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STOCK SYNTHESIS MODEL SENSITIVITY TO DATA WEIGHTING: AN EXAMPLE FROM PRELIMINARY MODEL RUNS PREVIOUSLY CONDUCTED FOR NORTH ATLANTIC BLUE SHARK

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SUMMARY

Stock Synthesis model sensitivity was evaluated to data weighting with a case study provided from preliminary Stock Synthesis model runs conducted for North Atlantic blue sharks. A two stage data weighting approach was investigated to iteratively tune (re-weight) variance adjustment factors for fleet-specific size data distributions (length composition) and fleet-specific relative abundance indices (CPUE) within a Stock Synthesis model. An example implementation of the approach is provided from preliminary model runs previously completed for North Atlantic blue sharks with Stock Synthesis. The two stage data weighting approach outlined here provides an example of a possible data weighting approach within an integrated stock assessment model that may be useful to explore in the upcoming shortfin mako assessment.

RÉSUMÉ

La sensibilité du modèle de Stock Synthèse à la pondération des données a été évaluée avec une étude de cas provenant de scénarios préliminaires du modèle de Stock Synthèse exécutés pour le requin peau bleue de l'Atlantique Nord. On a examiné une approche de pondération des données en deux étapes afin de calibrer selon un mode itératif (repondération) des facteurs d'ajustement de la variance pour des distributions de données de taille spécifiques à la flottille (composition par taille) et pour des indices d'abondance relative spécifiques à la flottille (CPUE) au sein d'un modèle de Stock Synthèse. Un exemple de mise en œuvre de l'approche est fourni à partir des scénarios préliminaires du modèle exécutés pour le requin peau bleue de l'Atlantique Nord avec Stock Synthèse. L'approche de pondération des données en deux étapes décrite dans le présent document fournit un exemple d'une approche possible de pondération des données au sein d'un modèle d'évaluation intégrée des stocks qu'il pourrait être utile d'explorer dans la prochaine évaluation du requin-taupe bleu.

RESUMEN

Se evaluó la sensibilidad del modelo Stock Synthesis a la ponderación de los datos con un estudio de caso proporcionado a partir de los ensayos del modelo Stock Synthesis llevados a cabo para la tintorera del Atlántico norte. Se investigó un enfoque de ponderación de los datos en dos etapas para ajustar iterativamente (reponderar) los factores de ajuste de la varianza para la distribución de los datos de talla específicos de la flota (composición por tallas) y los índices de abundancia relativa (CPUE) específicos de la flota dentro de un modelo stock synthesis. Se facilita un ejemplo de implementación del enfoque a partir de ensayos del modelo preliminar previamente llevado a cabo para la tintorera del Atlántico norte con stock synthesis. El enfoque de ponderación de datos de dos etapas descrito aquí proporciona un ejemplo de un posible enfoque de ponderación de datos dentro de un modelo de evaluación de stock integrado que podría ser útil explorar en la próxima evaluación de marrajo dientuso.

KEYWORDS

Stochastic models, Stock assessment, Shark fisheries, Pelagic fisheries, Blue shark

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1. Introduction

This working document addresses stock assessment research recommendations related to data weighting within an integrated stock assessment model that resulted from the last Shark Working Group meeting report (See Anon. 2016, their section 6.1 Research and statistics): "More guidance should be developed by the SCRS on the relative reliability and consistency of different data streams with each other, and with knowledge of the species biology and fisheries; and WGSAM [Working Group on Stock Assessment Methods] should develop guidelines on how SCRS species WGs should implement alternative hypotheses with Stock Synthesis. More specifically, the WGSAM should consider providing guidance to the Groups on how to assign variance adjustment factors and relative weights (lambdas) to the different data inputs to Stock Synthesis (fleet-specific size data distributions, relative abundance indices, etc.). Guidelines on appropriate diagnostics (e.g. likelihood profiles for R0 for each data component, convergence criteria, sensitivity to variance adjustment scheme, etc.) for Stock Synthesis should also be developed by the WGSAM."

Francis (2011) describes a two stage approach to assign variance adjustment factors to different data inputs (e.g., fleet-specific size data distributions and fleet-specific relative abundance indices) within an integrated stock assessment model. In stage one, variance adjustment factors are applied to the fleet-specific relative abundance indices externally to the integrated stock assessment model. In stage two, variance adjustment factors are applied to fleet-specific size data distributions within the integrated stock assessment model, for example based on fit to the fleet-specific size data distributions obtained and a resulting estimate of effective sample size, as described below.

A two stage Francis (2011) data weighting approach was investigated here to iteratively tune (re-weight) variance adjustment factors for fleet-specific size data distributions (length composition) and fleet-specific relative abundance indices (CPUE) within a Stock Synthesis model. This approach was investigated because it provides an example of a possible data weighting approach within an integrated stock assessment model that may be useful to explore in the upcoming shortfin mako assessment. An example implementation of the approach is provided from preliminary model runs previously completed for North Atlantic blue sharks with Stock Synthesis (Courtney 2016). The blue shark model was chosen as an example because the previous preliminary model runs were sensitive to the weighting assigned in the model likelihood to length composition data. In addition, the previous preliminary model runs used an ad hoc approach to scale the inverse CV weighting for some CPUE time series. For example, standardized CPUE time series resulted in unrealistically small annual CVs for some time series. These CVs were then scaled up to a fixed CV value of 20% in order to match the range of CVs estimated for other input CPUE time series. Model details for the previously conducted preliminary model runs are provided separately in Courtney (2016).

2. Materials and methods

Two examples of a two stage Francis (2011) data weighting approach are provided. In stage one of both examples we assume a minimum average standard error (SE; on the natural log scale) for each CPUE series. The minimum was based on fitting a simple smoother to the CPUE data (on the natural log scale) outside the model and estimating the residual variance[1] (e.g., Francis 2011; Lee *et al.* 2014a, 2014b). In stage two, the examples differ. In example one, the Francis (2011) method is applied to estimate the effective sample size of each length composition data set from the residuals of the Stock Synthesis model fit to the data. In example two, the McAllister and Ianelli (1997) method (using the harmonic mean) is applied to estimate the effective sample size of each length composition data from the residuals of the Stock Synthesis model fit to the data.

For comparison, example results obtained with the data weighting approaches described above are compared to those obtained previously for North Atlantic blue sharks with Stock Synthesis (See *Preliminary Run 6* in Courtney 2016).

2.1 Example model runs

As described for the preliminary model runs previously completed for North Atlantic blue sharks with Stock Synthesis (Courtney 2016), the CVs for each CPUE time series were obtained externally to the stock assessment model from the standardized fit obtained independently for each CPUE series (surveys S1 – S10; **Tables 1 and**

[1] Carvalho, F. and H. Winker. 2015. Stock assessment of south Atlantic blue shark (*Prionace glauca*) through 2013. ICCAT Document SCRS/2015/153 (withdrawn).

2, and Figure 1). The CVs obtained for each CPUE time series were assumed to be equal to the SE on the log scale. The observed sample sizes for length composition data were obtained as the number of sharks measured (fleets F1 – F5; **Tables 1 and 3, and Figure 1**).

2.1.1 Example Model Run 1

Stage 1. The CVs for each CPUE series were obtained externally to the Stock Synthesis model and adjusted externally to the model before being input in Stock Synthesis as follows. The annual CVs for each CPUE series were assumed to be equal to the SE on the log scale and adjusted based on our expectation that the stock assessment model would fit each CPUE data **at best** as well as a smoother (e.g., Francis 2011; Lee *et al.* 2014a, 2014b). The average annual SE (SE.in; on the log scale) was calculated for each CPUE series. The square root of the residual variance was calculated based on the fit of a simple smoother to each CPUE series on the log scale as

$$\mathrm{RMSE}_{smoother} = \sqrt{\left(\tfrac{1}{N}\right)\sum_{t=1}^{N}\left(Y_t - \hat{Y}_t\right)^2}$$

where Y_t is the observed CPUE in year t on the log scale, $\hat{Y}_t$ is the predicted CPUE in year t from the smoother fit to the data on the log scale, and N is the number of CPUE observations—rather than the degrees of freedom used in the estimation of the smoother fit— (e.g., Francis 2011; Lee *et al.* 2014a, 2014b). For these examples, a LOESS smoother was fit here to each CPUE data on the log scale. If SE.in for a CPUE series was less than $\mathrm{RMSE}_{smoother}$ for that CPUE series, then the input SE for the CPUE series was adjusted (SE.adj) in Stock Synthesis before running the model so that the new average SE was equal to $\mathrm{RMSE}_{smoother}$ (SE.in + SE.adj = $\mathrm{RMSE}_{smoother}$). If SE.in for a CPUE series was greater than or equal to the $\mathrm{RMSE}_{smoother}$ for that CPUE series then the SE of the CPUE series was not adjusted in the Stock Synthesis model.

Stage 2. After an initial model run with the input CVs adjusted for each CPUE as described above, the input sample sizes for the length composition data for fleets F1 – F5 were adjusted one time with variance adjustment multiplication factors so that the sample size entered for each length composition data set (fleets F1 – F5) was equal to the effective sample size obtained using the Francis (2011) method. In this example, the resulting variance adjustment factors for fleets F1 – F5 were 0.0019, 0.0047, 0.0046, 0.0573, and 0.0403, respectively, based on Stock Synthesis output (Methot and Wetzel 2013; Methot 2015) obtained with the program r4ss (Taylor *et al.* 2014).

2.1.2 Example Model Run 2

Stage 1 was the same as in *Example Model Run 1*.

Stage 2. After an initial model run with the input CVs adjusted for each CPUE as described above, the input sample sizes for the length composition data for fleets F1 – F5 were adjusted one time with variance adjustment multiplication factors so that the sample size entered for each length composition data set (fleets F1 – F5) was equal to the effective sample size obtained using the McAllister and Ianelli (1997) method (with a harmonic mean). In this example, the resulting variance adjustment factors for fleets F1 – F5 were 0.0094, 0.0251, 0.0142, 0.0963, and 0.1710, respectively, based on Stock Synthesis output (Methot and Wetzel 2013; Methot 2015).

2.2 Previously conducted preliminary model runs

2.2.1 Previously conducted Preliminary Run 6

The annual CVs for each CPUE time series, assumed to be equal to the SE on the log scale and obtained externally to the stock assessment model, were input in Stock Synthesis and used in the model likelihood as inverse CV "weights" for each annual abundance index, except for survey S9 (ESP-LL-N). For survey S9 (ESP-LL-N), the standardized CPUE obtained externally resulted in unrealistically small annual CVs (ESP-LL-N; **Table 2;** See *Preliminary Run 6* in Courtney 2016). Consequently, a constant CV of 20% was input in Stock Synthesis for survey S9 (ESP-LL-N) in order to scale up its CV to match the range of CVs estimated for other input CPUE time series. The observed sample sizes for length composition data, obtained externally to the stock assessment model as the number of sharks measured, were input in Stock Synthesis and used in the model likelihood as the initial estimate of effective sample size for length composition data (fleets F1 – F5; **Tables 1 and 3)**.

After an initial model run with CVs assigned to CPUE and sample sizes assigned to length composition data as described above, the input sample sizes for the length composition data for fleets F1 – F5 were adjusted one time with variance adjustment multiplication factors so that the sample size entered for each length composition data set (fleets F1 – F5) was equal to the effective sample size obtained using the Francis (2011) method. In this example, the resulting variance adjustment factors for fleets F1 – F5 were 0.0019, 0.0047, 0.0046, 0.0573, and 0.0403, respectively, based on Stock Synthesis output (Methot and Wetzel 2013; Methot 2015) obtained with the program r4ss (Taylor *et al.* 2014), which were the same as those obtained for *Example Model Run 1*.

2.2 Model convergence and diagnostics

Model convergence was based on whether or not the Hessian inverted (i.e., the matrix of second derivatives of the likelihood with respect to the parameters, from which the asymptotic standard error of the parameter estimates is derived). Other convergence diagnostics were also evaluated. Excessive CVs on estimated quantities (>> 50%) or a large final gradient (>1.00E-05) were indicative of uncertainty in parameter estimates or assumed model structure. The correlation matrix was also examined for highly correlated (> 0.95) and non-informative (< 0.01) parameters. Parameters estimated at a bound were a diagnostic for possible problems with data or the assumed model structure.

2.3 Evaluating model sensitivity

2.3.1 CVs of estimated parameters.

Model sensitivity was evaluated by comparing the CVs of estimated parameters.

2.3.2 Density plots

Model sensitivity was also evaluated by comparing density plots (based on standard error of parameter estimates obtained from the inverted Hessian matrix with r4ss; Taylor *et al.* 2014). Density plots were compared for the main scaling parameter in the model (equilibrium recruitment; SR_ln (R0)), and the resulting equilibrium unfished spawning output (SPB_Virgin). Spawning output for the North Atlantic blue shark Stock Synthesis model (Courtney 2016) was calculated as the sum of female numbers at age multiplied by pup production (males and females) at age at the beginning of each calendar year and defined as spawning stock fecundity (SSF). SSF was input in the assessment with the assumed fraction female fixed at 0.5.

2.3.3 Time series plots

Model sensitivity was also evaluated by comparing time series plots of predicted CPUE indices and estimated recruitment deviations obtained with the program r4ss (Taylor *et al.* 2014).

3. Results

3.1 Example model runs

For *Example Model Run 1* and *Example Model Run 2*, the CVs for each CPUE series were adjusted based on the RMSE obtained from a LOESS smoother as described above (**Figure 2**).

3.1.1 Example Model Run 1

Example Model Run 1 (sensitivity run 1) differed from the previously conducted *Preliminary Run 6* (Courtney 2016) only in stage one. In *Example Model Run 1*, the input CVs for each CPUE series were adjusted externally to the model based on our expectation that the stock assessment model would fit each CPUE data at best as well as a smoother. In contrast, in the previously conducted *Preliminary Run 6*, the input CVs for each CPUE series were not adjusted externally, except for survey S9 (ESP-LL-N) which were fixed at 20%. In stage two, both *Example Model Run 1* and the previously conducted *Preliminary Run 6* applied the Francis (2011) method to estimate the effective sample size of each length composition data set.

The Hessian matrix inverted and was presumably positive definite, no parameters were estimated above the maximum correlation threshold (cormax = 0.95), and no parameters were estimated at boundary conditions. However, the final gradient (3.68E-04) was relatively larger than that obtained for the previously conducted *Preliminary Run 6*. Two parameters were also estimated below the minimum correlation threshold (cormin = 0.01) (SizeSel_5P_3_F5 = 0.004776370; and SizeSel_5P_4_F5 = 0.000173253). The CVs of four of the selectivity parameters for fleet 4 and one selectivity parameter for fleet 5 were all >> 50% (**Table 4**).

3.1.2 Example Model Run 2

Example Model Run 2 (sensitivity run 2) differed from the previously conducted *Preliminary Run 6* (Courtney 2016) in both stage one and stage two. Stage one of *Example Model Run 2* was the same as *Example Model Run 1*. In stage two of the *Example Model Run 2*, the effective sample size of each length composition data set was estimated from the residuals of the integrated stock assessment model fit to each length composition data set using the McAllister and Ianelli (1997) method (harmonic mean). In contrast, in the previously conducted *Preliminary Run 6*, the effective sample size of each length composition data set was estimated using the Francis (2011) method.

The Hessian matrix inverted and was presumably positive definite, no parameters were estimated below the minimum correlation threshold (cormin = 0.01), and no parameters were estimated at boundary conditions. However, the final gradient (5.63E-04) was relatively larger than that obtained for the previously conducted *Preliminary Run 6*. Two parameter pairs were above the maximum correlation threshold (cormax=0.95) (InitF_1F1 and SR_LN(R0) corr = -0.977152; and SizeSel_1P_2_F1 and SizeSel_1P_1_F1 corr = -0.961405). The CVs of four of the selectivity parameters for fleet 4 were all >> 50% (**Table 5**).

3.2 Previously conducted preliminary model runs

For the previously conducted *Preliminary Run 6* (Courtney 2016), the Hessian matrix inverted and was presumably positive definite. The final gradient was relatively small (9.03E-06) and no parameters were estimated above the maximum correlation threshold *(cormax = 0.95)* or below the minimum correlation threshold (*cormin* = 0.01), and no parameters were estimated at boundary conditions. The CV of the parameter SizeSel_4P_3_F4 (360%) was >> 50%. However, *Preliminary Run 6* model results did not appear to be sensitive to the value estimated for this parameter (**Table 6**; Courtney 2016).

3.3 Evaluating model sensitivity

3.3.1. CVs of estimated parameters.

Several estimated selectivity parameters for *Example Model Run 1* (**Table 4**) and *Example Model Run* 2 (**Table 5)** had excessive CVs (>> 50%); some parameters were estimated either below the minimum correlation threshold (cormin = 0.01; *Example Model Run 1*) or above the maximum correlation threshold (cormax=0.95; *Example Model Run 2*); and the final gradients of both examples were relatively larger than that of previously conducted *Preliminary Run 6*. The excessive CVs for fleet 4 selectivity parameters (**Tables 4 and 5**) resulted in unreasonable uniform full selectivity for all lengths for fleet 4 (**Figure 3**). These results indicate that the previously conducted *Preliminary Run 6* is sensitive to two stage data weighting.

The excessive CVs and unreasonable uniform full selectivity for fleet 4 indicate that an investigation of alternative selectivity parameterizations for fleet 4 would be required before the parameter estimates and model results from *Example Model Run* 1 and *Example Model Run* 2 could be examined in any more detail. For example, during an assessment the implementation of selectivity would probably have been changed if the CVs of estimated selectivity parameters were excessive >> 50% or if some selectivity parameters were above or below the specified correlation thresholds. Consequently fits to length compositions, and R0 profiles were not investigated for any of the model runs conducted with two stage data weighting.

3.3.2. Density plots

Density plots of equilibrium recruitment SR_ln(R0) (**Figure 4)** and the resulting equilibrium unfished spawning output (SPB_Virgin) (**Figure 5**) differed substantially among model runs. This result indicates that the absolute scale of the population is sensitive to the two stage data weighting. However, the densities were also affected by the excessive CVs and uniform selectivity for fleet 4 (**Tables 4 and 5, and Figure 3**). Consequently, an investigation of alternative selectivity parameterizations for fleet 4 would be required before a more accurate model comparison of SR_ln(R0) and SPB_Virgin could be conducted.

3.3.3. Time series plots

Time series plots of recruitment deviations estimated with Stock Synthesis using two stage data weighting did not differ substantially from those obtained in the previously conducted *Preliminary Run 6* (**Figure 6**). Few of the recruitment deviations obtained with two stage data weighting (e.g., 2010) were outside the approximate 95% confidence intervals obtained for recruitment deviations in the previously conducted *Preliminary Run 6* (**Figure 6**).

Similarly, time series plots of Stock Synthesis model fits to CPUE obtained with two stage data weighting did not differ substantially from those obtained in the previously conducted *Preliminary Run 6* (**Figures 7 – 16**). As expected, fits to some CPUE time series obtained with two stage data weighting were less jagged than fits obtained in the previously conducted *Preliminary Run 6* (**Figure 12**) as would be expected by increasing the input CVs in Stock Synthesis. Fits to CPUE time series for Fleet S9 did differ somewhat among the model runs compared here, especially in the stock trajectory of the most recent years (**Figure 15**). This is important because an ad hoc approach had been used previously to fix the annual CVs for survey S9 (ESP-LL-N) at 20% in the previously conducted *Preliminary Run 6* (Courtney 2016).

4. Discussion

The two stage data weighting approach outlined here provides an example of a possible data weighting approach within an integrated stock assessment model that may be useful to explore in the upcoming shortfin mako assessment. For example, the two stage data weighting approach outline here revealed that the previously conducted *Preliminary Run 6* (Courtney 2016) appeared to be sensitive to both the variance adjustment factors applied to CPUE CVs in stage one as well as to the variance adjustment factors applied to length composition data in stage 2. These results may be a useful diagnostic of model miss-speciation in the previously conducted *Preliminary Run 6*. Consequently, the two stage data weighting approach implemented here may also provide a useful model diagnostic for the upcoming shortfin mako assessment.

As previously discussed (Courtney 2016), the blue shark model was sensitive to the variance adjustment factors applied to length composition data. In Stock Synthesis, the input sample sizes for composition (age or length) data should reflect the effective sample size for length composition data (Methot and Wetzel 2013: their equation A.3.5)-i.e., the actual number of fish in the (age or length) sample if the multinomial error model was strictly correct (Methot 1990: their equation L3). For example, it has been noted that a maximum sample size of 200 in Stock Synthesis applications would produce an expected CV of approximately 20% for a bin with 10% of the distribution's mass (Methot 2000: their equation 35). McAllister and Ianelli (1997) and the Francis (2011) developed approaches for automatically re-weighting compositional data within integrated models based on the residuals of integrated model fits to the composition data. Punt (in press) evaluated these approaches, among others, using simulated data sets and found that integrated model results were sensitive to which approach was used for tuning variance adjustment factors for composition data. Importantly, the choice of method used for tuning variance adjustment factors to composition data was most consequential when there was model miss-specification imposed within the simulated data sets Punt (in press).

We anticipate that the model sensitivity identified here for the previously conducted *Preliminary Run 6* would be reduced by incorporating additional structural assumptions into the stock assessment model, as recommended in the 2015 Shark Working Group assessment report (Anon. 2016). These recommendations include 1) modeling CPUE time series with conflicting trends separately, and 2) splitting length compositions into geographic regions with similar length frequency distributions. However, it might also be useful to continue to evaluate model sensitivity to a range of data weighting options in future assessments, for example those outlined here, in order to determine if the range in sensitive parameter values identified here (e.g., SR_ln (R0) and SPB_Virgin, **Figures 4 and 5**) could be reduced as more structural assumptions are included in the model.

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Table 1. Time series of catch, abundance, and length composition data considered for use in the preliminary SS3 model runs (See Table 1 in Courtney 2016).

Time series #	Symbol	Catch (t) and abundance (numbers or biomass)	Name	Definition	Length composition (10 cm FL bins)
1	F1	Catch (t)	EU	EU España + Portugal (1971-2013)	EU España + Portugal (1993-2013)
2	F2	Catch (t)	JPN	Japan (1971-2013)	Japan (1997-2013)
3	F3	Catch (t)	CTP	Chinese Taipei (1971-2013)	Chinese Taipei (2004-2013)
4	F4	Catch (t)	USA	USA (1981-2013)	USA (1992-2013)
5	F5	Catch (t)	VEN	Venezuela (1986-2013)	Venezuela (1994-2013)
6	F6	Catch (t)	CAN	Canada (1974-2007)	Mirror USA (F4)
7	F7	Catch (t)	CPR	China PR (1993-2013)	Mirror CTP (F3)
8	F8	Catch (t)	BEL	Belize (2009-2013)	Mirror VEN (F5)
9	F9	Catch (t)	OTH	Other (1978-2013)	Mirror CTP (F3)
10	S1	Relative abundance (numbers)	US-Log	US logbook (1986-2013) [1]	Mirror USA (F4)
11	S2	Relative abundance (numbers)	US-Obs	US observer (1992-2013)	Mirror USA (F4)
12	S3	Relative abundance (numbers)	JPLL-N-e	Japan (1971-1993)	Mirror JPN (F2)
13	S4	Relative abundance (numbers)	JPLL-N-l	Japan (1994-2013)	Mirror JPN (F2)
14	S5	Relative abundance (numbers)	IRL-Rec	Irish Rec. (1980-2006) [2]	Mirror CTP (F3)
15	S6	Relative abundance (numbers)	US-Obs-cru	[1957-1970] (1971-1991) [1992-2000] [3]	Mirror USA (F4)
16	S7	Relative abundance (biomass)	POR-LL	EU Portugal (1997-2013)	Mirror EU (F1)
17	S8	Relative abundance (numbers)	VEN-LL	Venezuela (1994-2013)	Mirror VEN (F5)
18	S9	Relative abundance (biomass)	ESP-LL-N	EU España (1997-2013)	Mirror EU (F1)
19	S10	Relative abundance (numbers)	CTP-LL-N	Chinese Taipei (2004-2013) [4]	Mirror CTP (F3)

1. Index S1 (US-Log) used the same data as S2 (US-Obs) and was not fit in model likelihood (lambda = 0).
2. Index S5 (IRL-Rec) was preliminary and was not fit in model likelihood (lambda = 0).
3. Index S6 (US-Obs_cru) overlapped with S2 (US-Obs) during the years 1992 – 2000; consequently, data from 1992 – 200 were excluded from S6 in the model.
4. Index S10 (CTP-LL-N) was preliminary, but was fit in the model likelihood because of its presumed extensive geographic coverage.

Table 2. Coefficients of variation (CV) corresponding to indices of relative abundance for North Atlantic blue shark surveys S1 – S10 (**Table 1**; See Table 4 in Courtney 2016).

Series	1	2	3	4	5	6	7	8	9	10
Units	**Numbers**	**Numbers**	**Numbers**	**Numbers**	**Numbers**	**Numbers**	**Biomass**	**Numbers**	**Biomass**	**Numbers**
Type	**Logbook**	**observer**			**nominal**					
Name (SS3)	**US-Log**	**US-Obs**	**JPLL-N-e**	**JPLL-N-l**	**IRL-Rec**	**US-Obs-cru**	**POR-LL**	**VEN-LL**	**ESP-LL-N**	**CTP-LL-N**
Survey (SS3)	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**
1957						0.17				
1958						0.16				
1959						0.25				
1960						0.38				
1961						0.35				
1962						0.27				
1963						0.25				
1964						0.17				
1965						0.17				
1966						0.23				
1967						0.21				
1968						0.21				
1969						0.22				
1970						0.32				
1971			0.534			0.23				
1972			0.386			0.21				
1973			0.452							
1974			0.316							
1975			0.335			0.19				
1976			0.470			0.29				
1977			0.267			0.2				
1978			0.316			0.11				
1979			0.242			0.11				
1980			0.290			0.09				
1981			0.357			0.09				
1982			0.362			0.09				
1983			0.368			0.1				
1984			0.499			0.1				
1985			0.444			0.1				
1986	0.221		0.393			0.09				
1987	0.169		0.346			0.1				
1988	0.168		0.489			0.12				
1989	0.168		0.444		0.179	0.39				
1990	0.167		0.489		0.195	0.17				
1991	0.167		0.470		0.078	0.11				
1992	0.167	0.314	0.428		0.188	0.1				
1993	0.167	0.291	0.399		0.242	0.09				
1994	0.166	0.289		0.499	0.171	0.1		1.075		
1995	0.166	0.292		0.546	0.094	0.1		0.867		
1996	0.166	0.503		0.510	0.082	0.3		1.898		
1997	0.167	0.330		0.522	0.095	0.13	0.084	0.685	0.008	
1998	0.168	0.346		0.534	0.103	0.15	0.076	0.666	0.008	
1999	0.170	0.342		0.489	0.118	0.13	0.077	0.843	0.008	
2000	0.172	0.319		0.282	0.122	0.12	0.083	0.737	0.008	
2001	0.172	0.393		0.560	0.087		0.089	0.771	0.008	
2002	0.174	0.394		0.623	0.182		0.086	1.034	0.008	
2003	0.177	0.366		0.589	0.111		0.082	1.262	0.009	
2004	0.175	0.297		0.687	0.171		0.084	1.525	0.009	0.120
2005	0.179	0.345		0.713	0.195		0.087	3.881	0.010	0.185
2006	0.181	0.310		0.687	0.203		0.084	2.244	0.010	0.062
2007	0.182	0.324		0.606	0.253		0.085	1.353	0.011	0.220
2008	0.174	0.321		0.687	0.453		0.085	1.164	0.011	0.275
2009	0.174	0.312		0.643	0.190		0.086	1.559	0.012	0.171
2010	0.175	0.308		0.643	0.406		0.089	1.543	0.010	0.101
2011	0.175	0.294		0.510	0.464		0.079	1.514	0.010	0.119
2012	0.176	0.336		0.510	0.483		0.081	1.000	0.010	0.109
2013	0.174	0.305		0.206	0.553		0.085	1.842	0.011	0.138

Table 3. Observed sample size (number of sharks measured) for available length composition in fleets F1 – F5 (**Table 1**; See Table 9 in Courtney 2016).

Year	F1 (EU)	F2 (JPN)	F3 (CTP)	F4 (USA)	F5 (VEN)
1992	0	0	0	35	0
1993	2025	0	0	363	0
1994	0	0	0	319	57
1995	0	0	0	105	94
1996	0	0	0	10	13
1997	914	2813	0	146	125
1998	562	1208	0	13	147
1999	2142	301	0	21	83
2000	2325	354	0	84	97
2001	4643	923	0	5	74
2002	1127	794	0	2	45
2003	5096	1907	0	9	26
2004	2455	1386	413	98	40
2005	3153	2488	289	39	4
2006	7242	2076	7373	85	14
2007	3359	2244	159	125	7
2008	4828	3729	192	129	26
2009	2754	1786	595	98	24
2010	7345	2226	287	511	44
2011	2639	1751	444	393	164
2012	10949	1970	359	10	169
2013	2606	1799	236	17	90

Table 4. *Example Model Run 1* (sensitivity run 1) non-recruitment parameter estimates; Parameters with a negative phase were fixed at their initial value; CV is calculated as the asymptotic standard error (Parm_StDev) divided by the estimated value (Value).

Num	Label	Value	Active_Cnt	Phase	Min	Max	Init	Status	Parm_StDev	PR_type	Prior	Pr_SD	CV (%)
16	SR_LN(R0)	8.700	1	1	2.3	13.82	7.04	OK	0.056	Normal	7.04	1000	0.6
65	InitF_1F1												
		0.048	45	1	0	1.9	0.1	OK	0.009	Normal	0.38	1000	17.9
74	SizeSel_1P_1_F1												
75	SizeSel_1P_2_F1	160.289	46	2	1	500	100	OK	35.887	Sym_Beta	100	0.05	22.4
76	SizeSel_1P_3_F1	0.034	47	3	0	1	0.15	OK	0.012	Sym_Beta	0.15	0.05	35.1
77	SizeSel_1P_4_F1	255.202	48	2	1	500	243	OK	13.003	Sym_Beta	243	0.05	5.1
78	SizeSel_1P_5_F1	0.097	49	3	0	1	0.08	OK	0.057	Sym_Beta	0.08	0.05	58.7
79	SizeSel_1P_6_F1	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1	0.05	NA
80	SizeSel_2P_1_F2	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0	0.05	NA
81	SizeSel_2P_2_F2	132.755	50	2	1	500	120	OK	9.237	Sym_Beta	120	0.05	7.0
82	SizeSel_2P_3_F2	0.077	51	3	0	1	0.15	OK	0.019	Sym_Beta	0.15	0.05	24.8
83	SizeSel_2P_4_F2	233.278	52	2	1	500	220	OK	15.402	Sym_Beta	220	0.05	6.6
84	SizeSel_2P_5_F2	0.057	53	3	0	1	0.07	OK	0.029	Sym_Beta	0.07	0.05	50.6
85	SizeSel_2P_6_F2	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1	0.05	NA
86	SizeSel_3P_1_F3	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0	0.05	NA
87	SizeSel_3P_2_F3	228.296	54	2	5	500	200	OK	12.097	Sym_Beta	200	0.05	5.3
88	SizeSel_4P_1_F4	53.636	55	3	0.01	60	25	OK	9.092	Sym_Beta	25	0.05	17.0
89	SizeSel_4P_2_F4	275.849	56	2	1	500	110	OK	552.436	Sym_Beta	110	0.05	200.3*
90	SizeSel_4P_3_F4	0.506	57	3	0	1	0.09	OK	1.518	Sym_Beta	0.09	0.05	300.0*
91	SizeSel_4P_4_F4	226.030	58	2	1	500	120	OK	571.599	Sym_Beta	120	0.05	252.9*
92	SizeSel_4P_5_F4	0.504	59	3	0	1	0.05	OK	1.526	Sym_Beta	0.05	0.05	302.7*
93	SizeSel_4P_6_F4	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1	0.05	NA
94	SizeSel_5P_1_F5	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0	0.05	NA
95	SizeSel_5P_2_F5	175.791	60	2	1	500	210	OK	12.186	Sym_Beta	210	0.05	6.9
96	SizeSel_5P_3_F5	0.054	61	3	0	1	0.05	OK	0.012	Sym_Beta	0.05	0.05	21.7
97	SizeSel_5P_4_F5	360.598	62	2	1	500	210	OK	54.474	Sym_Beta	210	0.05	15.1
98	SizeSel_5P_5_F5	0.511	63	3	0	1	0.05	OK	1.533	Sym_Beta	0.05	0.05	299.9*
99	SizeSel_5P_6_F5	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1	0.05	NA

*High CV >>50% .

Table 5. *Example Model Run 2* (sensitivity run 2) non-recruitment parameter estimates; Parameters with a negative phase were fixed at their initial value; CV is calculated as the asymptotic standard error (Parm_StDev) divided by the estimated value (Value).

Num	Label	Value	Active_Cnt	Phase	Min	Max	Init	Status	Parm_StDev	PR_type	Prior	Pr_SD	CV (%)
16	SR_LN(R0)	9.079	1	1	2.3	13.82	7.04	OK	0.198	Normal	7.04	1000	2.2
65	InitF_1F1	0.025	45	1	0	1.9	0.1	OK	0.006	Normal	0.38	1000	22.9
74	SizeSel_1P_1_F1	107.559	46	2	1	500	100	OK	7.337	Sym_Beta	100	0.05	6.8
75	SizeSel_1P_2_F1	0.098	47	3	0	1	0.15	OK	0.039	Sym_Beta	0.15	0.05	39.5
76	SizeSel_1P_3_F1	264.482	48	2	1	500	243	OK	4.492	Sym_Beta	243	0.05	1.7
77	SizeSel_1P_4_F1	0.132	49	3	0	1	0.08	OK	0.038	Sym_Beta	0.08	0.05	29.1
78	SizeSel_1P_5_F1	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1	0.05	NA
79	SizeSel_1P_6_F1	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0	0.05	NA
80	SizeSel_2P_1_F2	127.882	50	2	1	500	120	OK	3.921	Sym_Beta	120	0.05	3.1
81	SizeSel_2P_2_F2	0.083	51	3	0	1	0.15	OK	0.010	Sym_Beta	0.15	0.05	11.9
82	SizeSel_2P_3_F2	223.874	52	2	1	500	220	OK	6.508	Sym_Beta	220	0.05	2.9
83	SizeSel_2P_4_F2	0.054	53	3	0	1	0.07	OK	0.009	Sym_Beta	0.07	0.05	17.3
84	SizeSel_2P_5_F2	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1	0.05	NA
85	SizeSel_2P_6_F2	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0	0.05	NA
86	SizeSel_3P_1_F3	217.033	54	2	5	500	200	OK	7.598	Sym_Beta	200	0.05	3.5
87	SizeSel_3P_2_F3	55.567	55	3	0.01	60	25	OK	6.320	Sym_Beta	25	0.05	11.4
88	SizeSel_4P_1_F4	276.637	56	2	1	500	110	OK	551.575	Sym_Beta	110	0.05	199.4*
89	SizeSel_4P_2_F4	0.506	57	3	0	1	0.09	OK	1.515	Sym_Beta	0.09	0.05	299.2*
90	SizeSel_4P_3_F4	225.070	58	2	1	500	120	OK	566.232	Sym_Beta	120	0.05	251.6*
91	SizeSel_4P_4_F4	0.505	59	3	0	1	0.05	OK	1.522	Sym_Beta	0.05	0.05	301.4*
92	SizeSel_4P_5_F4	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1	0.05	NA
93	SizeSel_4P_6_F4	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0	0.05	NA
94	SizeSel_5P_1_F5	211.867	60	2	1	500	210	OK	12.483	Sym_Beta	210	0.05	5.9
95	SizeSel_5P_2_F5	0.063	61	3	0	1	0.05	OK	0.008	Sym_Beta	0.05	0.05	13.3
96	SizeSel_5P_3_F5	106.299	62	2	1	500	210	OK	47.450	Sym_Beta	210	0.05	44.6
97	SizeSel_5P_4_F5	0.031	63	3	0	1	0.05	OK	0.010	Sym_Beta	0.05	0.05	31.7
98	SizeSel_5P_5_F5	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1	0.05	NA
99	SizeSel_5P_6_F5	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0	0.05	NA

*High CV >>50% .

Table 6. *Preliminary Run 6* (See Table 11 in Courtney 2016) non-recruitment parameter estimates; Parameters with a negative phase were fixed at their initial value; CV is calculated as the asymptotic standard error (Parm_StDev) divided by the estimated value (Value).

Num	Label	Value	Active_Cnt	Phase	Min	Max	Init	Status	Parm_StDev	PR_type	Prior	Pr_SD	CV (%)
16	SR_LN(R0)	8.789	1	1	2.3	13.82	7.04	OK	0.146	Normal	7.04	1000	1.7
65	InitF_1F1	0.046	45	1	0	1.9	0.1	OK	0.012	Normal	0.38	1000	26.1
74	SizeSel_1P_1_F1	171.635	46	2	1	500	100	OK	51.767	Sym_Beta	100.00	0.05	30.2
75	SizeSel_1P_2_F1	0.029	47	3	0	1	0.15	OK	0.011	Sym_Beta	0.15	0.05	37.7
76	SizeSel_1P_3_F1	251.752	48	2	1	500	243	OK	13.177	Sym_Beta	243.00	0.05	5.2
77	SizeSel_1P_4_F1	0.098	49	3	0	1	0.08	OK	0.051	Sym_Beta	0.08	0.05	52.0
78	SizeSel_1P_5_F1	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1.00	0.05	NA
79	SizeSel_1P_6_F1	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0.00	0.05	NA
80	SizeSel_2P_1_F2	130.939	50	2	1	500	120	OK	9.218	Sym_Beta	120.00	0.05	7.0
81	SizeSel_2P_2_F2	0.079	51	3	0	1	0.15	OK	0.020	Sym_Beta	0.15	0.05	26.0
82	SizeSel_2P_3_F2	230.031	52	2	1	500	220	OK	14.903	Sym_Beta	220.00	0.05	6.5
83	SizeSel_2P_4_F2	0.057	53	3	0	1	0.07	OK	0.026	Sym_Beta	0.07	0.05	45.8
84	SizeSel_2P_5_F2	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1.00	0.05	NA
85	SizeSel_2P_6_F2	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0.00	0.05	NA
86	SizeSel_3P_1_F3	224.418	54	2	5	500	200	OK	12.015	Sym_Beta	200.00	0.05	5.4
87	SizeSel_3P_2_F3	52.088	55	3	0.01	60	25	OK	9.247	Sym_Beta	25.00	0.05	17.8
88	SizeSel_4P_1_F4	108.567	56	2	1	500	110	OK	3.872	Sym_Beta	110.00	0.05	3.6
89	SizeSel_4P_2_F4	0.131	57	3	0	1	0.09	OK	0.017	Sym_Beta	0.09	0.05	12.8
90	SizeSel_4P_3_F4	10.746	58	2	1	500	120	OK	38.707	Sym_Beta	120.00	0.05	360.2*
91	SizeSel_4P_4_F4	0.036	59	3	0	1	0.05	OK	0.005	Sym_Beta	0.05	0.05	14.7
92	SizeSel_4P_5_F4	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1.00	0.05	NA
93	SizeSel_4P_6_F4	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0.00	0.05	NA
94	SizeSel_5P_1_F5	215.389	60	2	1	500	210	OK	25.063	Sym_Beta	210.00	0.05	11.6
95	SizeSel_5P_2_F5	0.064	61	3	0	1	0.05	OK	0.018	Sym_Beta	0.05	0.05	28.3
96	SizeSel_5P_3_F5	104.847	62	2	1	500	210	OK	101.137	Sym_Beta	210.00	0.05	96.5
97	SizeSel_5P_4_F5	0.030	63	3	0	1	0.05	OK	0.021	Sym_Beta	0.05	0.05	69.2
98	SizeSel_5P_5_F5	1.000	_	-88	1	24	1	NA	_	Sym_Beta	1.00	0.05	NA
99	SizeSel_5P_6_F5	0.000	_	-88	0	1	0	NA	_	Sym_Beta	0.00	0.05	NA

*High CV >>50% .

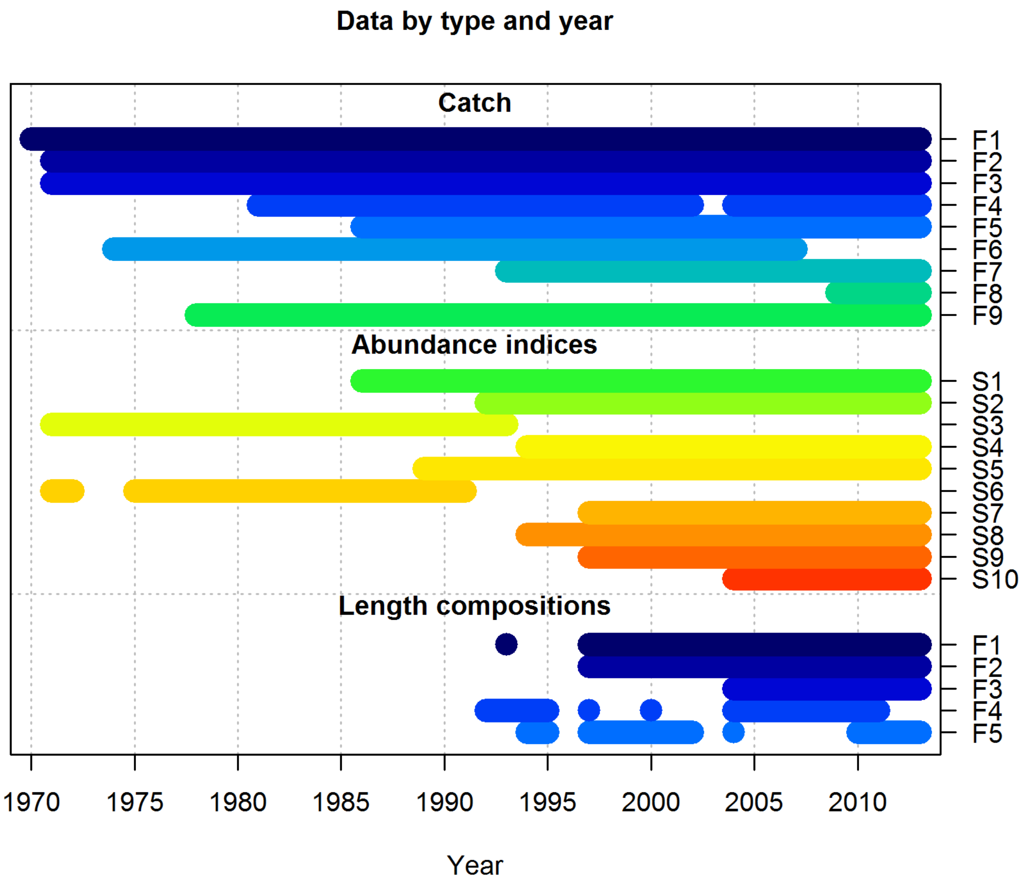


Figure 1. Time series of catch, abundance, and length composition data considered for use in the preliminary SS3 model runs (See Figure 7 in Courtney 2016).

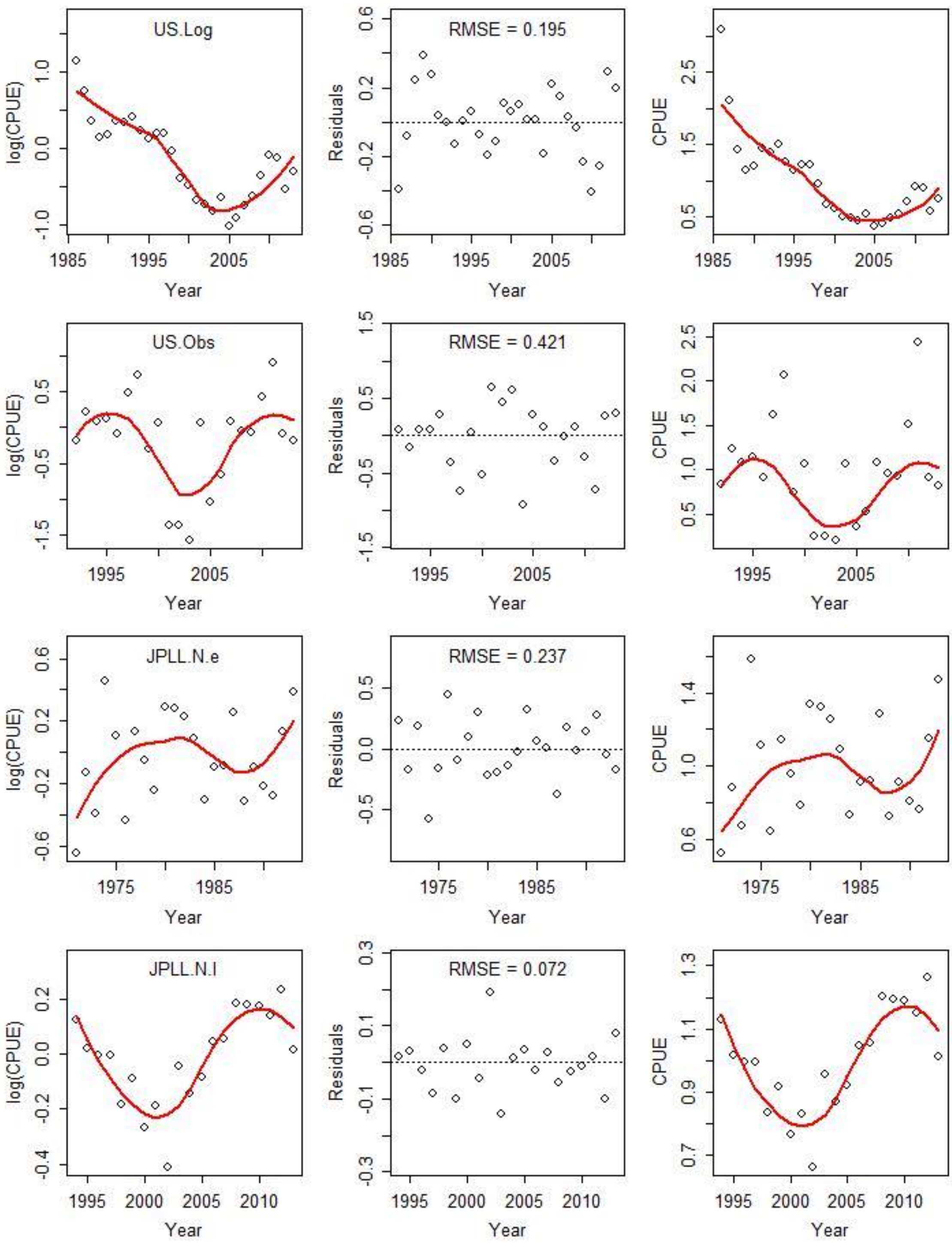


Figure 2. LOESS smoother fits used to estimate the $RMSE_{smoother}$ for each CPUE series in *Example Model Run 1* and *Example Model Run 2*; Left panel: Smoother fits to log (CPUE) data; Middle panel: Residual plots and estimated RMSE for each CPUE series and time-block (where applicable); Right panel: LOESS smoother fits illustrated for CPUE indices.

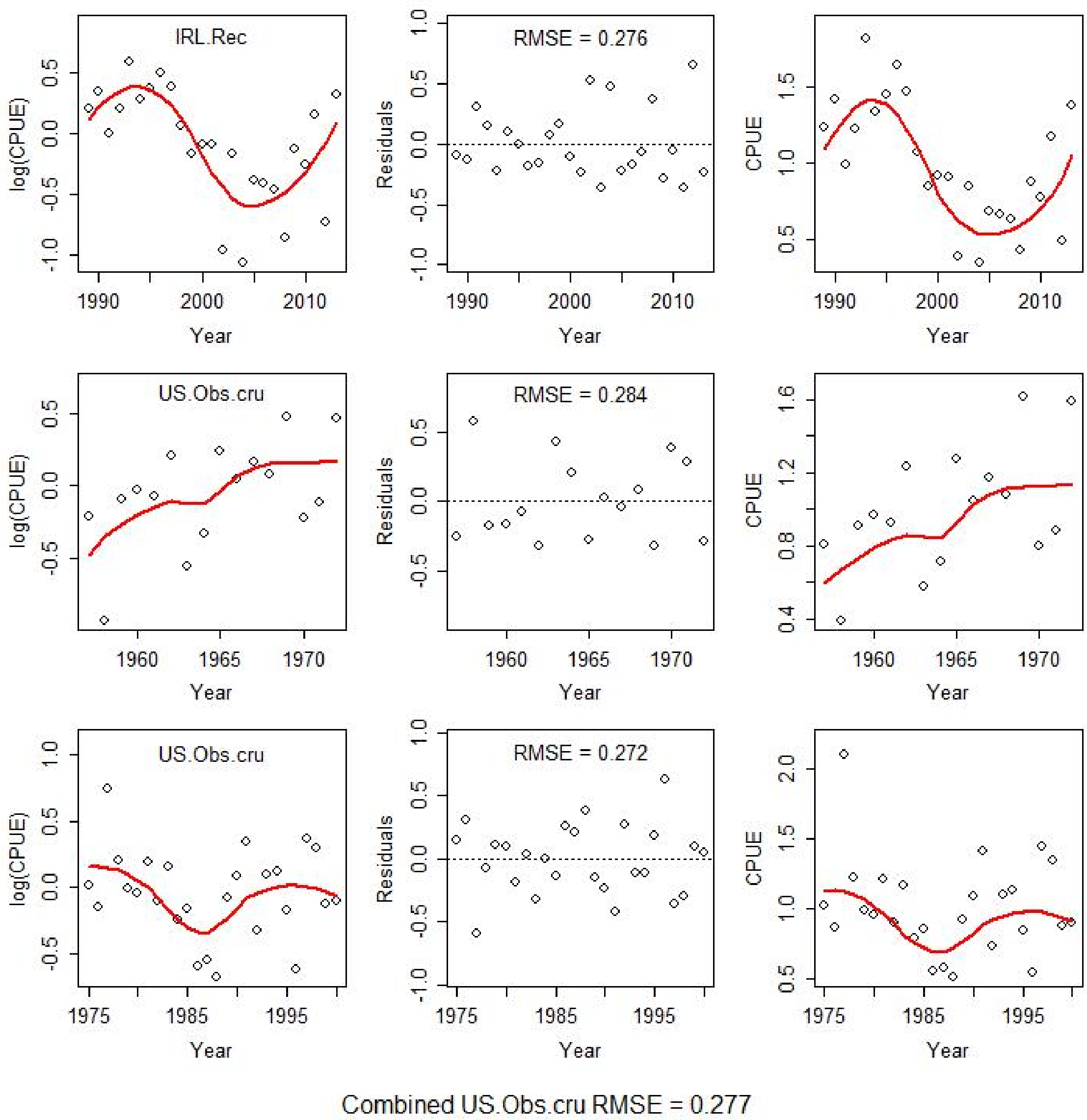


Figure 2. Continued.

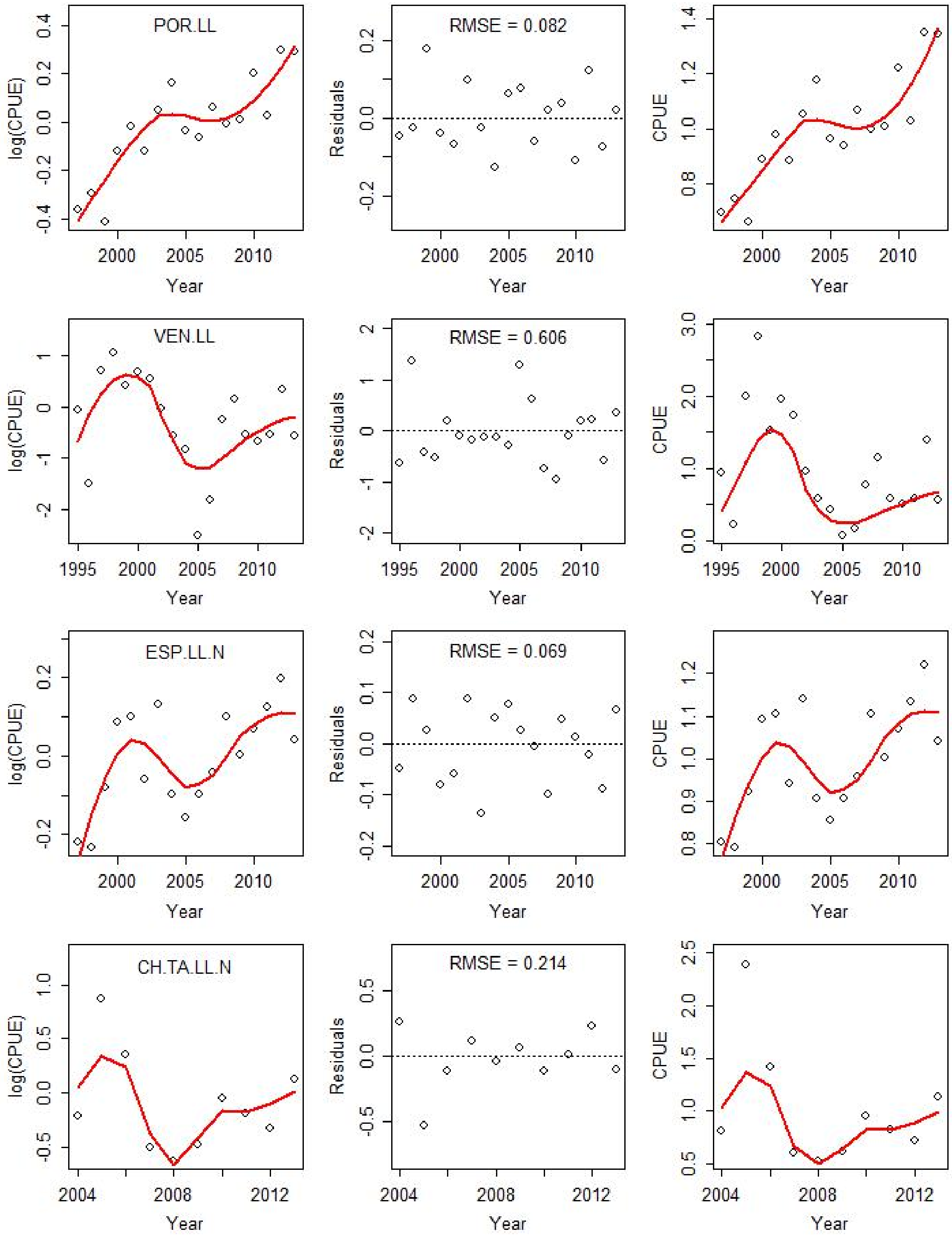


Figure 2. Continued.

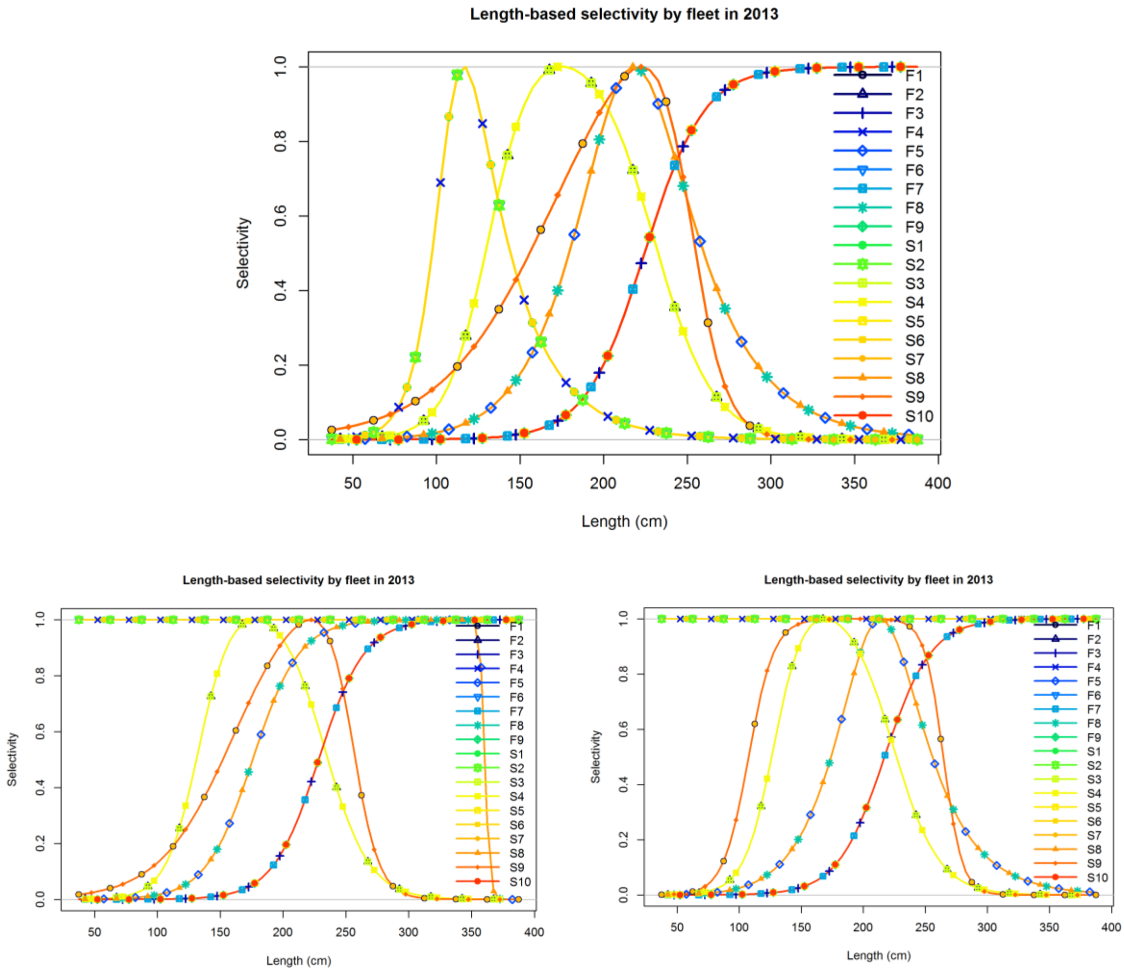


Figure 3. Selectivity at length (cm FL) obtained for previously conducted *Preliminary Run 6* (Courtney 2016; upper panel), *Example Model Run 1* (left lower panel), and *Example Model Run 2* (right lower panel).

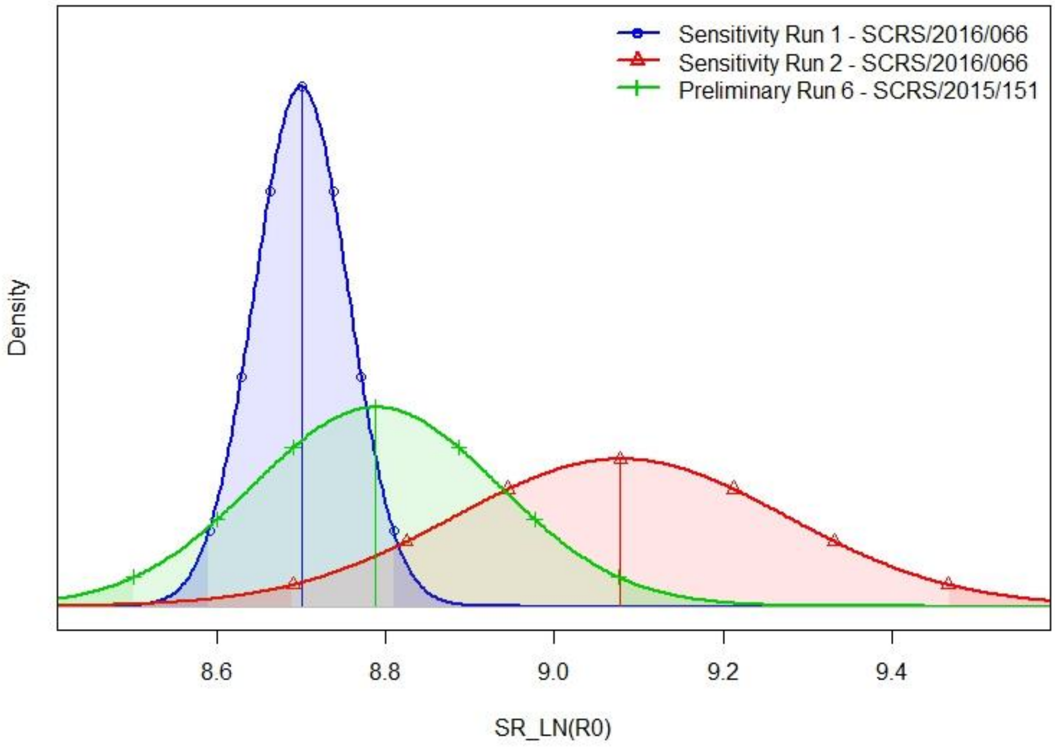


Figure 4. Density plots for the main scaling parameter in the model (equilibrium recruitment; SR_ln(R0)) among different model runs compared here.

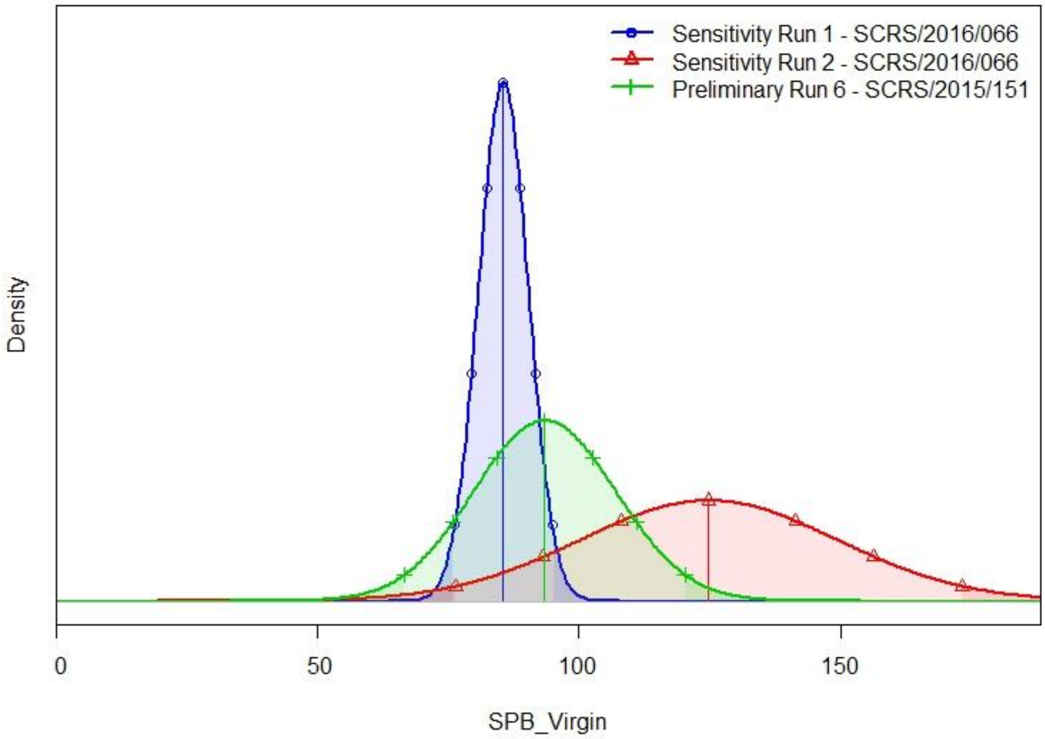
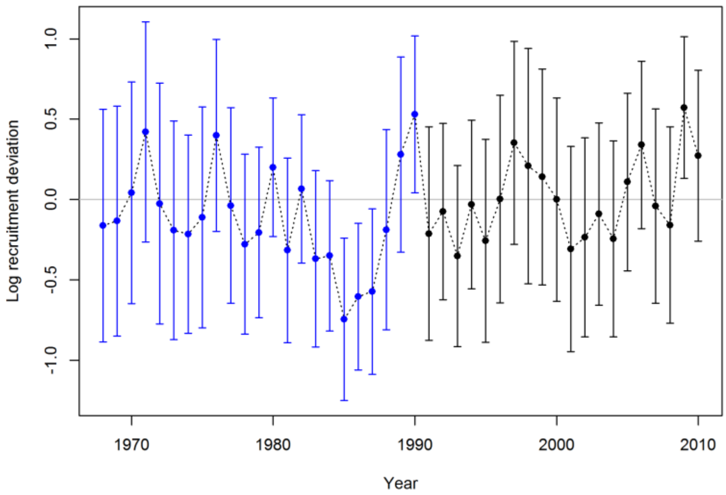


Figure 5. Density plots for equilibrium unfished spawning output (SPB_Virgin) among different model runs compared here.



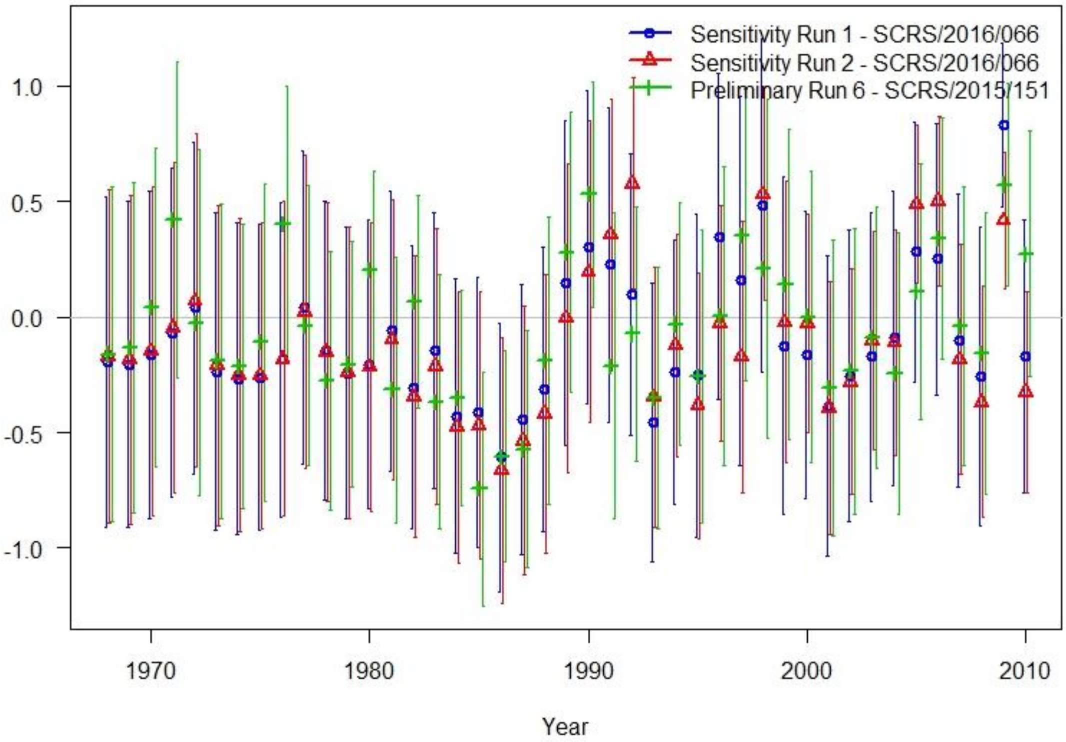


Figure 6. Estimated log recruitment deviations for the early (1968 – 1990, blue) and main (1991 – 2010, black) recruitment periods with associated 95% asymptotic intervals obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel).

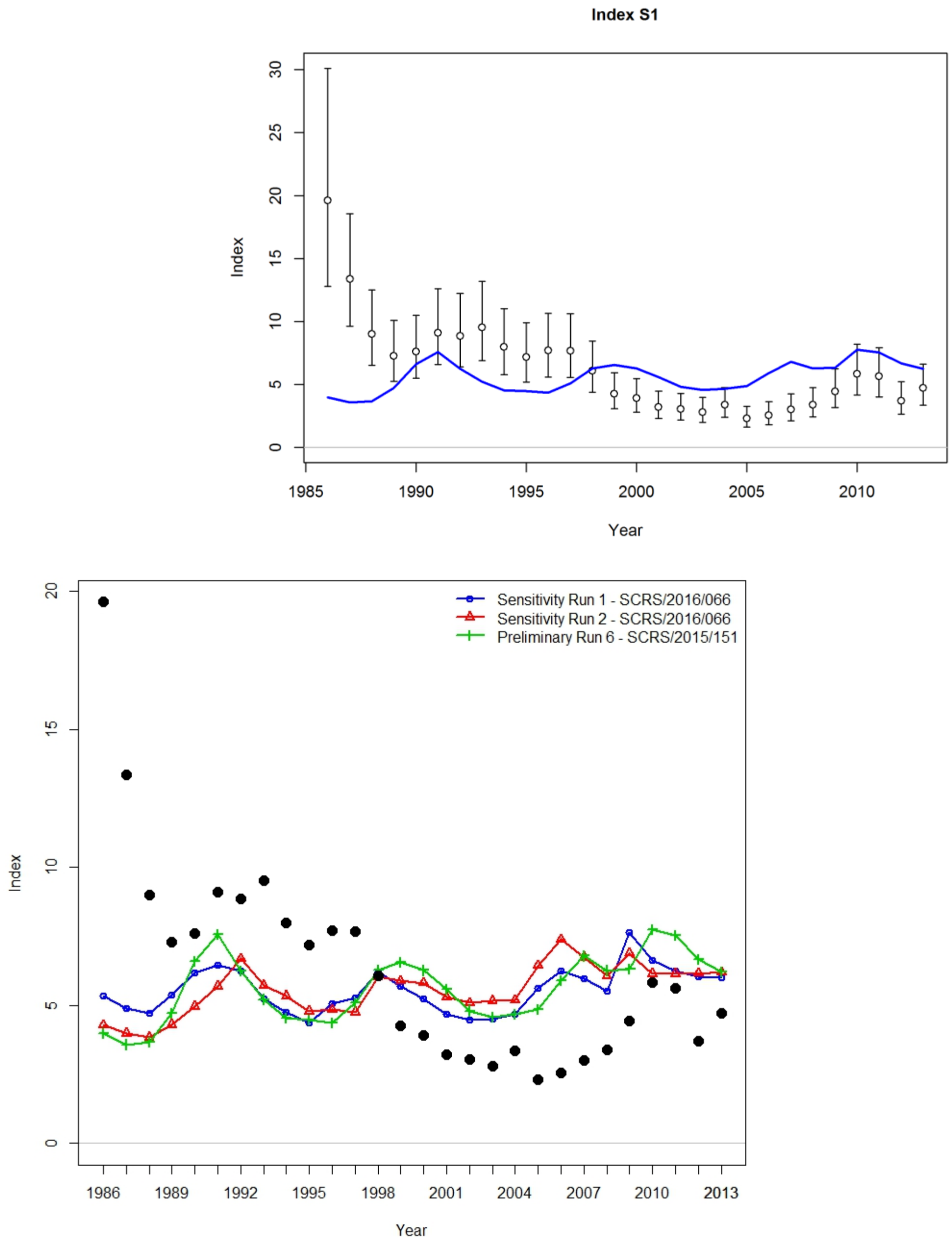


Figure 7. Index S1 (US-Log) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel); Note that index S1 (US-Log) was only included in the model for exploratory purposes, was not fit in the model likelihood (lambda = 0), and had no influence on model results or predicted values.

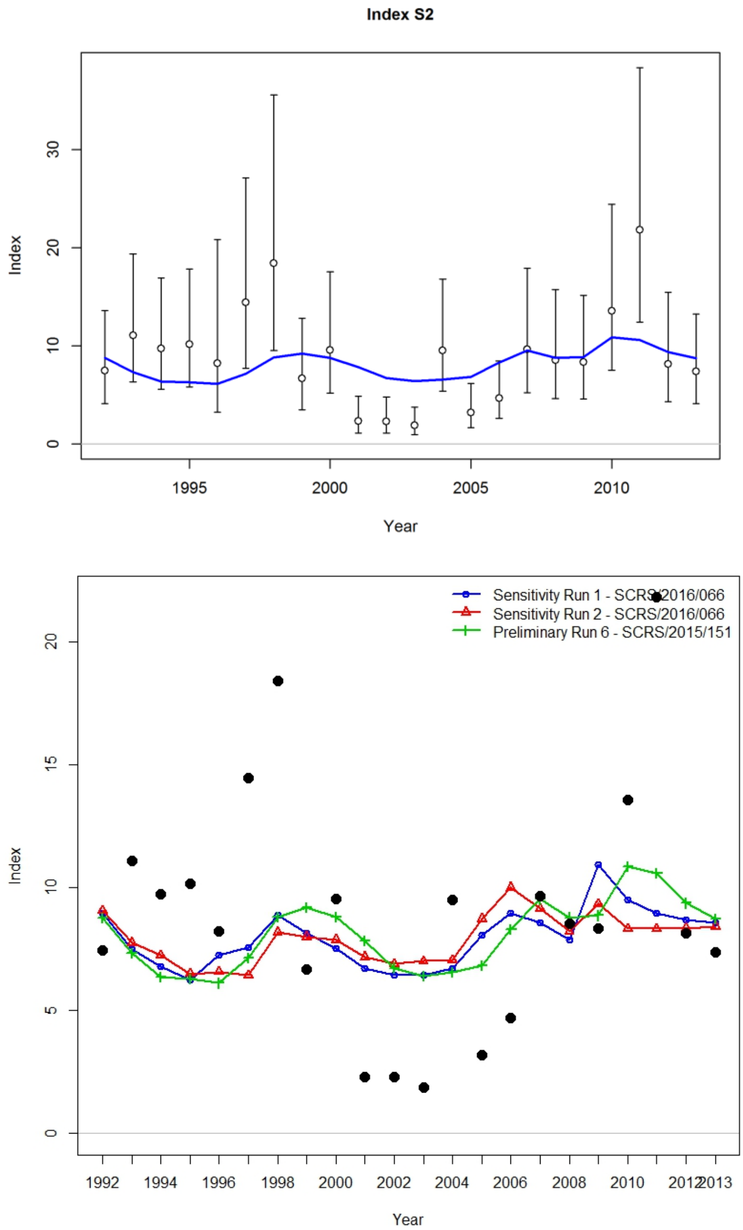


Figure 8. Index S2 (US-Obs) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel).

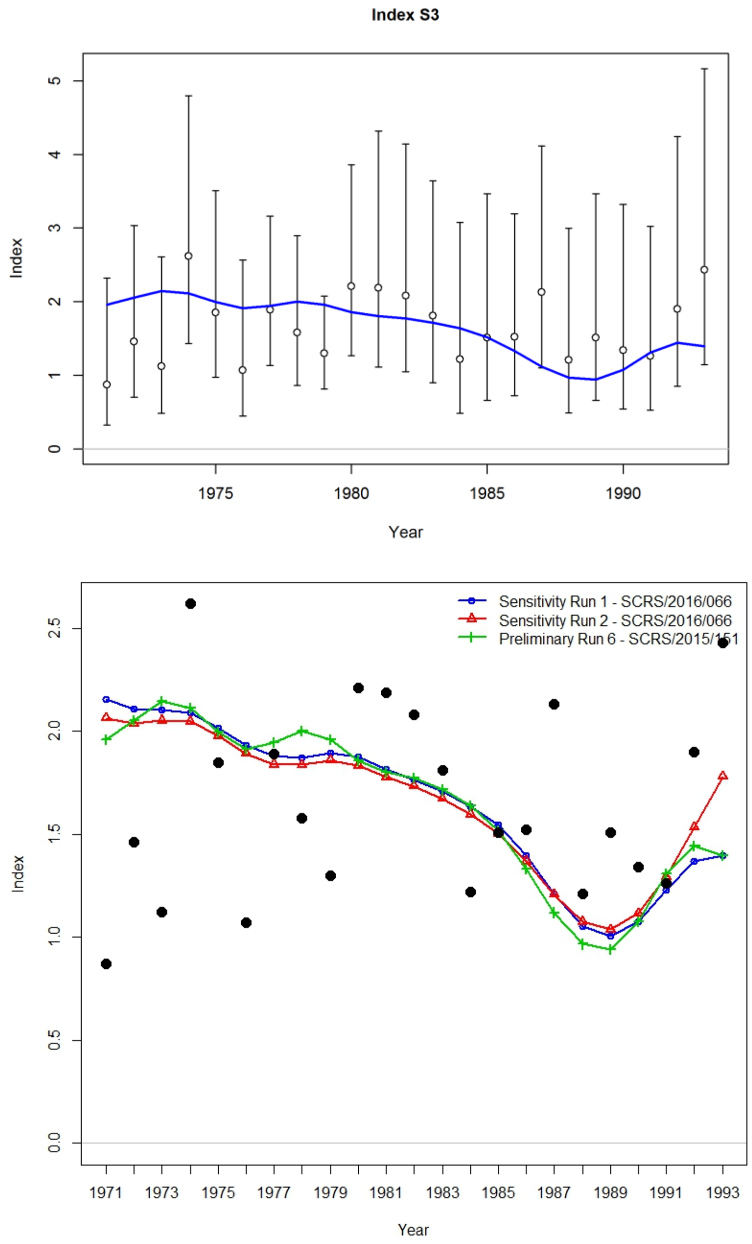


Figure 9. Index S3 (JPLL-N-e) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel).

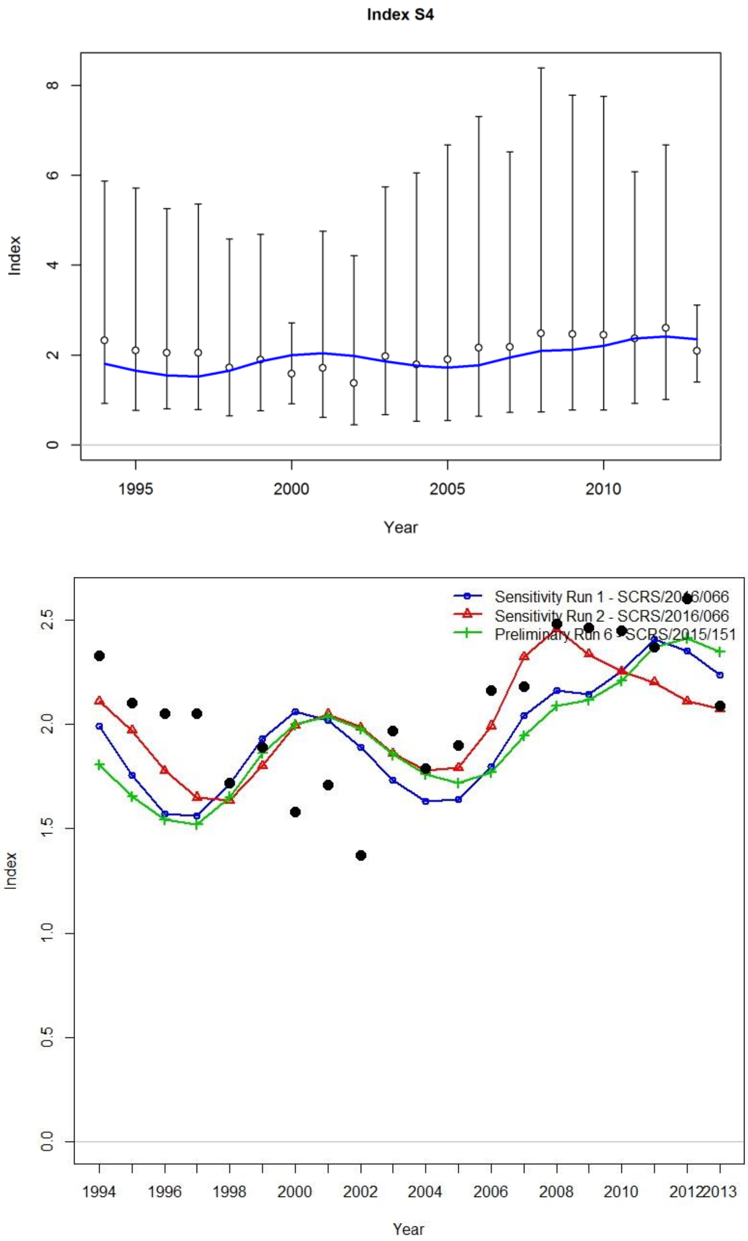


Figure 10. Index S4 (JPLL-N-l) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel).

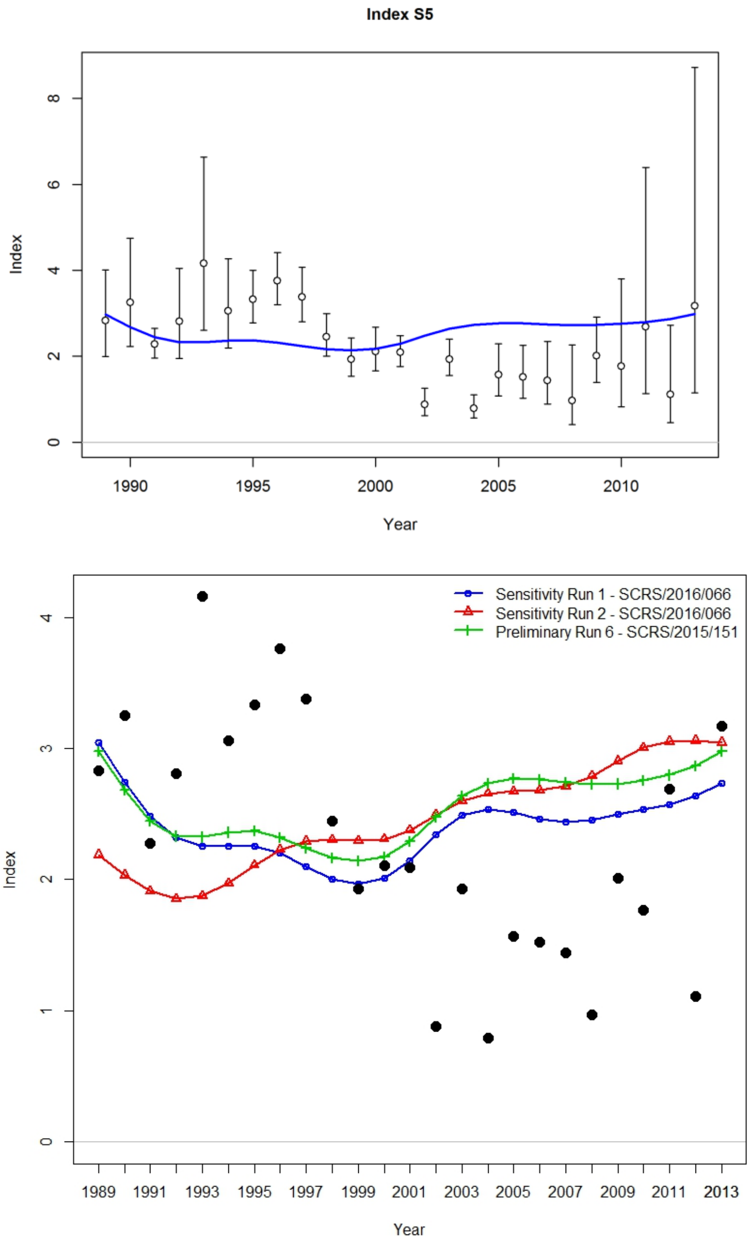


Figure 11. Index S5 (IRL-Rec) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel); Note that index S5 (IRL-Rec) was only included in the model for exploratory purposes, was not fit in the model likelihood (lambda = 0), and had no influence on model results or predicted values.

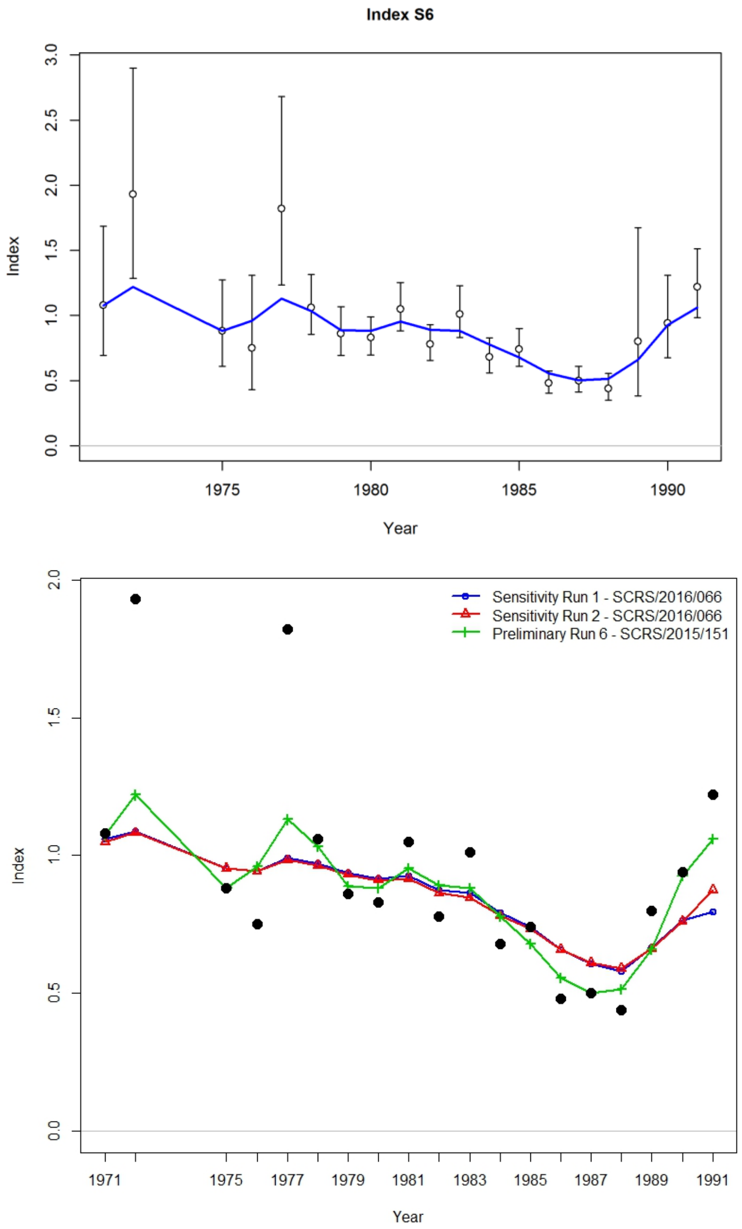


Figure 12. Index S6 (US-Obs-cru) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel); Note that index S6 (US-Obs_cru) overlapped with S2 (US-Obs) during the years 1992 – 2000, and data from those years were excluded from the model fit to S6.

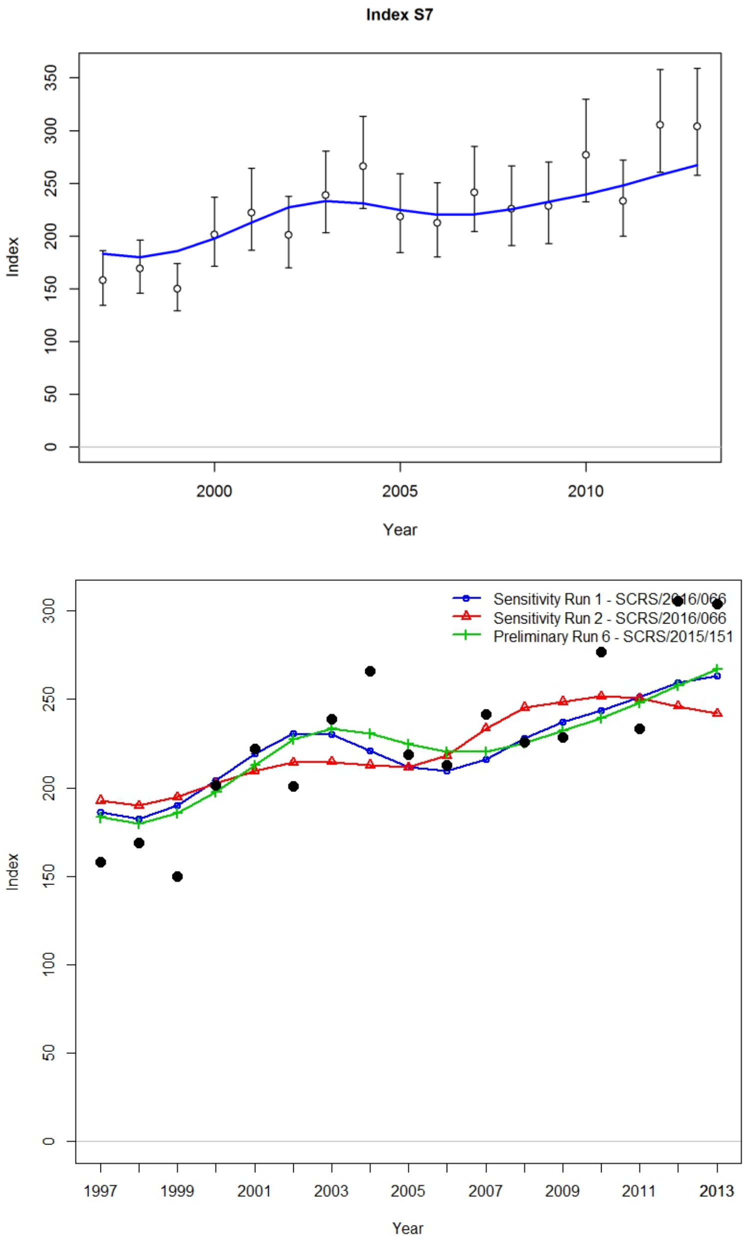


Figure 13. Index S7 (POR-LL) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel).

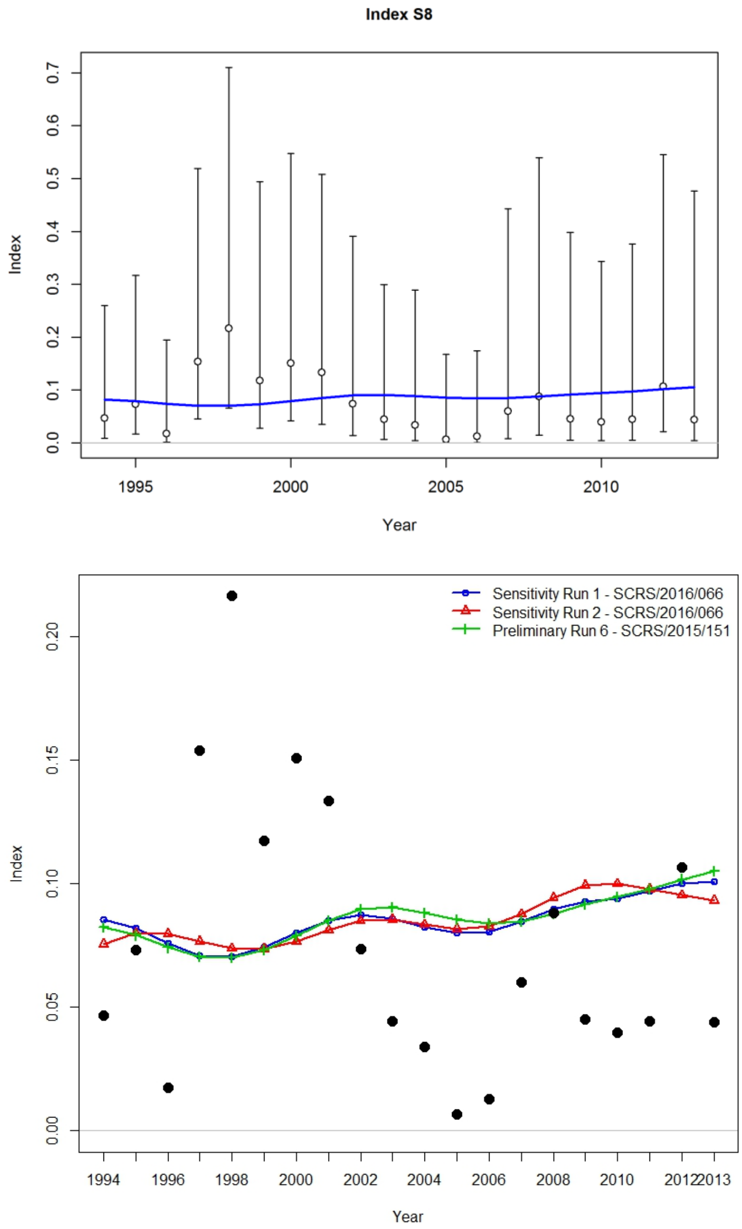


Figure 14. Index S8 (VEN-LL) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel).

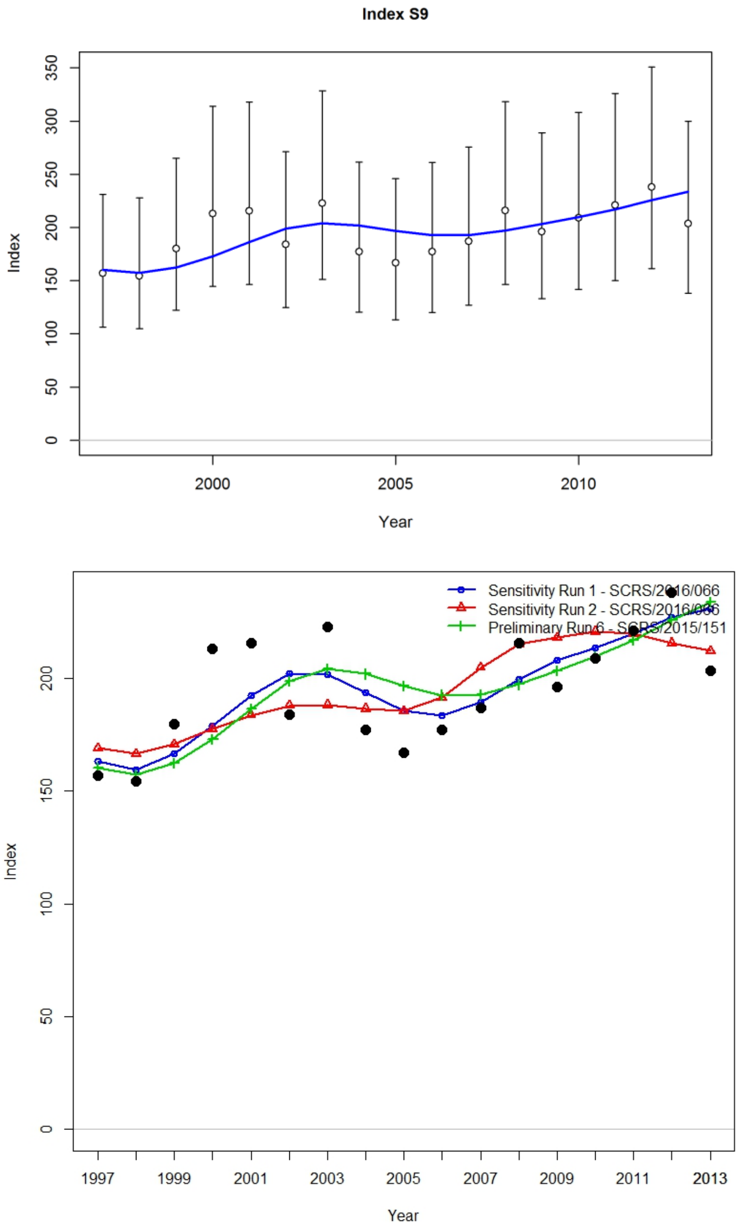


Figure 15. Index S9 (ESP-LL-N) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel).

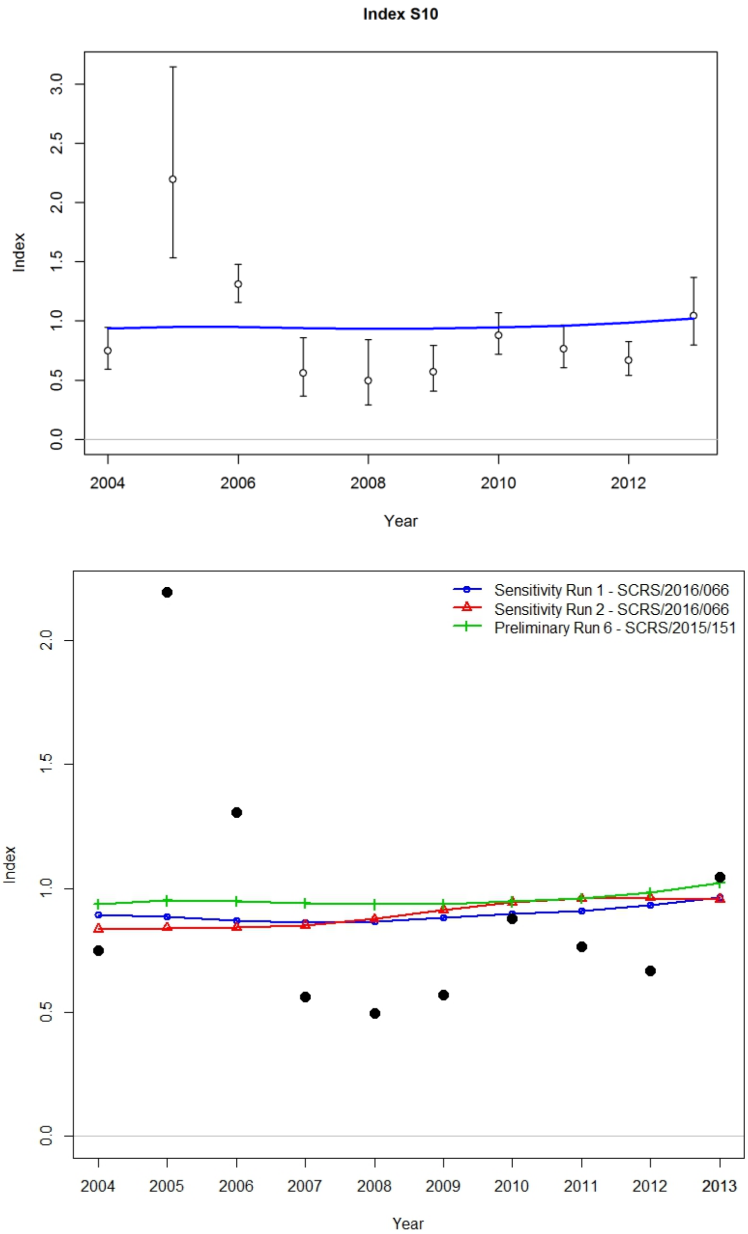


Figure 16. Index S10 (CTP-LL-N) predicted (blue line) and observed (open circles with 95% confidence intervals assuming lognormal error) standardized index of relative abundance obtained for previously conducted *Preliminary Run 6* (Courtney 2016, SCRS/2015/151; upper panel) and model runs compared here (lower panel).