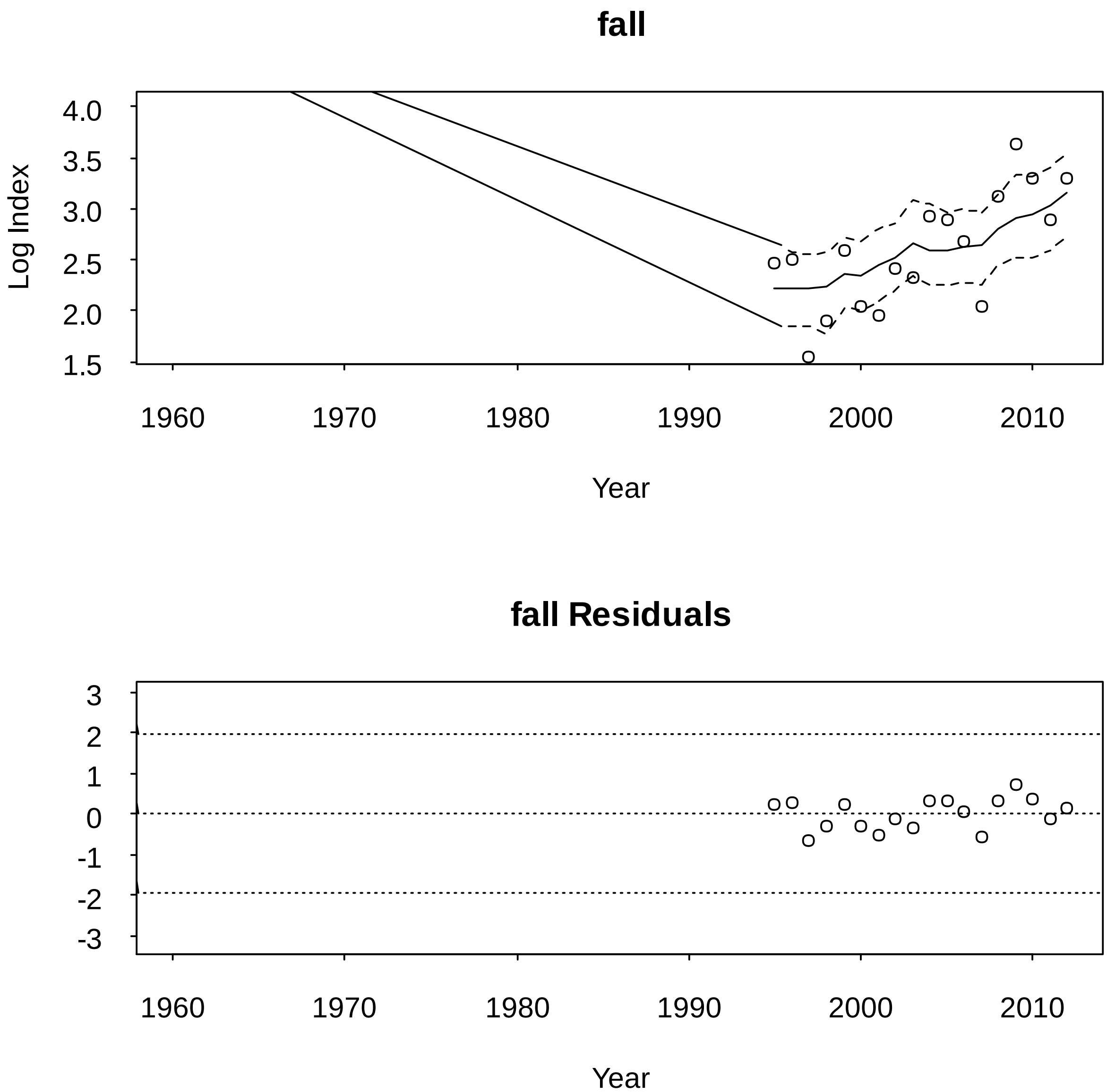
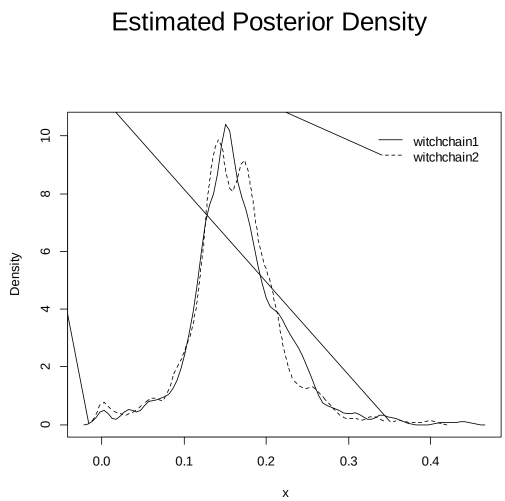
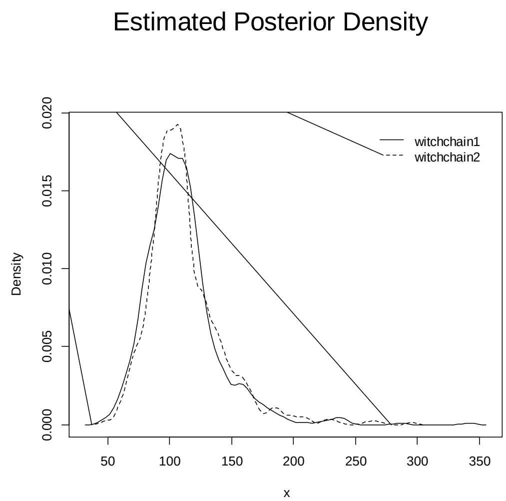


Figure A1.7. Observed (dots) and predicted (line, median with 95% credible intervals) log survey index for the fall Campelen series (top) from the surplus production model for Div. 3NO witch flounder. The standardized residuals are shown in the bottom panel.

R



K



Sigma

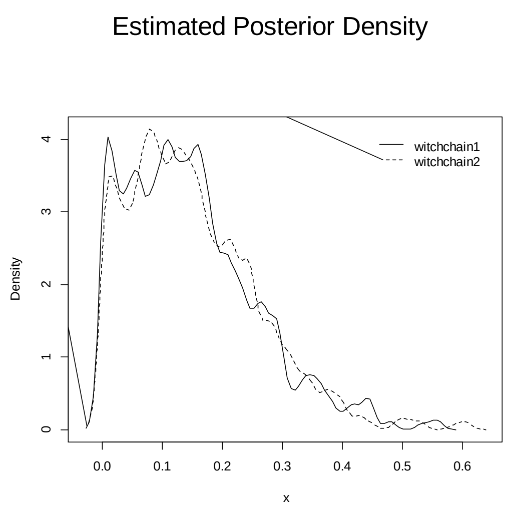
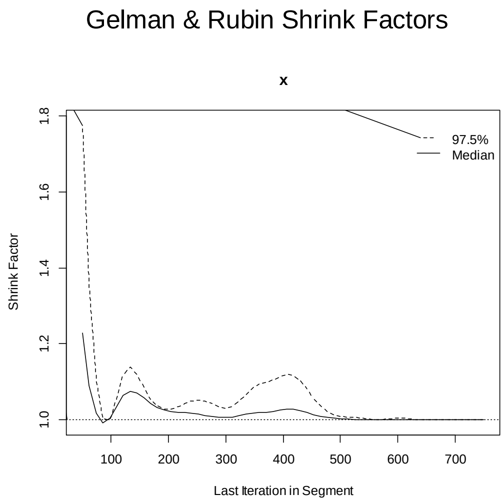
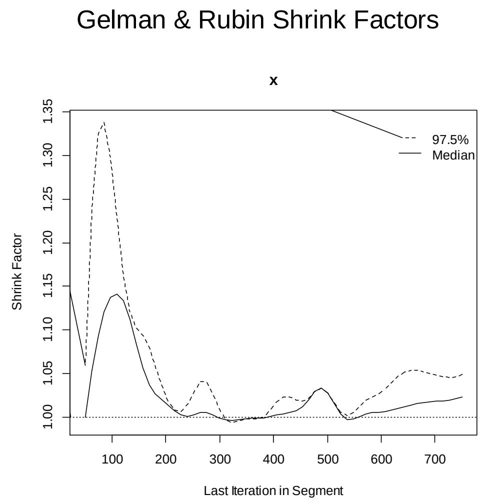


Figure A1.8. Posterior densities for the 2 chains for r, K and sigma from the surplus production model for Div. 3NO witch flounder.

R



K



Sigma

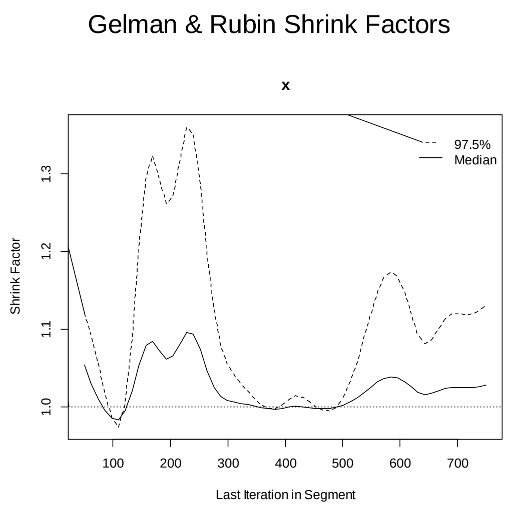
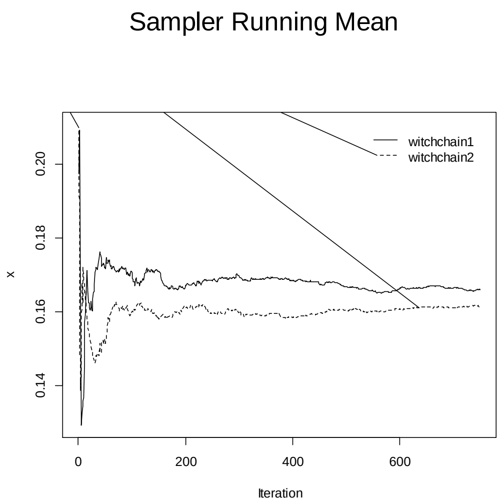
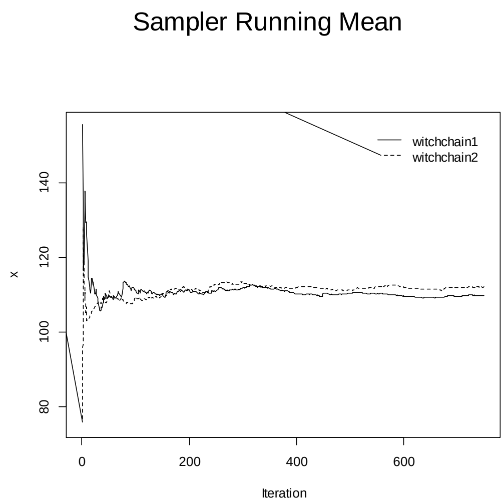


Figure A1.9. Gelman-Rubin shrink factors for r, K and sigma from the surplus production model for Div. 3NO witch flounder. Note that the y-axis scale is different for each plot.

R



K



Sigma

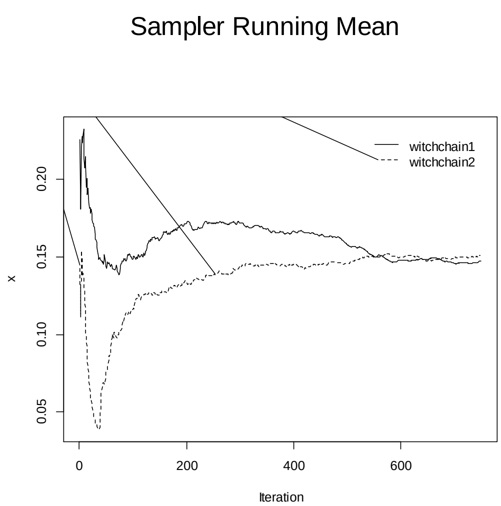
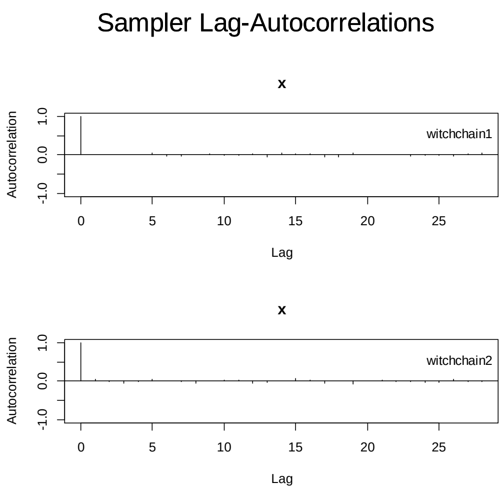
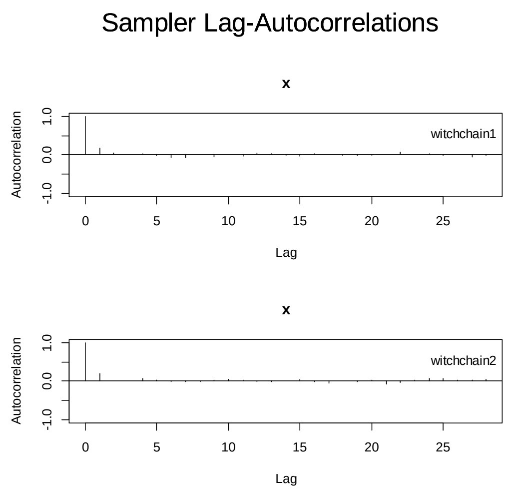


Figure A1.10. Sampler running mean for r, K and sigma from the surplus production model for Div. 3NO witch flounder. Note that the y-axis scale is different for each plot.

R



K



Sigma

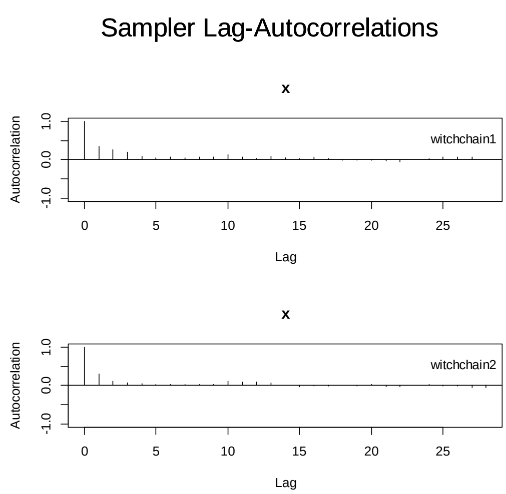


Figure A1.11. Sampler lag-autocorrelations for each chain for r, K and sigma from the surplus production model for Div. 3NO witch flounder.

After exploring the use of uniform prior on log q, use of a gamma prior was explored. This was modeled on the formulation of priors on q used by Meyer and Millar (1999a). The choice of data was based on the results of the previous modelling and on examination of the tuning indices. The data used were the Canadian spring survey (Campelen or equivalent) as two series each with its own prior: the 1984-1990 period when deep water coverage was minimal; 1991-2012; Canadian fall Campelen or equivalent (1990-2012).

Initial priors were:

Run G1

```
# Prior for intrinsic rate of increase, r, x=0.1, sd=2

r ~ dlnorm(-5.3,0.167)I(0,1)

# Prior distribution of K, x=100, sd=50

K~dlnorm(4.49,4.48)I(0,3000)

# Prior distribution of q's

pq.splate~dgamma(5,5)

q.splate<-1/pq.splate

pq.fallcam ~ dgamma(5,5)

q.fallcam<-1/pq.fallcam

pq.spearly~dgamma(5,5)

q.spearly<-1/pq.spearly

# Prior for process noise, sigma

sigma ~ dgamma(0.1,0.1)

isigma2 <- 1/sigma

# Prior for observation errors, tau.

a0<-1

b0<-1

tau.splate~dgamma(a0,b0)

itau2.splate <- 1/tau.splate

tau.fallcam~dgamma(a0,b0)

itau2.fallcam <- 1/tau.fallcam

tau.spearly~dgamma(a0,b0)

itau2.spearly <- 1/tau.spearly

# Prior for initial population size as proportion of K, P[1].
```

Pin~dunif(0.5, 1)

Results – all posteriors updated from priors, no evidence of truncation, parameter estimates reasonable, process error very small.

Priors run G2

As G1 but more informative prior for sigma, with same mean smaller variance

Prior for process noise, sigma

sigma ~ dgamma(5,5)

isigma2 <- 1/sigma

In this formulation sigma is higher but looks to be truncated at the lower end by the prior, parameters not as well estimated

Priors run G3

As G1 but less informative prior for sigma, with same mean larger variance

Prior for process noise, sigma

sigma ~ dgamma(0.01,0.01)

isigma2 <- 1/sigma

In this formulation sigma is very low, the posterior does not update much from the prior. K appears bimodal (although iterations are limited) and r is truncated on the left

Priors run G4

As G1 but with uniform prior on sigma

Prior for process noise, sigma

sigma ~ dunif(0,10)

isigma2 <- pow(sigma, -2)

Level of sigma seems more reasonable. Other parameters not much changed from G1

Priors run G5

Same as G4 but with wider bound on r

Prior for intrinsic rate of increase, r, x=0.1, sd=2

r ~ dlnorm(-5.3,0.167)I(0,2)

Results the same as G4, not affected by changing the bound on r

Priors run G6

Same as G5 but with wider prior on the q

pq.splate~dgamma(3,3)

q.splate<-1/pq.splate

pq.fallcam ~ dgamma(3,3)

q.fallcam<-1/pq.fallcam

pq.spearly~dgamma(3,3)

q.spearly<-1/pq.spearly

Results very similar to G5, little effect of broadening the prior on q

Further broadening of the prior on the q made the estimates of parameters less precise. There is some tendency for Bratio to increase and MSY to decrease, both becoming less precise as the prior on q is broadened. However, the formulations with the gamma distributions on the prior for q and uniform on the sigma were overall only little affected by changing the priors and provided a much better fit to the data, compared to formulations with a uniform prior on log q. Comparisons of some of the key parameters for some of the models is given in Table A1.4.

Model formulation G4 seemed to give the best overall model fit. This model was run with 3 chains, 400 000 iterations with a burn in of 100 000 and thinning at 100. Diagnostics for this model are given here.

The priors for all of the estimated parameters were updated by the data so that the posteriors differed from the priors (Figures A1.12-A1.14).

Process error showed no major trend (Figure A1.15) and was small (0.11) compared to the observation error which was 0.30 for spring early, 0.19 for the fall Campelen and 0.23 for the spring late.

Model fit to the observed indices was generally good with small residuals (Figure A1.16-A1.18). In the most recent years there was some patterning with the last 7 spring residuals being negative (although only 1 is outside of the 95% credible intervals) and 6 of the last 8 fall residuals being positive. This is the result of the more rapid increase in the fall survey in recent years relative to the spring survey. For both surveys the last predicted point (2012) is very close to the observed.

A variety of convergence diagnostics were examined, focusing on the main parameters of r, K and sigma.

In a converged model the MC error should be small relative to the standard deviation for each chain.

K

SUMMARY STATISTICS:

Chain: witchchain1

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
119.268	30.88214	0.5638282	1.034934	0.9785482	0.01359065	66.6885	117.05	188.3025

Chain: witchchain2

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
119.5662	33.0283	0.6030116	1.196573	1.16781	-0.1414972	66.7495	117	194.00

Chain: witchchain3

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
117.7041	27.77909	0.5071745	0.7989894	0.8195153	-0.1770256	67.31725	116.5	179.22

R

SUMMARY STATISTICS:

Chain: witchchain1

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.1407	0.05678995	0.00104	0.001232217	0.001227846	0.007662588	0.03584475	0.1329	0.2846125

Chain: witchchain2

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.1411668	0.05785806	0.00106	0.001530868	0.001522394	-0.02637694	0.03902775	0.1341	0.27942

Chain: witchchain3

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.1409522	0.05626954	0.00103	0.001355215	0.001182735	-0.02140767	0.0400365	0.1328	0.2834175

Sigma

SUMMARY STATISTICS:

Chain: witchchain1

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.119435	0.095187	0.001737869	0.00327433	0.003387378	-0.1723633	0.0064852	0.09297	0.356755

Chain: witchchain2

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.1211544	0.09579	0.001748825	0.004478862	0.003467599	0.02244198	0.00385395	0.09915	0.357425

Chain: witchchain3

Mean	SD	Naive SE	MC Error	Batch SE	Batch ACF	0.025	0.5	0.975
0.1153233	0.09417	0.001719219	0.005079046	0.00475	-0.1376366	0.003928725	0.09281	0.3448475

Figure A1.19 shows the posterior densities for the two chains. They should be similar if the model has converged. The two chains are quite similar for each of the parameters but may indicate that further iterations and/or thinning may be warranted.

Gelman-Rubin shrink factors should be near 1 in a converged model and this was the case for Run G4 (Figure A1.20) with an estimate of 1.002 for r, 1.003 for K and 1.002 for sigma.

The estimates from the different chains should become very similar in a model that has converged. This is shown by the sampler running mean in Figure A1.21 and Run G4 meets this criteria for the three main parameters.

If a model has converged the autocorrelation should become very small as lag increases and should be small at quite short lags. The autocorrelation plots show this to be the case (FigureA1.22).

The final convergence diagnostic examined was the Geweke where the estimate should be between 2 and -2.

K

Chain: witchchain1

Z-Score 0.5231363

p-value 0.6008794

Chain: witchchain2

Z-Score -0.1411347

p-value 0.8877636

Chain: witchchain3

Z-Score -0.9740130

p-value 0.3300501

R

Chain: witchchain1

Z-Score -0.7015073

p-value 0.4829865

Chain: witchchain2

Z-Score 0.1753936

p-value 0.8607704

Chain: witchchain3

Z-Score 1.3750174

p-value 0.1691261

Sigma

Chain: witchchain1

Z-Score 0.1606662

Chain: witchchain2

Z-Score 0.3544216

p-value 0.7230229

Chain: witchchain3

Z-Score 1.1716999

p-value 0.2413175

Table A1.4. Results of selected formulations of surplus production models for Div. 3NO witch flounder. See text for more detailed description.

RUN	1 uniform priors	G1 gamma priors	G2 more informative sigma	G4 uniform on sigma	G5 wider bound on r	G6 wider prior q
R	0.35 0.80 1.31	0.08 0.12 0.18	5 e-4 0.19 0.54	0.04 0.13 0.28	0.04 0.13 0.28	0.03 0.12 0.25
K	100.7 119.6 215.1	94.16 122.1 166.5	47.2 99.5 225.8	66.4 115 187.5	66.5 115.8 186.1	70.0 122.4 194.1
MSY	10.45 24.64 50.99	2.86 3.89 5.26	0.01 4.61 13.25	1.16 3.89 6.87	1.21 3.89 6.85	0.90 3.83 6.39
Bratio	0.03 0.07 0.22	0.26 0.43 0.81	0.18 0.51 1.43	0.21 0.50 0.90	0.24 0.50 1.01	0.24 0.51 1.09
Process error	0.34 0.57 0.87	7 e-11 1e-4 0.04	0.07 0.20 0.47	0.01 0.11 0.35	0.01 0.10 0.35	0.003 0.09 0.33
Obs err springadj	0.31 0.46 0.67					
Obs err fall	0.37 0.59 0.90	0.11 0.21 0.43	0.04 0.15 0.39	0.09 0.19 0.43	0.09 0.19 0.41	0.1 0.19 0.40
Obs err ATC	0.36 0.83 2.28					
Obs err Spain1	0.34 0.72 1.68					
Obserr Spain2	0.05 0.48 1.71					
Obserr Russia	0.36 0.63 1.35					
Obserr spring early	NA	0.10 0.30 1.30	0.04 0.26 1.26	0.09 0.30 1.31	0.09 0.30 1.28	0.09 0.28 1.19
Obserr spring late	NA	0.13 0.24 0.51	0.09 0.23 0.56	0.12 0.23 0.51	0.12 0.23 0.51	0.12 0.23 0.50
Obserr spring engels	NA					
Obserr spring campelen	NA					
Obserr fall camp	NA					

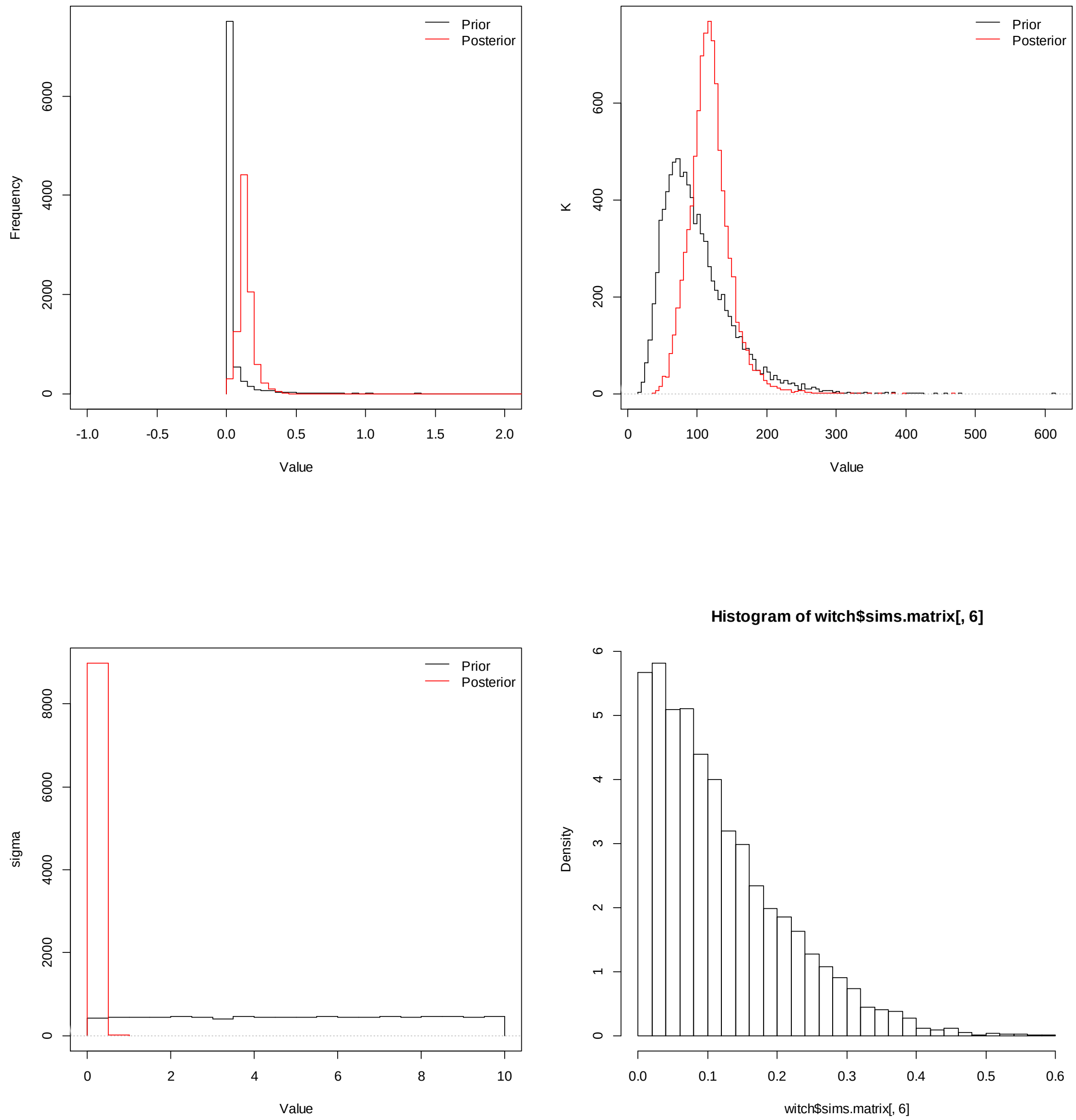


Figure A1.12. Histograms of priors (black lines) and posteriors (red lines) for r, K and sigma (process error) from a surplus production model for Div. 3NO witch flounder. In addition a histogram with smaller bin size is shown for sigma to explore possible truncation.

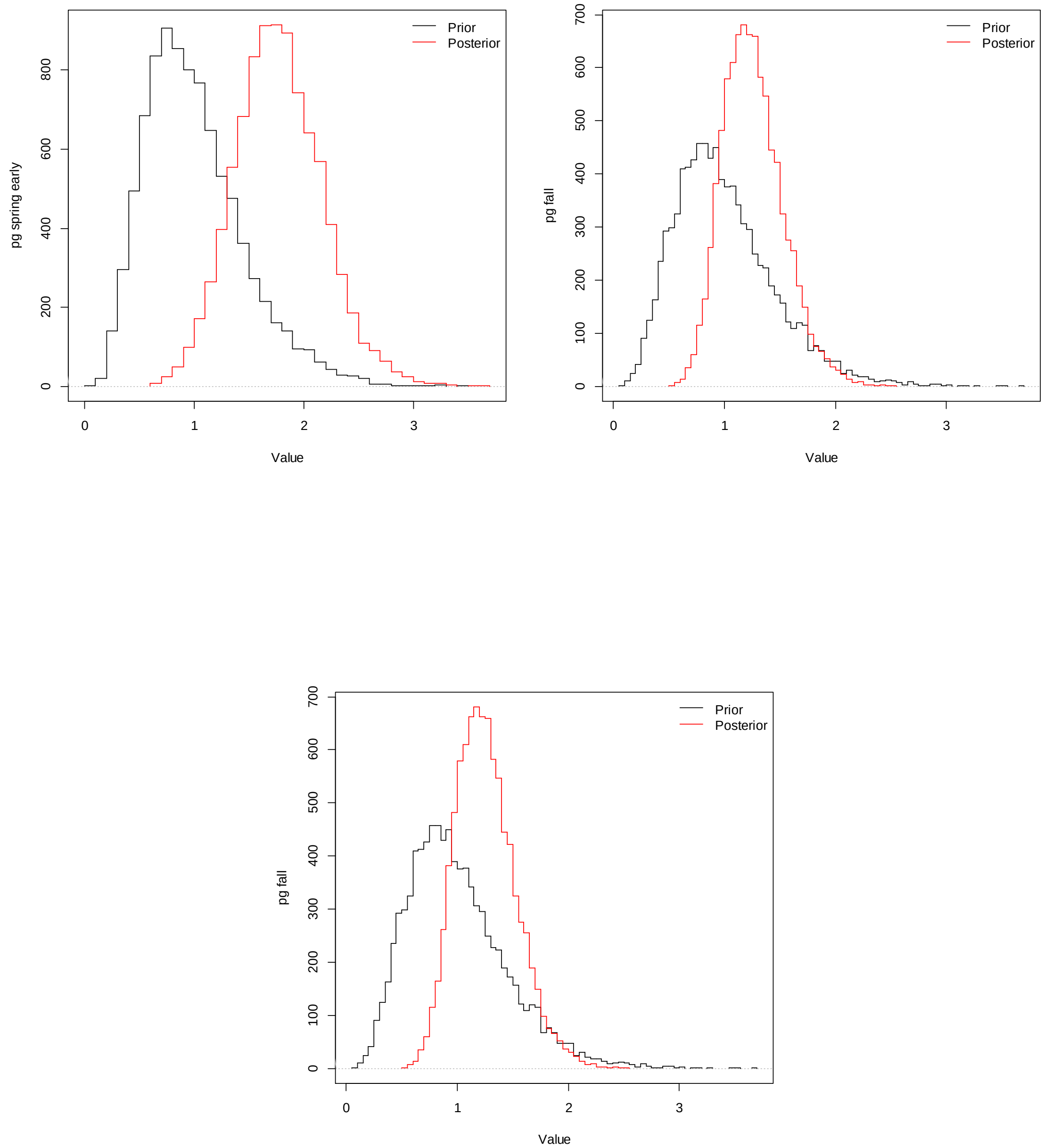


Figure A1.13. Histograms of priors and posteriors for the catchabilities for the surveys used in the surplus production model for Div. 3NO witch flounder. The series are spring early, fall and spring late.

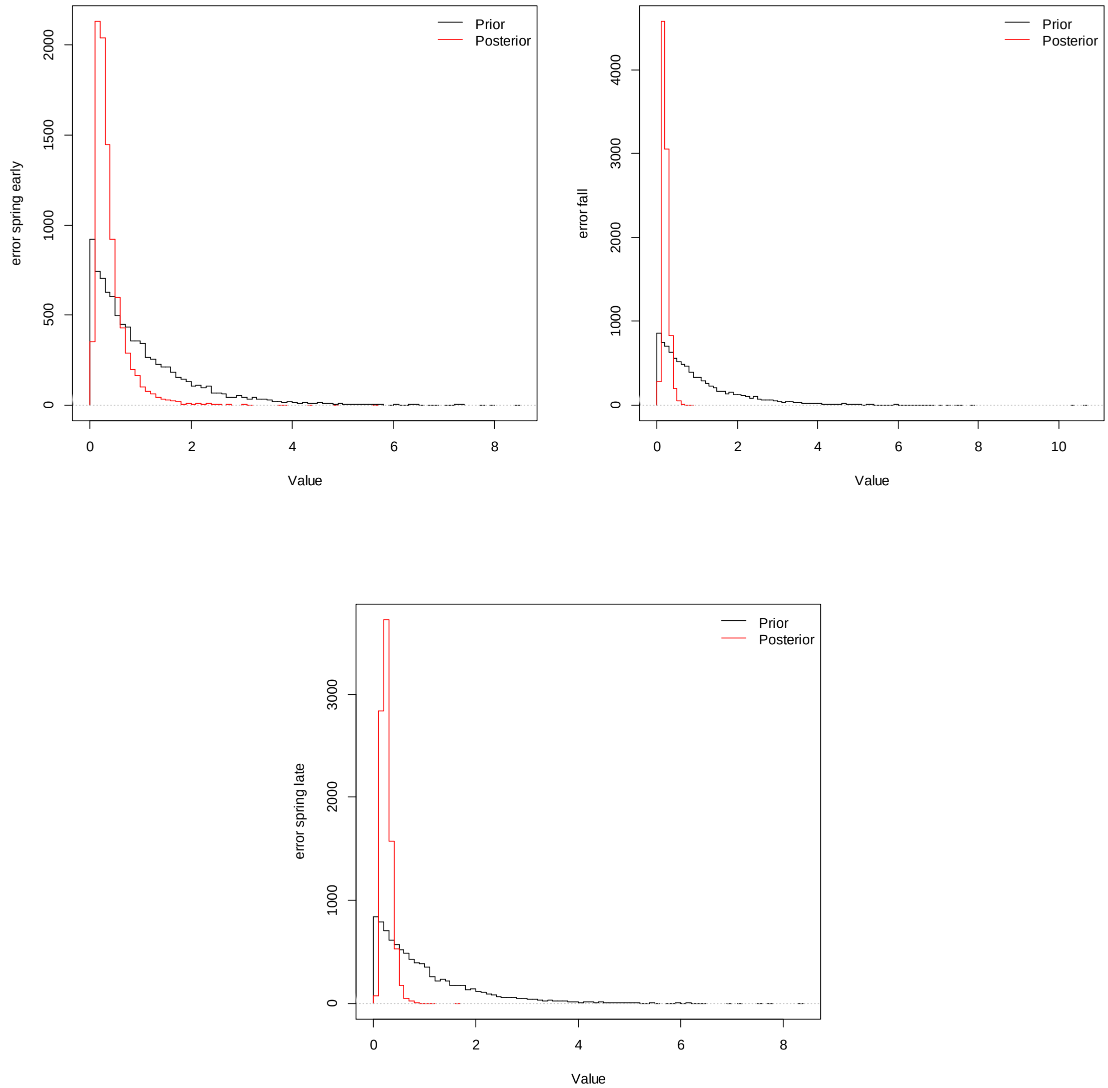


Figure A1.14. Histograms of priors and posteriors for the observation error for the surveys used in thesurplus production model for Div. 3NO witch flounder. The series are spring early, fall and spring late.

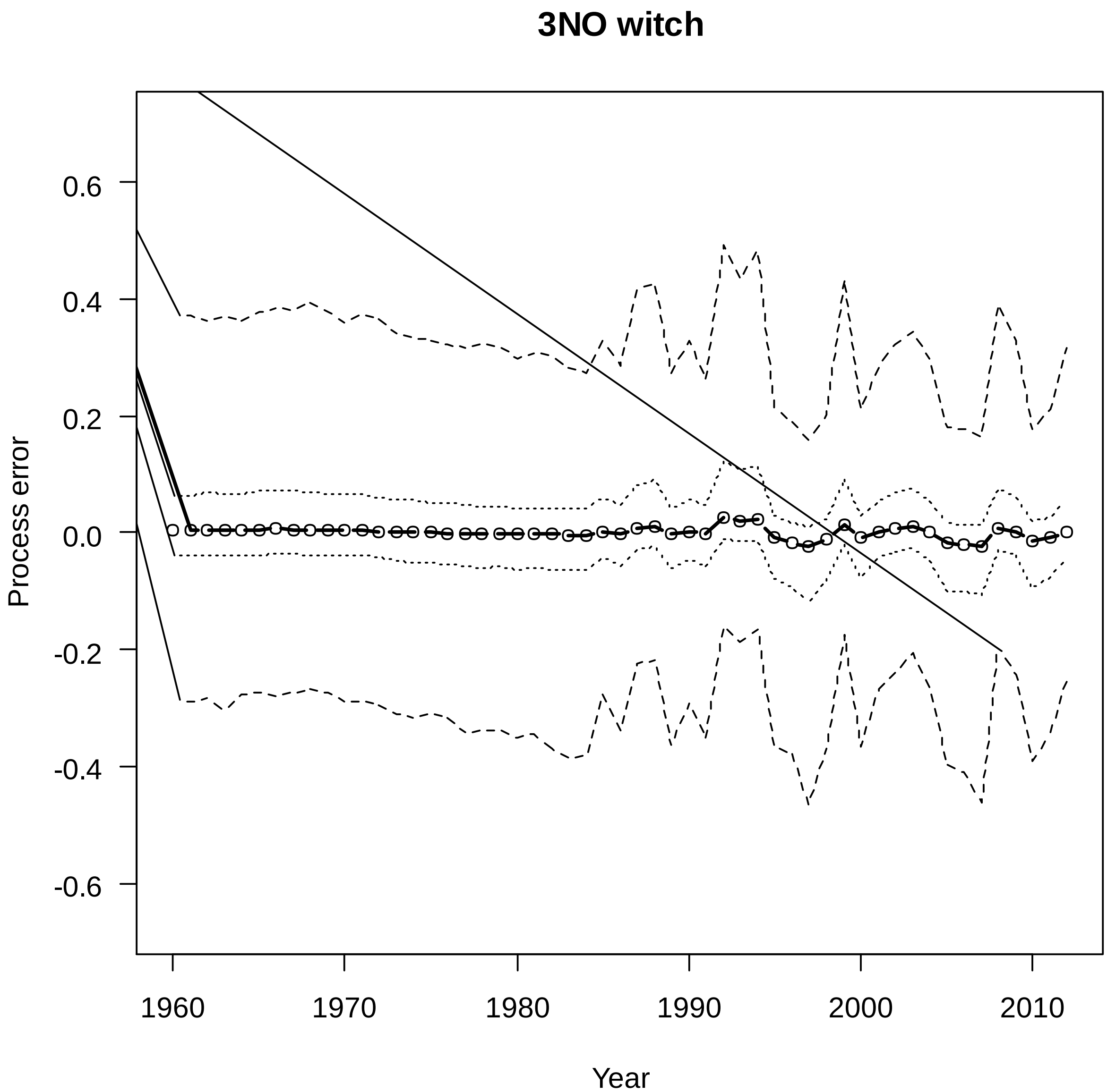
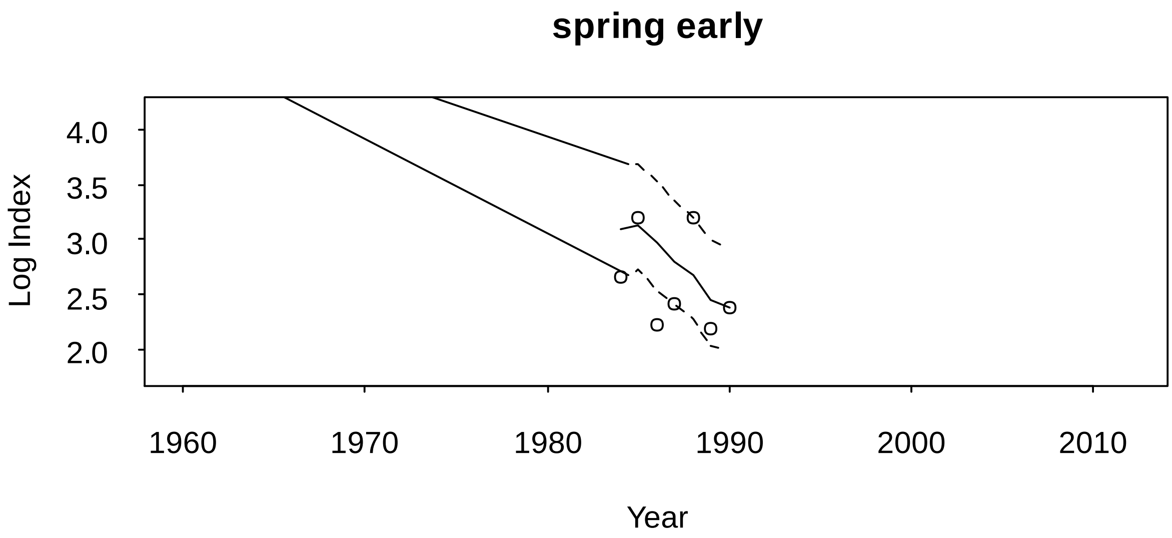


Figure A1.15. Process error from the surplus production model for Div. 3NO witch flounder. The median (heavy line with circles), 50% (dotted line) and 95% (dashed line) credible intervals are shown.



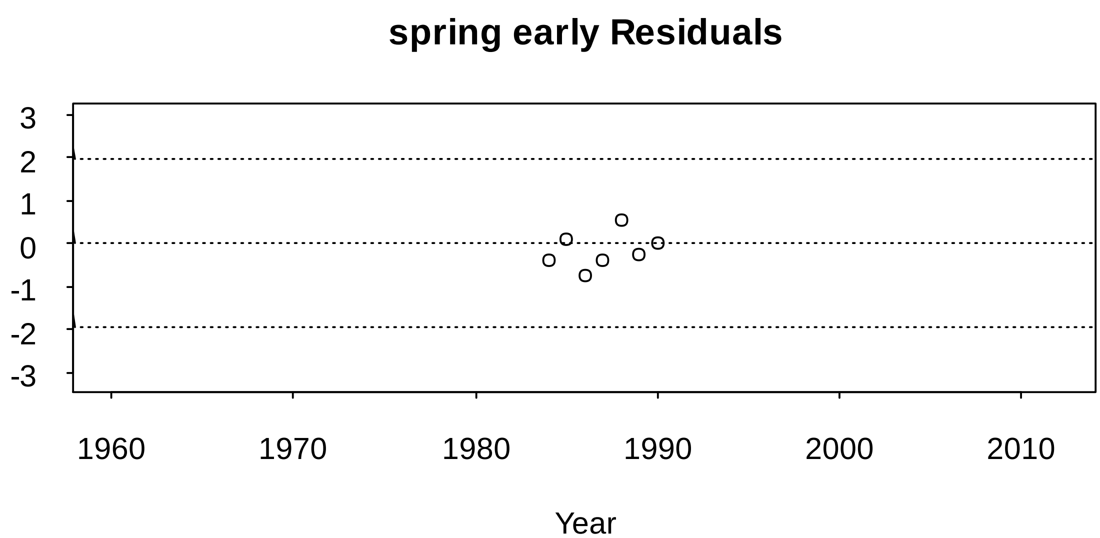


Figure A1.16. Observed (dots) and predicted (line, median with 95% credible intervals) log survey index for the Canadian spring survey 1984-1990 (spring early top) from the surplus production model for Div. 3NO witch flounder. The standardized residuals are shown in the bottom panel.

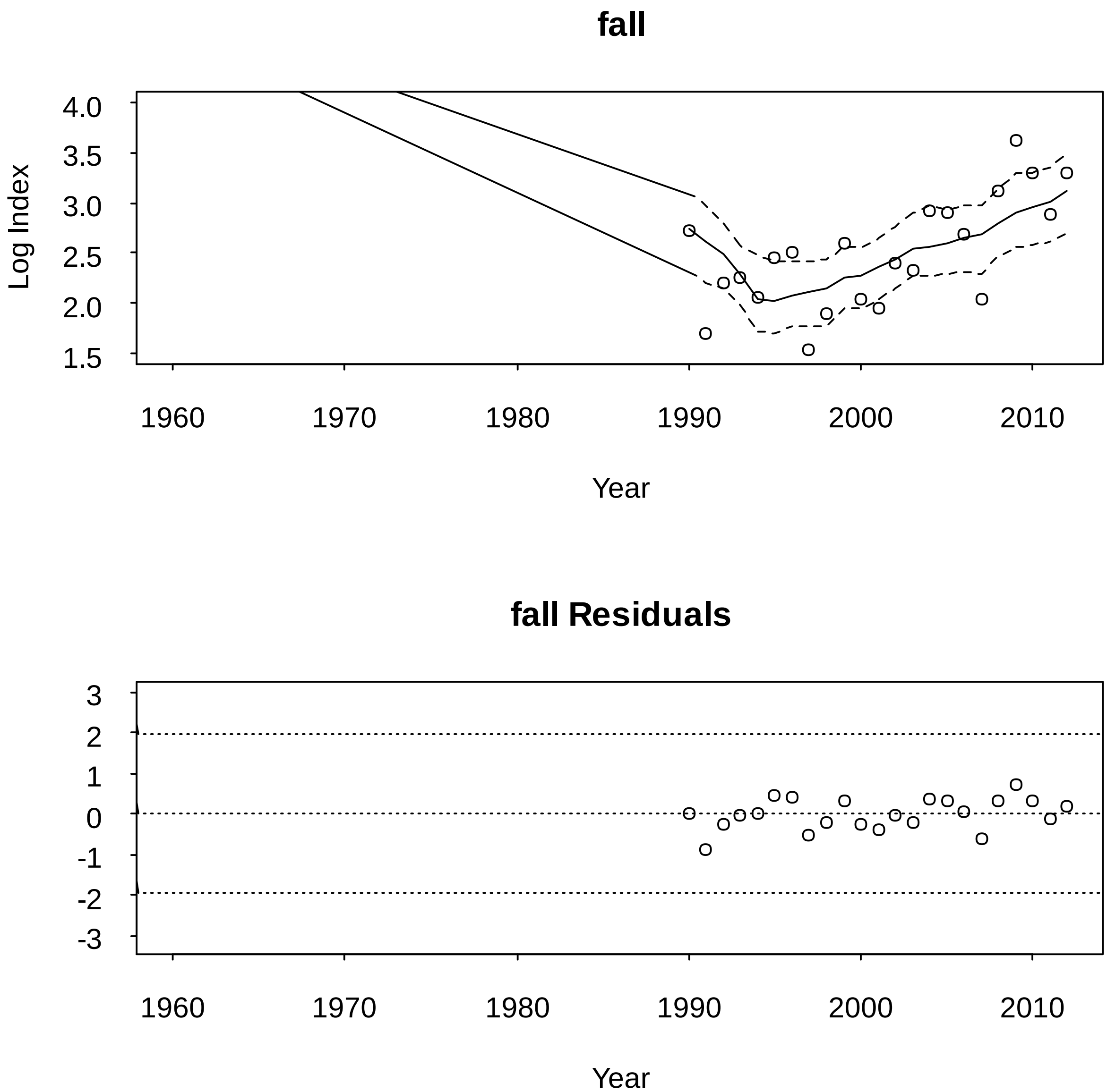


Figure A1.17. Observed (dots) and predicted (line, median with 95% credible intervals) log survey index for the fall Campelen series (top) from the surplus production model for Div. 3NO witch flounder. The standardized residuals are shown in the bottom panel.

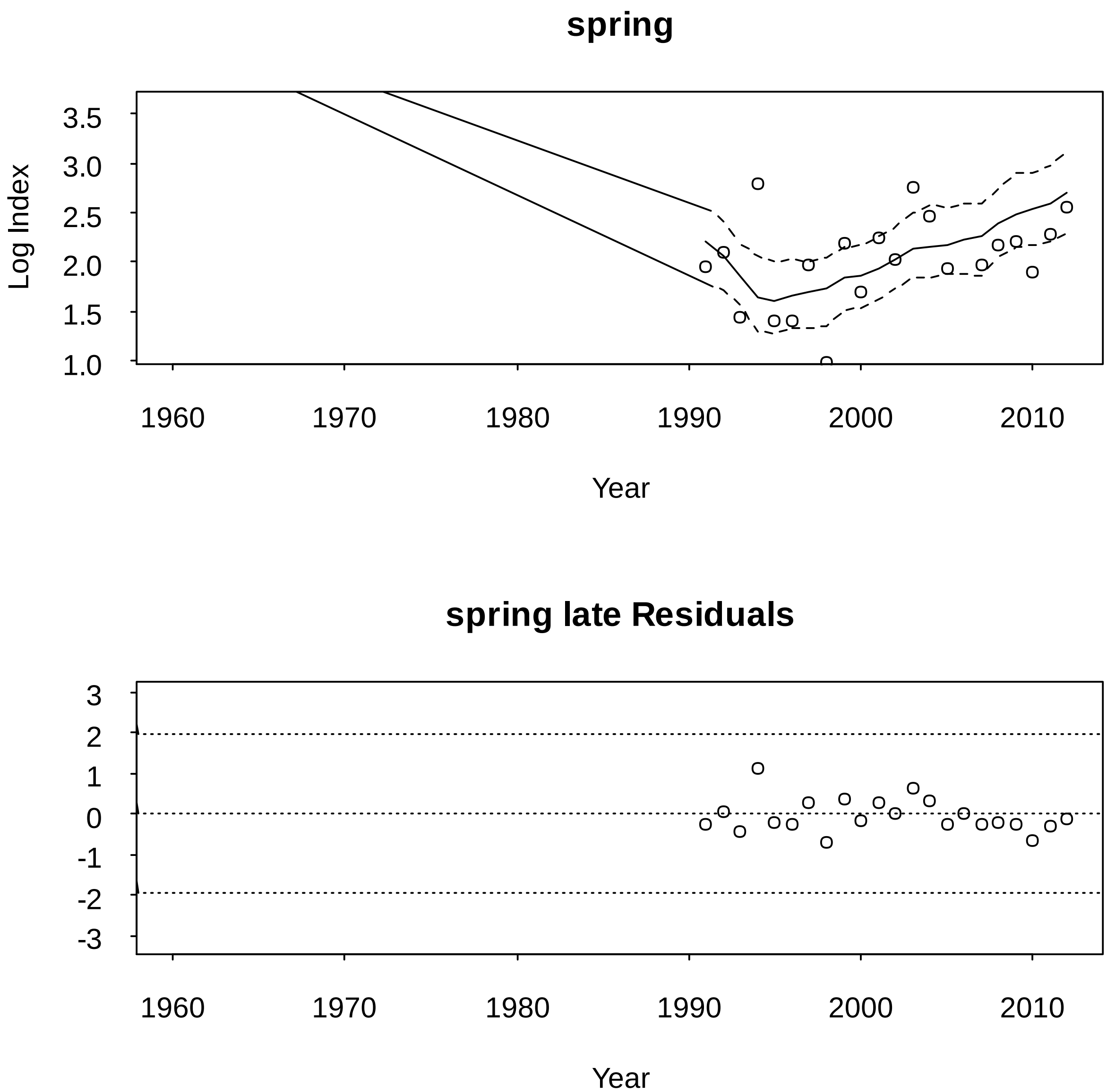
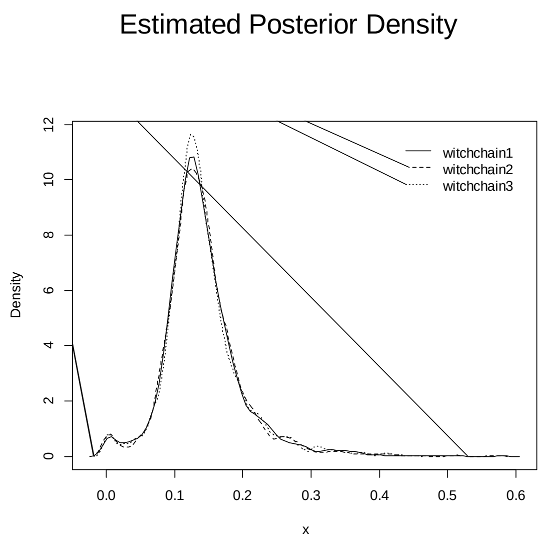
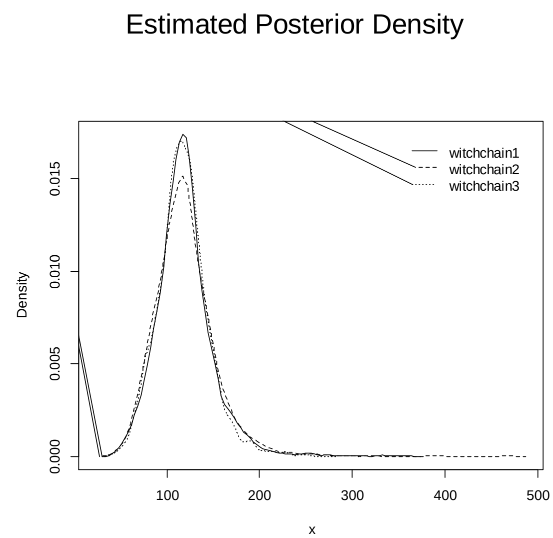


Figure A1.18. Observed (dots) and predicted (line, median with 95% credible intervals) log survey index for the Canadian spring Campelen series 1991-2012 (spring late top) from the surplus production model for Div. 3NO witch flounder. The standardized residuals are shown in the bottom panel.

R



K



Sigma

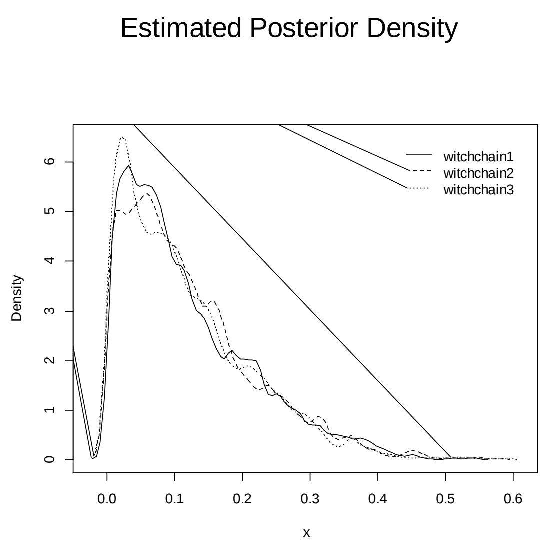
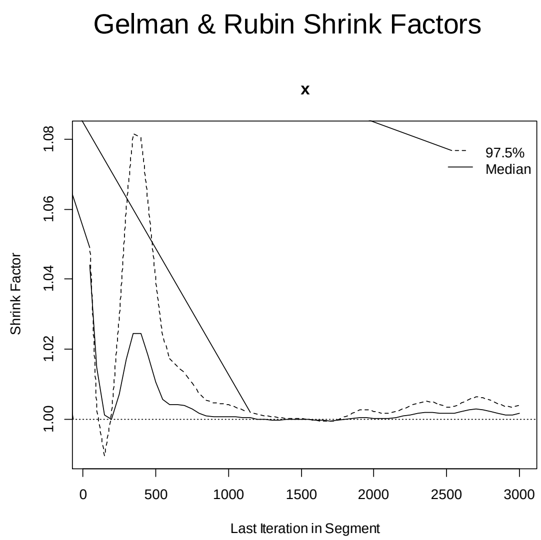
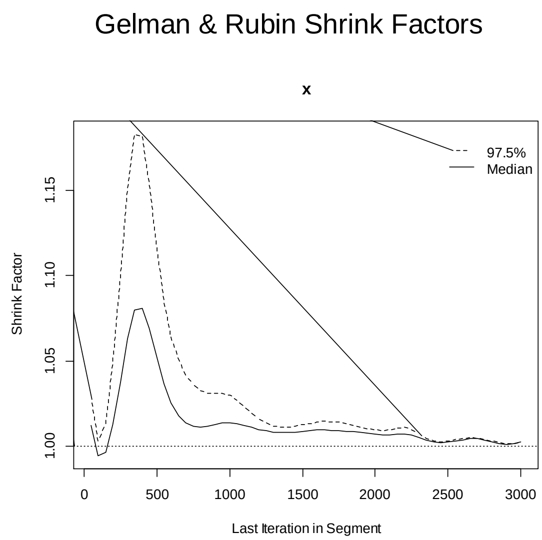


Figure A1.19. Posterior densities for the 3 chains for r, K and sigma from the surplus production model for Div. 3NO witch flounder.

R



K



Sigma

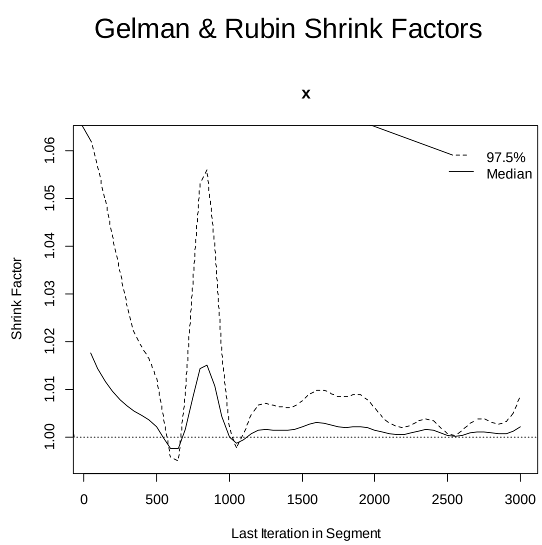
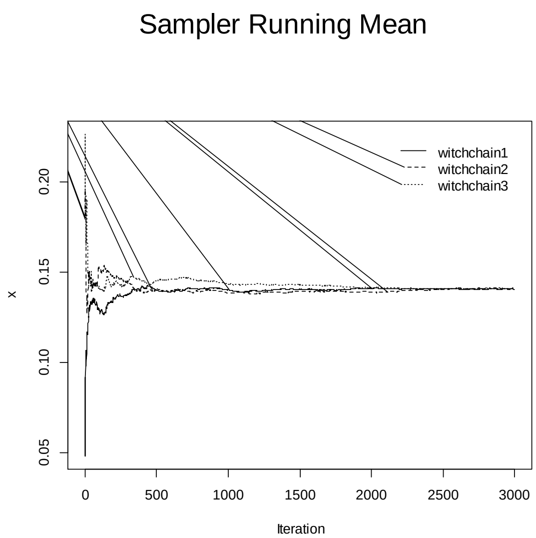
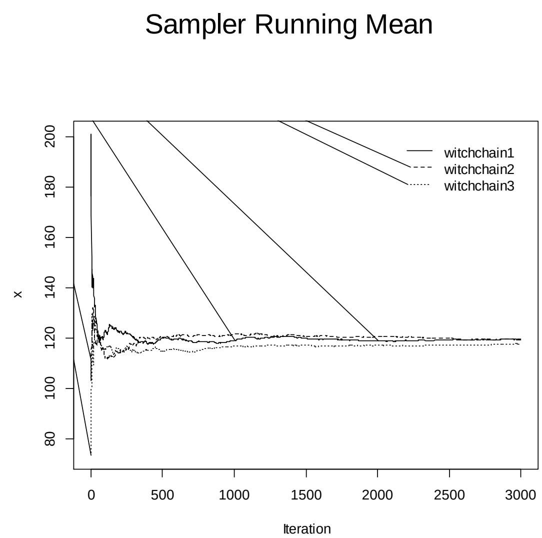


Figure A1.20. Gelman-Rubin shrink factors for r, K and sigma from the surplus production model for Div. 3NO witch flounder. Note that the y-axis scale is different for each plot.

R



K



Sigma

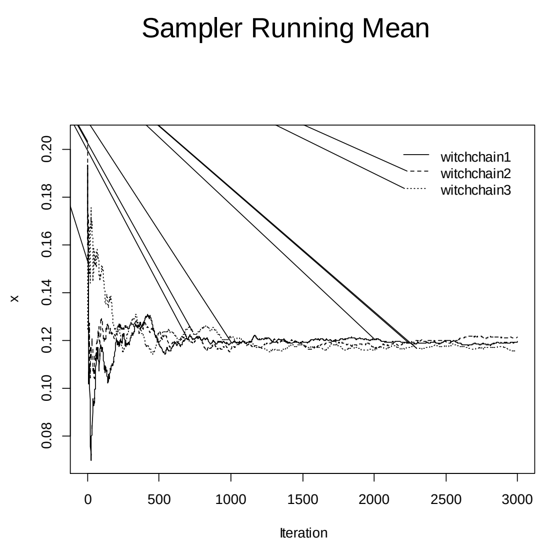
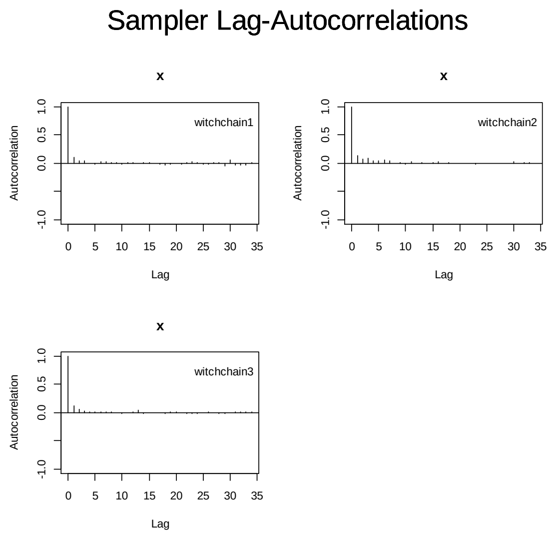
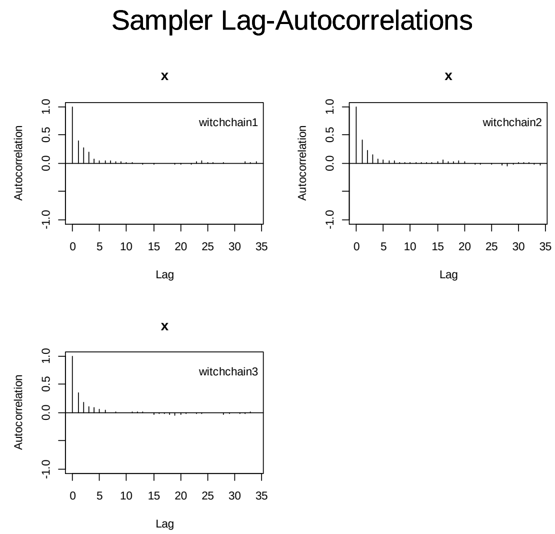


Figure A1.21. Sampler running mean for r, K and sigma from the surplus production model for Div. 3NO witch flounder. Note that the y-axis scale is different for each plot.

R



K



Sigma

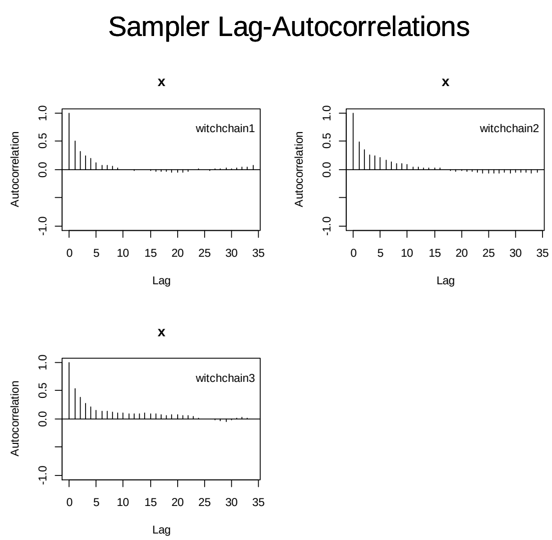


Figure A1.22. Sampler lag-autocorrelations for each chain for r, K and sigma from the surplus production model for Div. 3NO witch flounder.