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OPTIONS FOR AN OBSERVATION ERROR MODEL FOR NORTH ATLANTIC ALBACORE MSE

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SUMMARY

When conducting a Management Strategy Evaluation the Observation Error Model is the component of the Operating Model that generates fishery-dependent and/or fishery-independent resource monitoring data for input to a Management Procedure. In this paper we explore options for the Observation Error Model used to test the North Atlantic albacore Management Procedure. The options include (i) single indices derived from Operating Models abundance, catch per unit of effort and overall selectivity and (ii) multiple fleet specific indices for biased and unbiased CPUE. We recommend the unbiased multiple CPUE indices for the North Atlantic albacore evaluation of HCRs using MSE. Fleet specific CPUE and variability of the indices can explain the recent assessment of this stock.

RÉSUMÉ

Pour réaliser une évaluation de la stratégie de gestion, le modèle d'erreur d'observation est la composante du modèle opérationnel qui génère des données de suivi de la ressource dépendantes ou indépendantes des pêcheries à saisir dans une procédure de gestion. Dans le présent document, plusieurs possibilités de modèle d'erreur d'observation sont étudiées pour tester la procédure de gestion du germon de l'Atlantique Nord. Ces possibilités incluent : (i) des indices uniques calculés à partir de l'abondance, de la prise par unité d'effort et de la sélectivité globale de modèles opérationnels et (ii) indices spécifiques à de multiples flottilles pour des CPUE biaisées et non biaisées. Les indices de CPUE multiples non biaisés sont recommandés pour l'évaluation des HCR du germon de l'Atlantique Nord au moyen d'une MSE. La CPUE spécifique à la flottille et la variabilité des indices peuvent expliquer l'évaluation récente de ce stock.

RESUMEN

Al realizar una evaluación de estrategias de ordenación el modelo de error de observación es el componente del modelo operativo que genera datos de seguimiento del recurso dependientes y/o independientes de la pesquería para utilizarlos como entradas en un procedimiento de ordenación. En este documento se exploran las opciones para el modelo de error de observación utilizado para probar el procedimiento de ordenación para el atún blanco del norte. Las opciones incluyen (i) índices únicos derivados de la abundancia, captura por unidad de esfuerzo y selectividad global de los modelos operativos, e (ii) índices específicos de múltiples flotas para CPUE sesgadas y no sesgadas. Se recomiendan los índices de CPUE múltiples no sesgados para la evaluación de HCR para el atún blanco del Atlántico norte mediante una MSE. Las CPUE específicas de la flota y la variabilidad de los índices pueden explicar la evaluación reciente de este stock.

KEYWORDS

Albacore, Observation Error Model, Operating Model, Management Strategy Evaluation, Selectivity, Uncertainty

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Introduction

The foundational objective of the International Commission for the Conservation of Atlantic Tunas (ICCAT) is to maintain populations at levels that can permit the maximum sustainable yield (or above). For that, a series of recommendations have fostered the development of reference points (Rec. 11-04) and guidelines of decision making including Harvest Control Rules (Rec. 11-13 and Rec. 15-04). In 2016, the Commission adopted a multiannual conservation and management program for North Atlantic albacore (Rec. 16-06). This Rec. requests that "*in 2017, the SCRS shall refine the testing of candidate reference points (e.g., $SSB_{THRESHOLD}$, SSB_{LIM} and F_{TARGET}) and associated harvest control rules (HCRs) that would support the management objective expressed in paragraph 2 above. The SCRS shall also provide statistics to support decision-making in accordance with the performance indicators in Annex 2. The result of the analyses described in paragraph 12 will be discussed in a dialogue between scientists and managers to be organised in 2017, either during a meeting of the SWGSM or as an inter-sessional meeting of Panel 2. Based on the SCRS inputs and advice provided pursuant to paragraph 12 above and the dialogue process indicated in paragraph 13, the Commission shall then endeavor in 2017 to adopt HCRs for the North Atlantic albacore, including pre-agreed management actions to be taken under various stock conditions*".

In 2016, the ability of a series of Harvest Control Rules (HCR) to achieve management objectives for North Atlantic albacore was evaluated using Management Strategy Evaluation (MSE) (Merino *et al.*, 2016) and discussed in ICCAT's Panel 2 meeting (ICCAT, 2016a). That study used a MSE framework containing an Observation Error Model (OEM) that used the Operating Models' (OM) biomass time series with a normal error term to generate catch per unit of effort (CPUE) series that would be plugged into a biomass dynamic model in the Management Procedure (MP) component. This means that the analysis was undertaken using a theoretical CPUE index representative of the exploitable biomass and not the fishable biomass. ICCAT's 2016 Working Group on Stock Assessment Methods (WGSAM) suggested that consideration should be given to simulating actual CPUE series (ICCAT, 2016d). Also in 2016, the SCRS developed a schedule for the development of MSE and Harvest Control Rules, which included further evaluations of HCRs through MSE for North Atlantic albacore. In the workplan agreed by the SCRS for North Atlantic albacore as part of the multiyear Albacore Research program, priority was given to developing a OEM that considers actual CPUE series' structure, age-classes and other properties (ICCAT, 2016b).

In MSE an Operating Model is used to simulate resource dynamics in order to evaluate the performance of a Management Procedure. Where the MP is the combination of pre-defined data, together with an algorithm to which such data are input to provide a value for a management control measure. To link the OM and the MP it is necessary to develop an Observation Error Model to generate fishery-dependent or fishery-independent resource monitoring data. The OEM reflects the uncertainties, between the actual dynamics of the resource and perceptions arising from observations and assumptions by modelling the differences between the measured value of a resource index and the actual value in the OM (Kell and Mosqueira, 2017c). In this paper we describe alternatives for the development of an OEM for use in the North Atlantic albacore MSE.

The OM is based upon the Multifan-CL assessment conducted during the 2013 ICCAT North Atlantic Albacore stock assessment and a series of alternatives (Merino *et al.*, 2017). While the Management Procedure is based on the biomass dynamic stock assessment conducted in 2016 (Kell *et al.*, 2017b). The biomass dynamic stock assessment model assumes that total historical catches are known without error and uses indices of relative abundance to estimate population growth rate (r) and virgin biomass (K). In this paper we explore options for an OEM by combining OMs biomass trends, catch per unit of effort series, fleet specific and overall selectivity patterns and analyses of the indices used in the latest stock assessment of North Atlantic albacore, including their residuals of fit. We develop a procedure to simulate CPUE from the OM and compare the properties of the simulated to those used in the assessment. We also explain how the results shown here encourage modifications to the MSE framework used in 2016 in order to produce more accurate results.

Material and Methods

When fitting the albacore stock assessments, commercial catch per unit effort (CPUE) is used as a proxy for relative abundance. In MSE, indices of abundance can be generated from OMs. Originally ten scenarios were considered for North Atlantic albacore when fitting Multifan-CL. The scenarios are described and the results summarized in (Kell *et al.* 2017a). Following this, additional OM scenarios have been proposed and these are documented. Using the trajectories of the OMs, a series of indices have been generated. First, estimated overall stock, catch, fishing mortality and selectivity values have been used to generate three individual indices. The OMs were initially conditioned from the fits to CPUEs in the 2013 stock assessment and they include estimated selection patterns and residuals, which are explored and compared to the residuals of the 2016 biomass dynamic assessment. The 2016 stock assessment of this stock was made using a biomass dynamic model that was fitted using five indices (**Table 1**) as proxies of relative abundance (ICCAT, 2016c). Three of them were also part of the 2013 assessment with Multifan-CL and therefore included in the updated OMs (ICCAT, 2013; Merino *et al.*, 2017). In 2013, US and Venezuelan LL indices were included in the China Taipei index. US index refers to ages 3-8. In order to estimate US and Venezuelan LL indices we used the selectivity of the KoreaPaCu LL index from 2013. This would allow covering the range of ages with the selected indices. From these, we have generated four individual fleet's indices using their selectivity patterns. In addition, an additional index has been generated for Chinese Taipei longline considering a 10% bias (following this fleet's CPUE residuals of fit (ICCAT, 2016c)).

The five alternatives for generating CPUE indices are the following:

1) *$Index_1$ ~Stock:* In the previous MSE developed for this stock (Merino *et al.*, 2016), a single index was generated adding a normal error term to each of the stock trajectories. This means that the indices were representative of the exploitable biomass and not the fishable biomass.
   $Index_1 = Stock\ x\ \varepsilon$ (eq. 1)

2) *$Index_2$ ~CPUE*: The OMs contain information of alternative trajectories for catch and fishing mortality (*fbar*) that do not necessarily coincide with stock biomass trends. We have estimated a single overall CPUE index from the total catch and estimated harvest rates. This index is still representative of the exploitable biomass and not the fishable biomass as the catch and harvest rates used are not age specific.
   $Index_2 = \frac{\text{Total Catch}}{\text{fbar}} x\ \varepsilon$ (eq. 2)

3) *$Index_3$ ~CPUE & Selectivity*: In this case, the catch per unit of effort is estimated corrected by the selectivity pattern. The catch of each age class (*a*) is multiplied by its overall selectivity (across fleets) and divided by the overall fishing mortality (eq. 3). Here also a single index is generated:

   $Index_3 = \frac{\sum_a^{max} Catch_a\ x\ Selectivity_a}{\text{fbar}} x\ \varepsilon$ (eq. 3)

4) *$Indices_4$ ~ Fleet specific CPUE & Selectivity*: In this case, the catch per unit of effort is estimated with each fleet's selectivity pattern. The catch of each age class (*a*) is multiplied by its fleets' selectivity and divided by the overall fishing mortality (eq. 4). Here, four fleets' (*f*) indices are generated:

   $Index_{4,f} = \frac{\sum_a^{max} Catch_{a,f}\ x\ Selectivity_{a,f}}{fbar} x\ \varepsilon$ (eq. 4)

5) *$Indices_5$ ~ Fleet specific CPUE, Selectivity and bias*: Finally, we have replicated *$Indices_4$* but with a modification for Chinese Taipei LL index. The residuals of fit for this fleet's index in 2016 suggest a possible bias and we have explored a 10% yearly increase in catchability.

The indices generated are used to fit the biomass dynamic model *mpb*, which was used in the 2016 stock assessment of North Atlantic albacore (ICCAT, 2016c). The fits are made using the same specifications and modelling choices as in 2016, i.e. using the Fox model, CPUE series from the years specified in **Table** 1 and the same starting values used in 2016. The estimated trajectories of relative biomass and the residuals of fit of indices 4 and 5 are compared to the 2016 stock assessment.

Then, the base case OM is projected into the future with a 40% CV on its stock recruitment relationship. The projected OM is then used to generate the five indices for fitting with the biomass dynamic model.

Finally, variability is added to the simulated indices for 2016. Series of indices are generated with increasing variability to explore the range of variability that the model can handle and regularly produce reliable estimates of biomass and fishing mortality.

Results

Figures 1 and 2 show the base case OM from 2013 Multifan-CL and the overall selectivity pattern of North Atlantic albacore that are used to generate the indices 1, 2 and 3 (**Figure 3**). In **Figure 3**, it is noted that the peaks of stock biomass are anticipated by the indices built upon CPUE. For example, in the mid 1950s decade Indices 2 and 3 show a major peak which is noted on the stock trajectory two-three years later at lower level. The same happens at the end of the series, where both Index 2 and Index 3 show a sharp increase in 2010-2012, which is smoother in the stock. Also, the indices decrease in the last year (Index 3) and two years (Index 2), that may anticipate a decline of the overall stock.

Figure 4 shows the monthly CPUE indices used to fit Multifan-CL scenarios in 2013 and that are compared to the indices used in the 2016 stock assessment (**Figure 5**). Spanish baitboat index trajectory increases overall in both series with a sharp increase in the latest (**Figure 5**). The Japanese LL index used in the 2016 assessment started in 1998 with a declining trend followed by a recovery from the mid 1990s to 2003, which is also seen in the 2013 index. From 2004 to 2007 the index declined and since then increased at the same pace as the overall indices trend. Both Venezuelan LL and US continuity LL indices follow an increasing pattern since the early 1990s, but it is not directly comparable with the index used in 2013, that contains seldom information for these years. In 2016, the stock assessment was mostly driven by the Chinese Taipei LL index (ICCAT, 2016c). In 2013, the Chinese Taipei index shows an increasing trend that is appreciated since the end of the 1990s, with a decline after 2005 and a recovery after 2008. In 2016, the index shows a similar trend without the marked decline in 2005, but followed by a notable increase in the last two years of the series, which could eventually produce a marked increase in the estimated stock biomass.

Figures 6 and 7 show the residuals of fit from the 2013 stock assessment with Multifan-CL and the residuals from 2016 stock assessment with the biomass dynamic model. Note the differences on the residuals for China Taipei LL, which follow opposite trends in 2013 and 2016. The residuals of KoreaPaCuLL and Venezuela LL also follow opposite trends while Japanese LL residuals are homogeneously distributed in 2013 but show a negative trend in 2016. Note that in the 2016 stock assessment, the last two years of the Japanese LL index were removed from the analysis (ICCAT, 2016c).

Figure 8 shows the selectivity's of the fleets used to generate CPUE indices 4 and 5. Note that the Spain BB fishes the lowest age classes of the stock and therefore, this fleet is prone to perceive the impacts of variability in recruitment.

Figure 9 shows the four simulated CPUE series using data from the OMs for the periods shown in **Table 1**. Note that Indices 5 are equivalent to Indices 4 except for China Taipei. Both the trajectories of 4D and 5D are compared to the Chinese Taipei late Longline index in **Figures 4 and 5**, the indices used in the 2013 and 2016 stock assessments. Both indices 4D and 5D show the declining trend after 2005 (seen in the 2013 stock assessment index) and the marked increase in the last years, which also follows the recruitment peak shown in **Figure 1** (top) after 2008.

Using the specifications of the 2016 stock assessment, i.e. Fox model, starting values used, indices range, catch data (**Table 2**), the biomass dynamic model was fitted to the five sets of indices.

Figure 10 shows the relative biomass trajectory from the base case OM and the estimated trajectories using the indices explored here. **Figure 10** also shows the estimated trajectory in the 2016 stock assessment. The OM shows a declining trend until the 1990s decade where a recovery is appreciated towards levels above B_{MSY}, that are surpassed in the last year. The main discrepancy across the scenarios with the biomass dynamic model relies on the year where the recovery starts and its final point. In 2016, the albacore working group estimated that the stock started to recover at the end of the 1980s, whereas the indices tested here estimate that it starts at the end of the 1990s except for the group of Index 5 (10% bias assumed for China Taipei LL index), which also estimates an earlier recovery. There is also discrepancy on the endpoint. Adding CPUE and selectivity information to the indices sharpens the recovery of the stock in the final years. However, the fits to Indices 1-4 estimate the biomass in the last year to be below B_{MSY}, in contrast to what is shown in the OM. The trajectory and final point of the fit using the bias index for China Taipei (*Index 5*) is similar to the results obtained in the 2016 stock assessment.

Figure 11 shows the residuals of fit from Indices 4 and 5. The residuals of fit to Indices 4 show an appreciable autocorrelation in the case of KoreaPaCu LL and Japan LL. However, the estimated trajectory for both indices 4 and 5 seems to be consistent with both indices. The Spanish BB index also follows a similar pattern in both fits but with smaller deviations for the Indices 4 fit.

A series of sensitivity runs were made in 2016 to elucidate the influence of each of the indices and this highlighted that China Taipei LL was the most influential index of the assessment. However, the index used may be biased in relation to the estimated biomass (see **Figure 7**). Here, the fit using Index 4 shows a more homogeneous distribution of residuals for China Taipei.

The base case OM is projected into 2035 with a 40% CV on its stock recruitment relationship (**Figure 12**). The projected OM is used to generate the five indices (**Figure 13**) and they are used to fit the biomass dynamic model with catch from the OM (**Figure 14**). The bias index for China Taipei was 3% this time. The simulated indices show a declining trend in the last years except for the China Taipei indices with and without bias. The residuals of fit of Indices 4 and 5 are shown in **Figure 15**. **Figure 14** again shows that adding fleet specific selectivity information improves the estimate of relative biomass. In this case too, there are differences between the biased and unbiased scenarios. The residuals show autocorrelated patterns for KoreaPaCu LL and Japan LL. With regards to China Taipei LL, the fit to the 3% index also shows a positive bias.

Next was to explore the impact of variability in the indices (*Index 4*) on the biomass dynamic model's capacity to estimate biomass and fishing mortality trends of the Reference Case OM accurately. We run the indices simulated for 2016 with a lognormal deviation at each point: Indexi,t=Indexi,t x logN(0, CV). 100 iterations were run with each randomized index for each CV value explored and compared to the model estimates with CV=0. **Figure 16** shows the estimated relative biomass and fishing mortality with CV=0 (green), averaged estimate for each CV (blue) and each of the iterations within each group (black). **Figure 16** shows that the same group of indices (Index 4) produces stable estimations across iterations. This **Figure** also shows that while increasing the CV of the indices, the average estimate deviates from the estimate with CV=0, and does it in two ways, i.e. two groups or types of trajectories are seen, both at biomass levels above the estimate with CV=0. A group of trajectories does not seem to estimate the historical exploitation of the stock and estimate that the stock has been well above B_{MSY} since 1930s. The second group is somehow an intermediate trajectory of the previous and the trajectory with CV=0. Here, the stock declines to B_{MSY} and recovers since 1980s approximately.

Discussion

The available fisheries-dependent information is used to generate CPUE series for use in stock assessment as abundance indices. ICCAT's albacore working group recognizes the difficulty on collecting reliable CPUE indices for stock assessments (ICCAT, 2013). The indices used in the last two assessments of this the North Atlantic albacore stock show conflicting trends, potential bias and variability that produce impacts on assessments' results. The conflicting trends observed reflect the abundance of different fractions of the population exploited by each of the fleets fishing albacore. For example, Spain baitboat fishes individuals from ages 1-3 mostly and hence, their indices are more influenced by recruitment variability. Japanese longlines fish young individuals (mostly age 4) but also mature. China Taipei longline and US and Venezuela longlines mostly exploit adults (age 4 and beyond). The 2016 stock assessment was mostly driven by the China Taipei index. The residuals of the 2016 stock assessment suggest marked biases for the China Taipei index that may have produced an overly optimistic view of stock status. With regards to variability, this reflects observation or measurement errors and could potentially also explain the high values seen in the China Taipei index for the years 2014 and 2015.

In order to generate simulated CPUE indices for use in a MSE framework and for them to be comparable to the indices currently used, a series of alternatives are proposed in this document. All alternatives pivot around the trends and parameters of the Operating Models conditioned from the 2013 stock assessment (Merino *et al.*, 2017). First, *Index 1* is simulated by adding a normally distributed error term to the stock biomass. This index was used in the preliminary MSE framework (Merino *et al.*, 2016). This index is technically easy to implement on the MSE but reflects the abundance of the entire population and therefore, does not reflect the different trends potentially observed when using fishery dependent information to build CPUE indices. The same problem is found for *Index 2* which is directly estimated from catch and overall fishing mortality trends from the Operating Models. Third, *Index 3* is also a single index but reflects the overall selectivity of the stock. Using this index will still not permit simulating conflicting trends but it will capture the abundance of the exploitable population, as requested by the WGSAM (ICCAT, 2016d).

Index 4 and *Index 5* aim at generating fleet specific indices that reflect their selectivity pattern and catch. Results show that the fits to the biomass dynamic model are very similar when using a single index with the overall selectivity pattern (*Index 3*) and when generating fleet specific indices (*Index 4*). However, the simulated fleet specific indices allow generating conflicting trends and probably reflect better the CPUE series used in the 2016 stock assessment. *Index 5* was designed to produce an overly optimistic stock assessment and to compare with the China Taipei index used in 2016. This was achieved by adding a 10% increasing trend in catchability since the beginning of the series and the residual patterns are comparable to the 2016 stock assessments. However, using *Index 5* in the MSE framework would require estimating the amount of bias for the China Taipei index in the future.

Using *Index 4* as a reference, several iterations were run with lognormal variability added to each of the points of the indices. This aims at reflecting measurement error on the CPUE indices and can potentially generate fits comparable to the 2016 stock assessment too. In brief, using *Index 4* would allow simulating a number of potentially conflicting indices that would reflect each fishery's performance and assign deviations from abundance to measurement or observation error. The MSE framework is run iteratively and it is expected that some of the simulated stock assessments within the Management Procedure component will reflect the state of the stock accurately while others will do it with error.

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Index	*Years used*
Chinese Taipei late Longline	1999-2014
Japan bycatch Longline	1988-2012
Spanish Baitboat	1981-2014
US continuity Longline	1987-2014
Venezuela Longline	1991-2014

Table 1. CPUE series used in the 2016 stock assessment and their time range.

Software	Model	Catch series	Starting values
mpb	Fox (biomass dynamic)	1930-2014	Intrinsic growth rate: r=0.1 Carrying capacity: K= 3.6 x 10^6 tonnes Biomass at t=0 (fixed): 1 x K

Table 2. Specifications of the biomass dynamic model used in the 2016 stock assessment.

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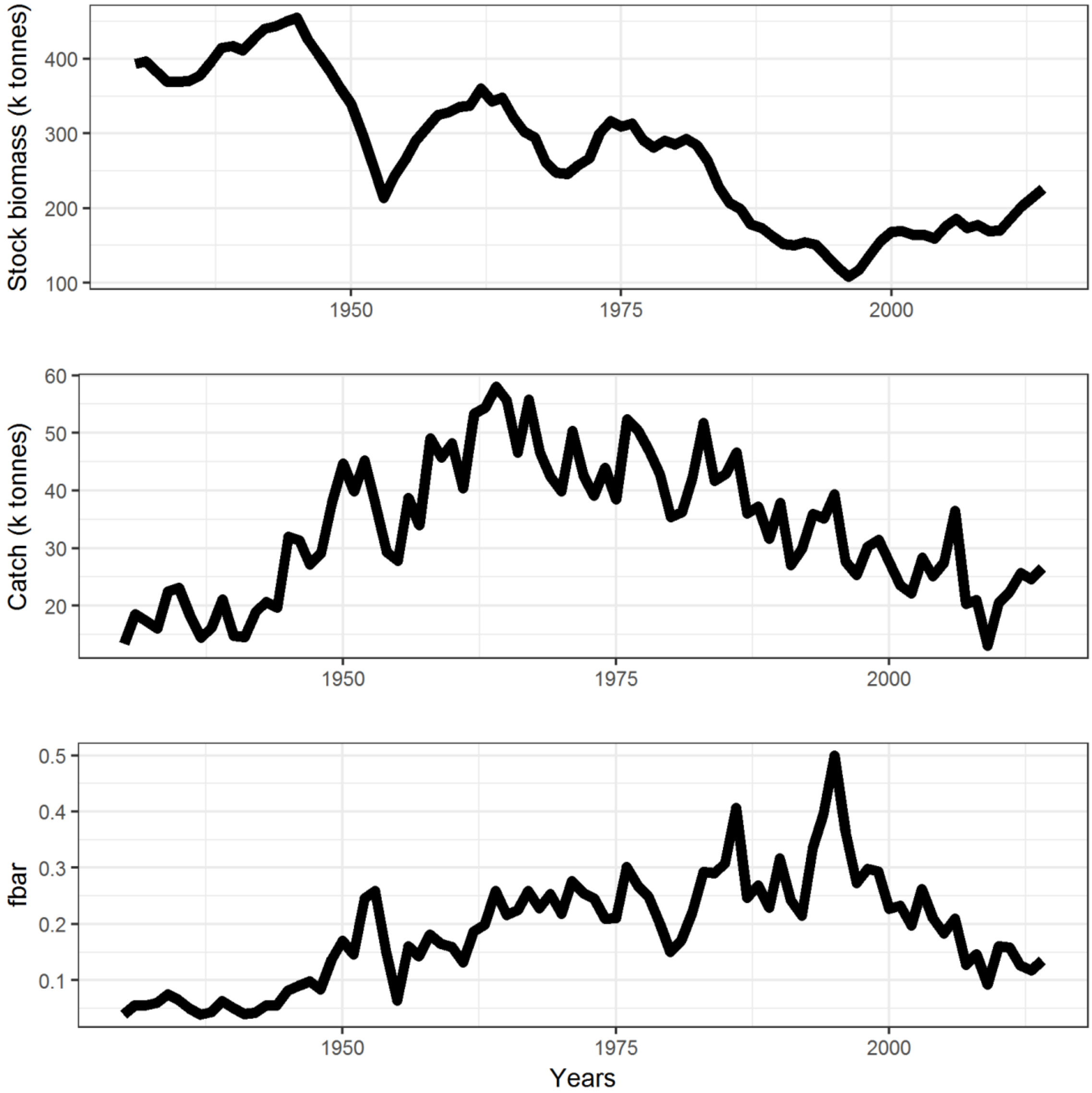
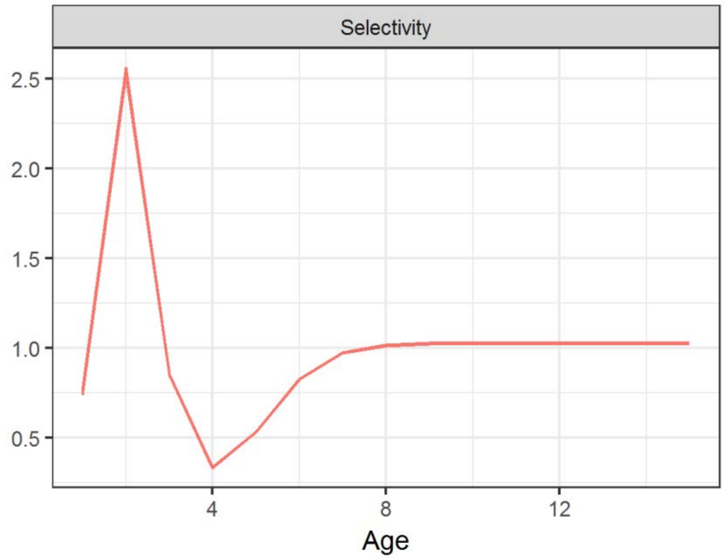


Figure 1. Time series of stock biomass, catch and fishing mortality from the base case OM.



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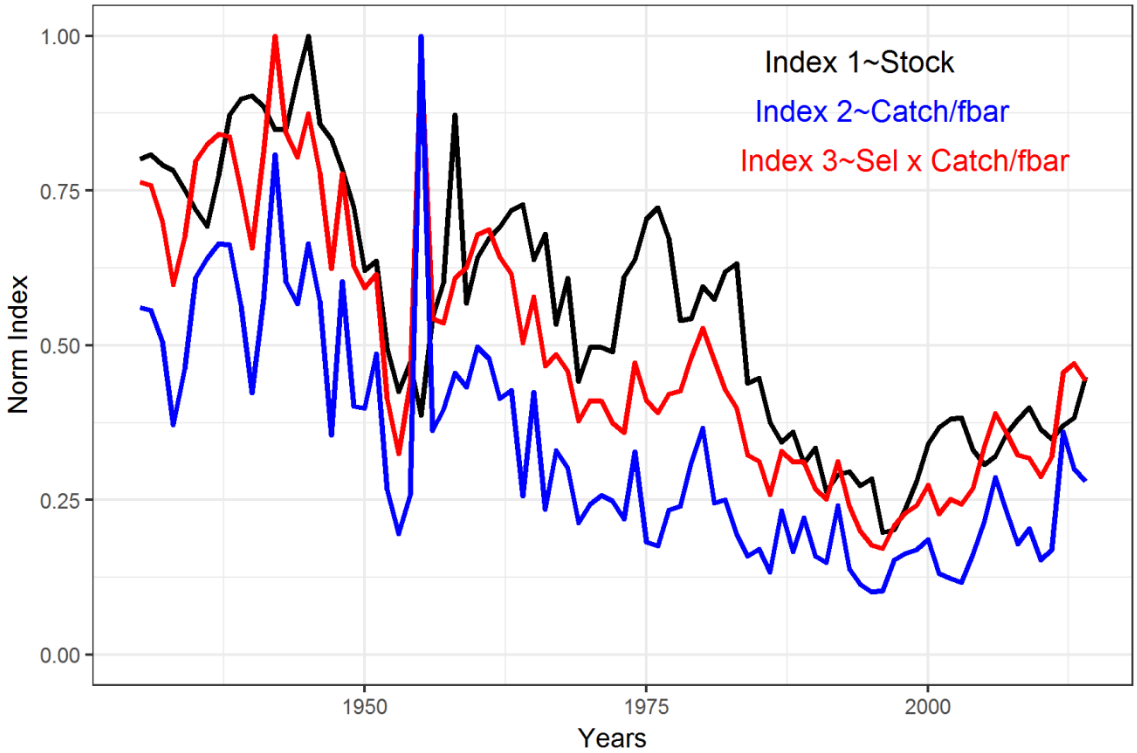
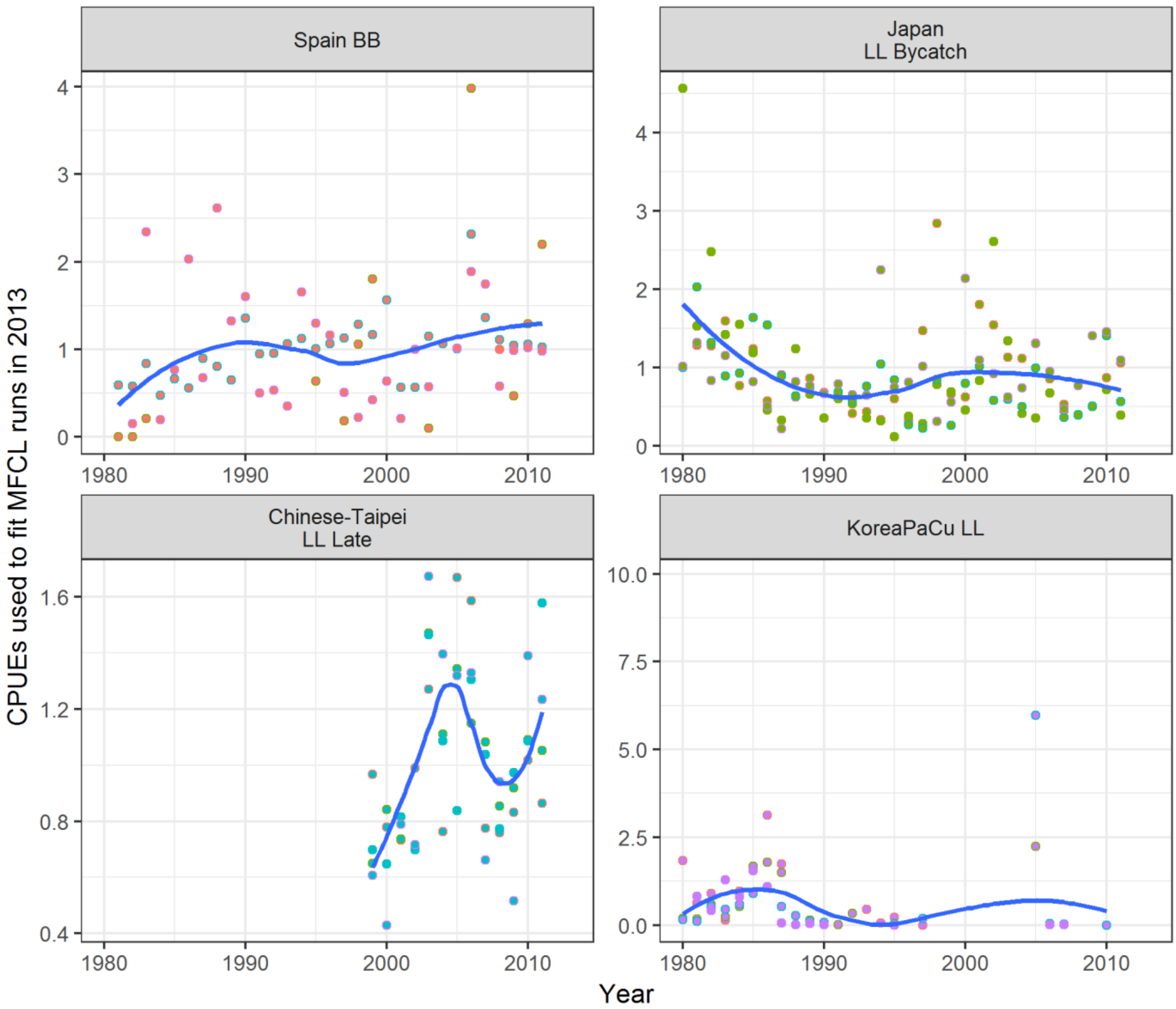


Figure 3. Indices generated directly from the base case OM.



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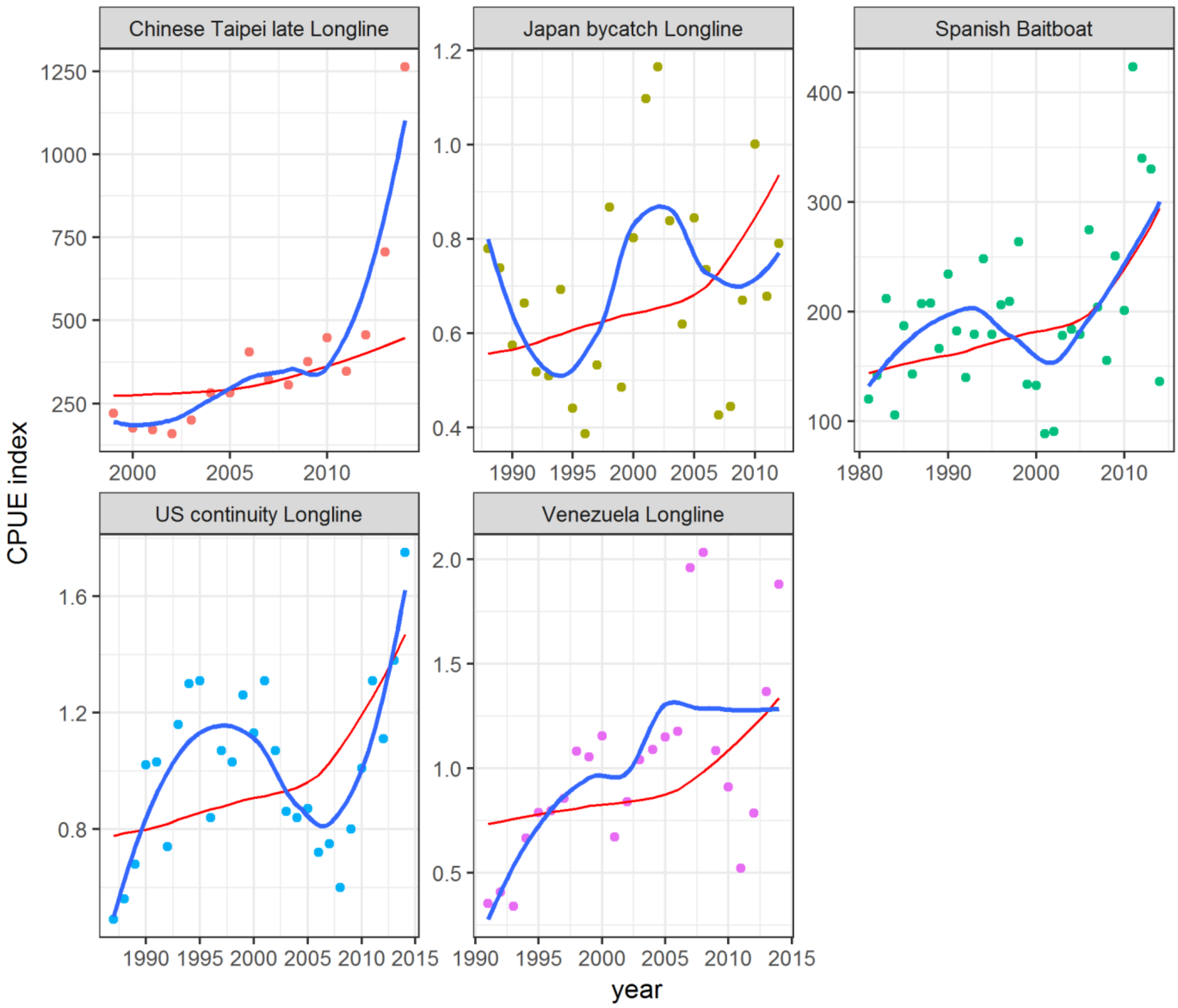

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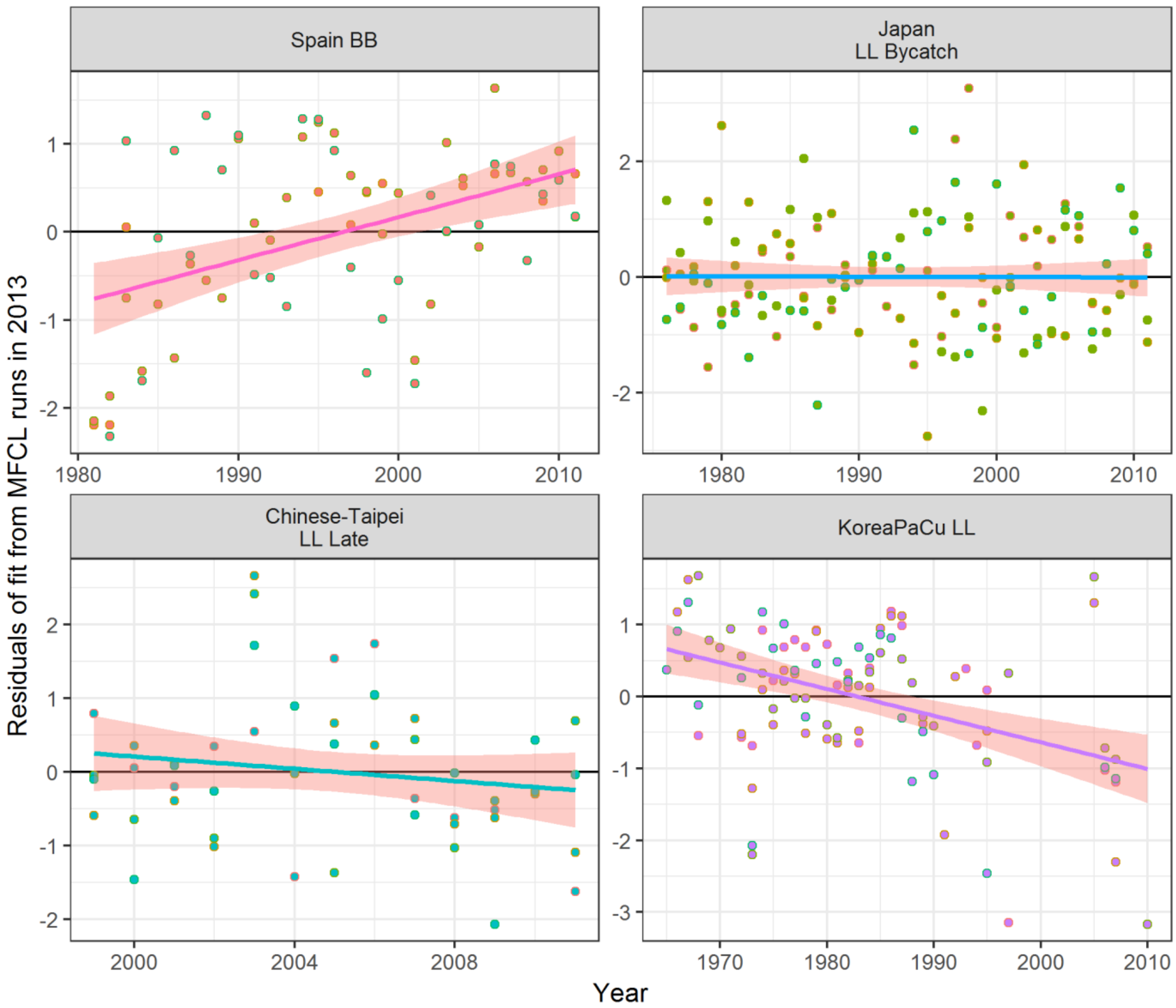


Figure 6. Residuals of fits of the CPUE indices used in the 2013 stock assessment.

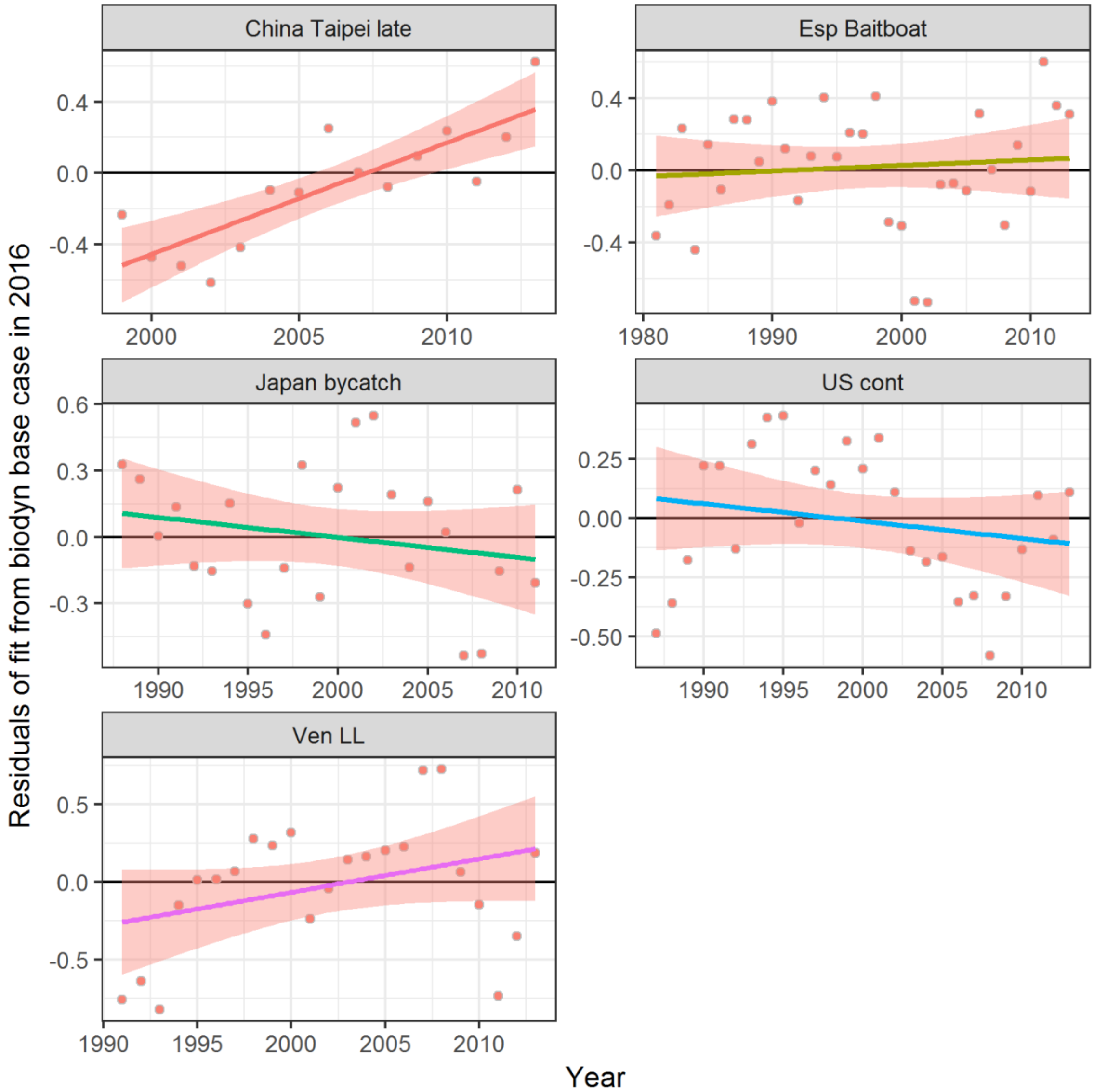
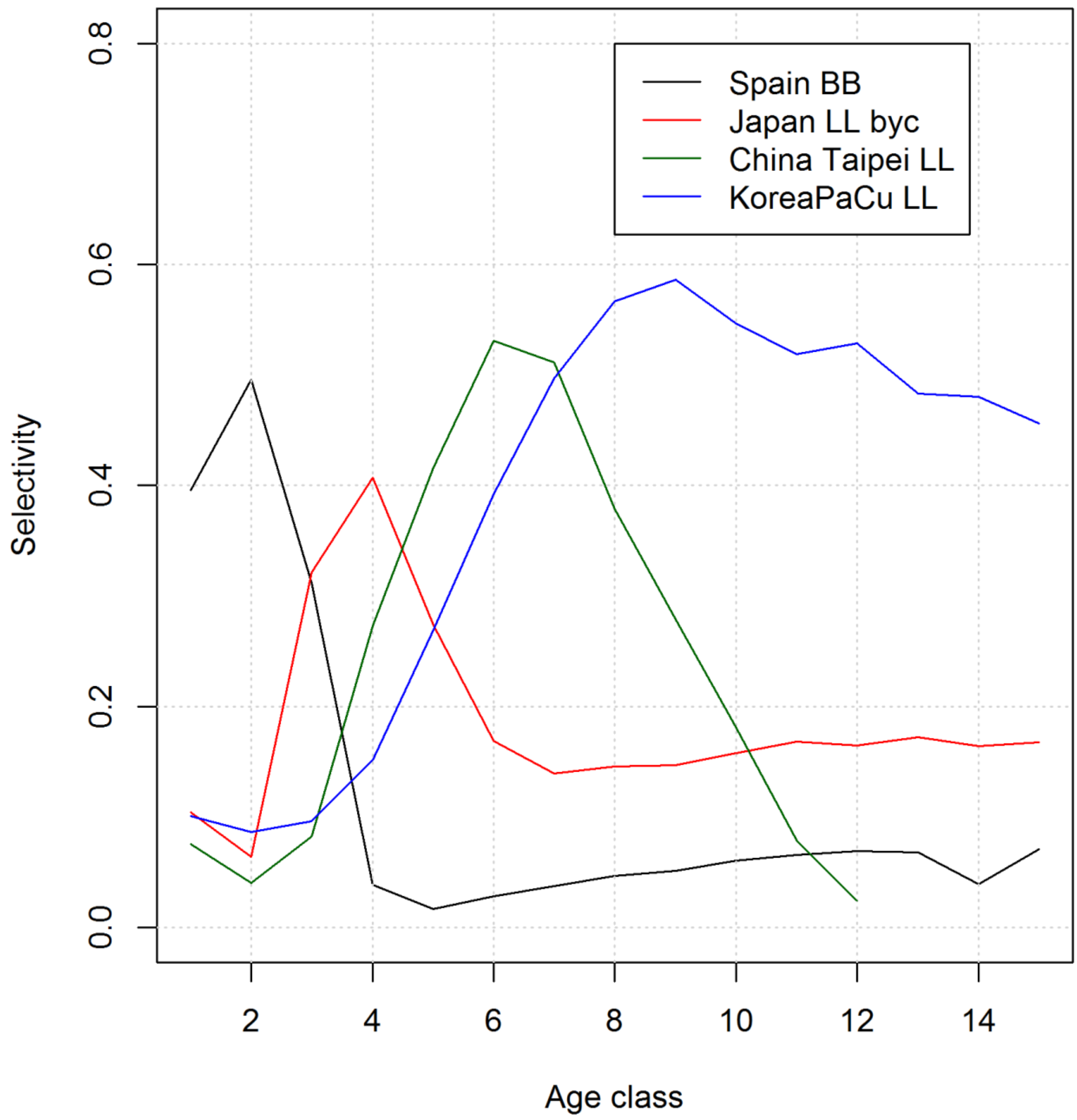


Figure 7. Residuals of fits of the CPUE indices used in the 2016 stock assessment.



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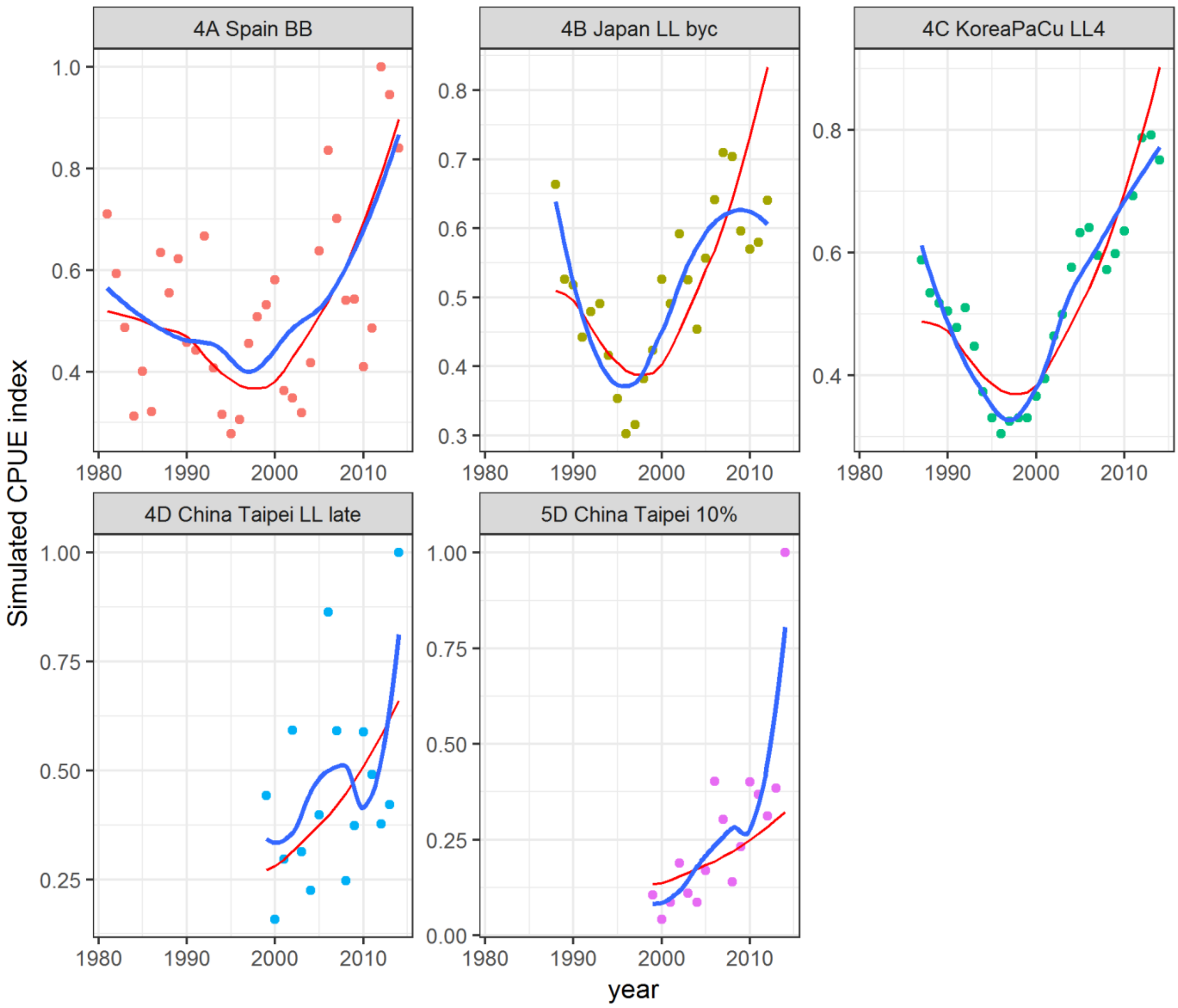

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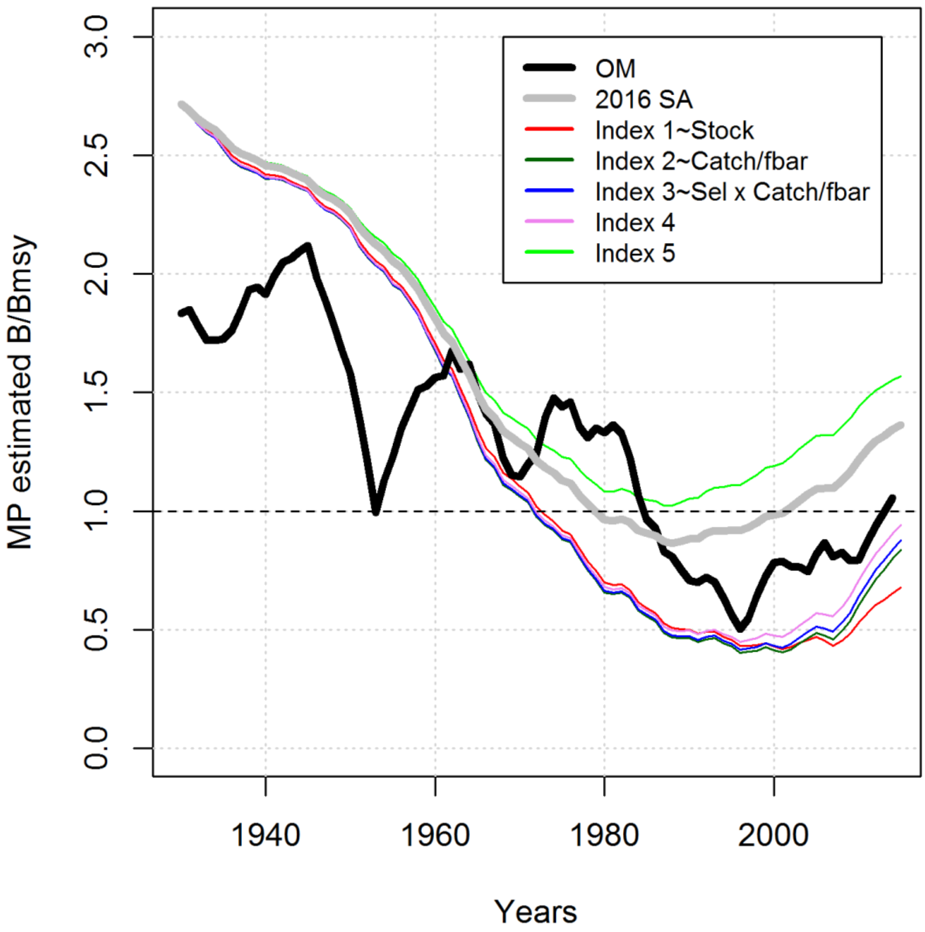

Figure 10. Relative biomass from the base case OM (black) and estimated from alternative indices: (gray) indices used in the 2016 stock assessment, Index 1 (red) , Index 2 (darkgreen), Index 3 (blue), Index 4 (pink), Index 5 (green).

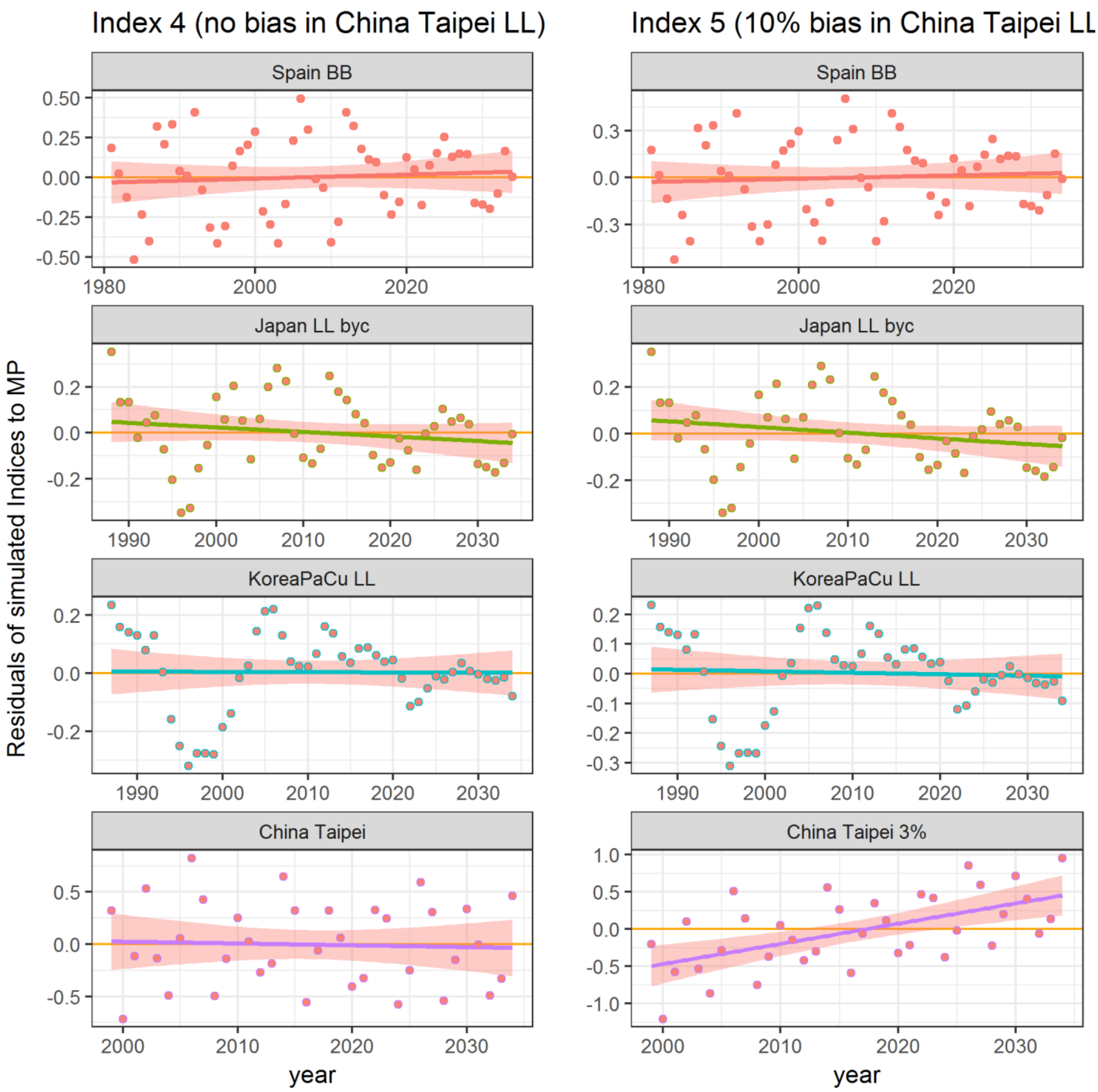

Figure 11. Residuals of CPUE indices grouped as Index 4 and Index 5.

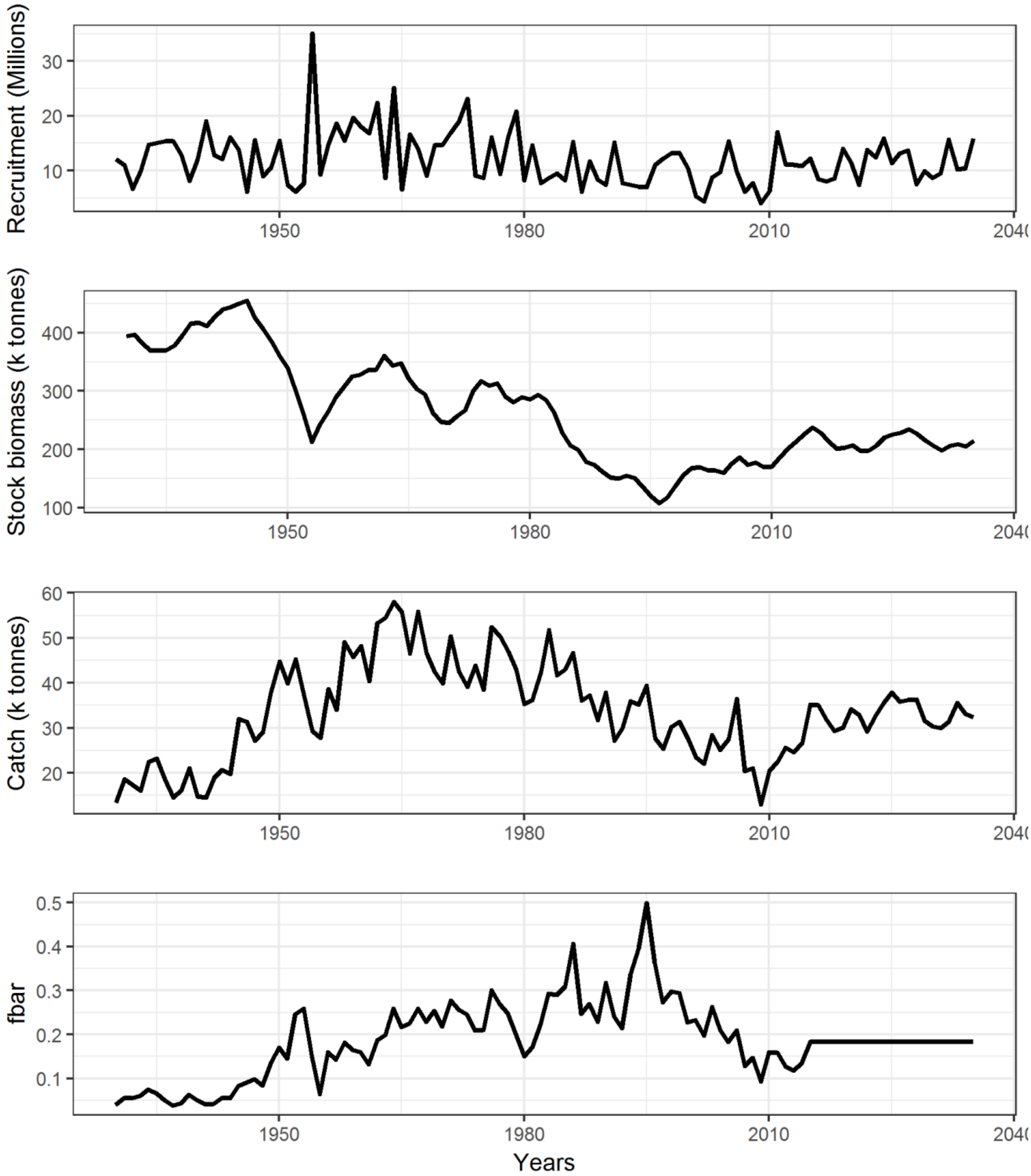

Figure 12. Base case OM projected with a 40% variability on recruitment.

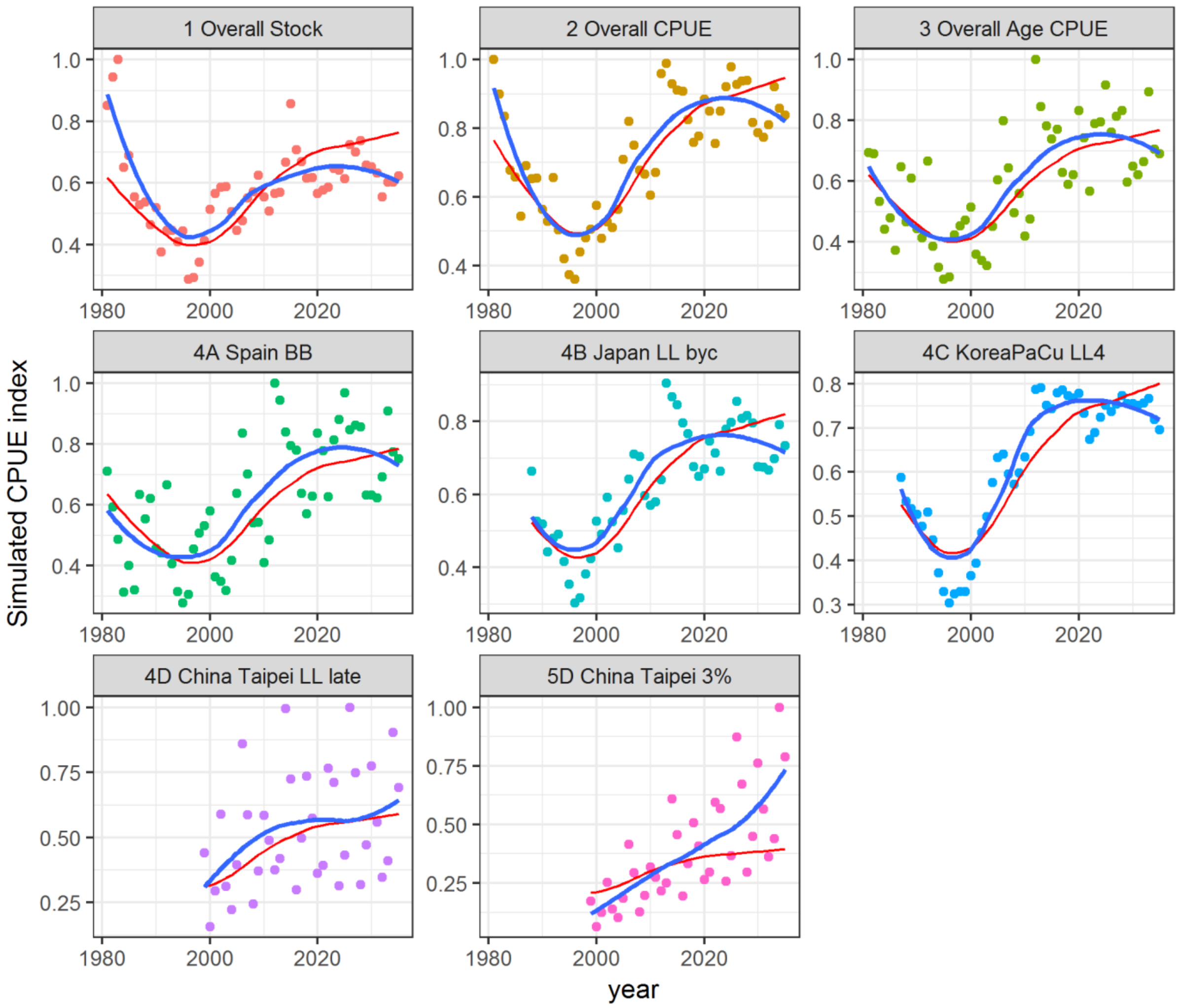

Figure 13. Simulated CPUEs from OM base case projected to 2035.

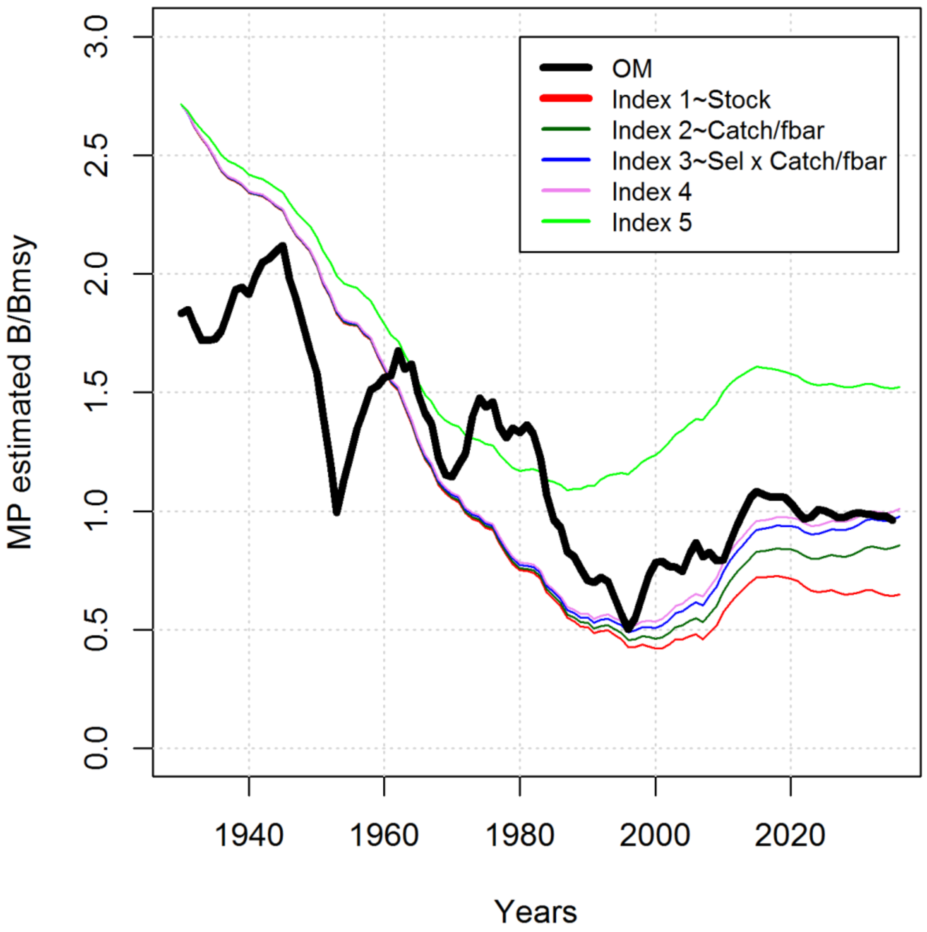

Figure 14. Projection of OM base case with $F=F_{MSY}$ to 2035 and fit to catch and different indices.

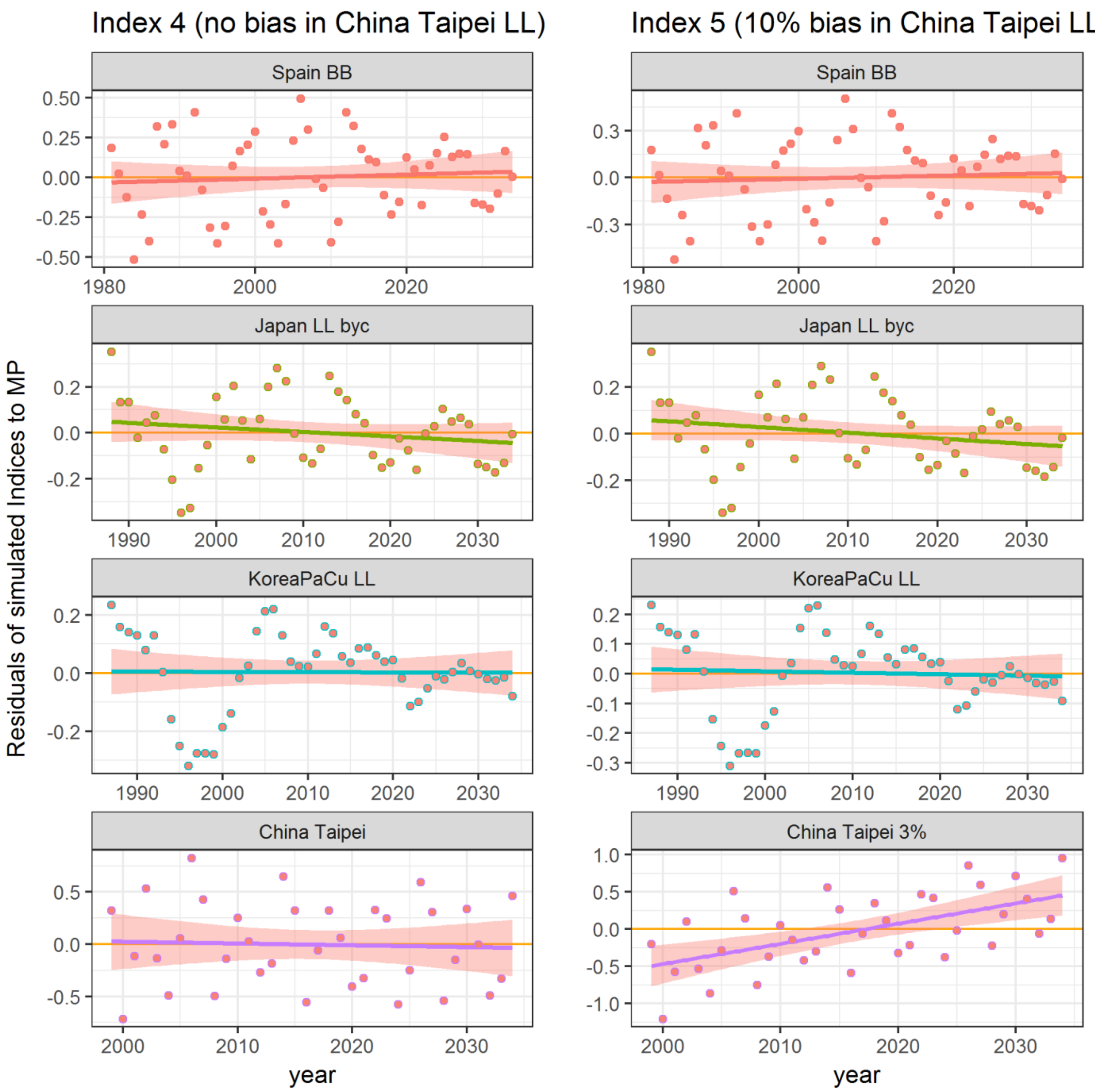

Figure 15. Residuals of fit of Indices 4 and 5.

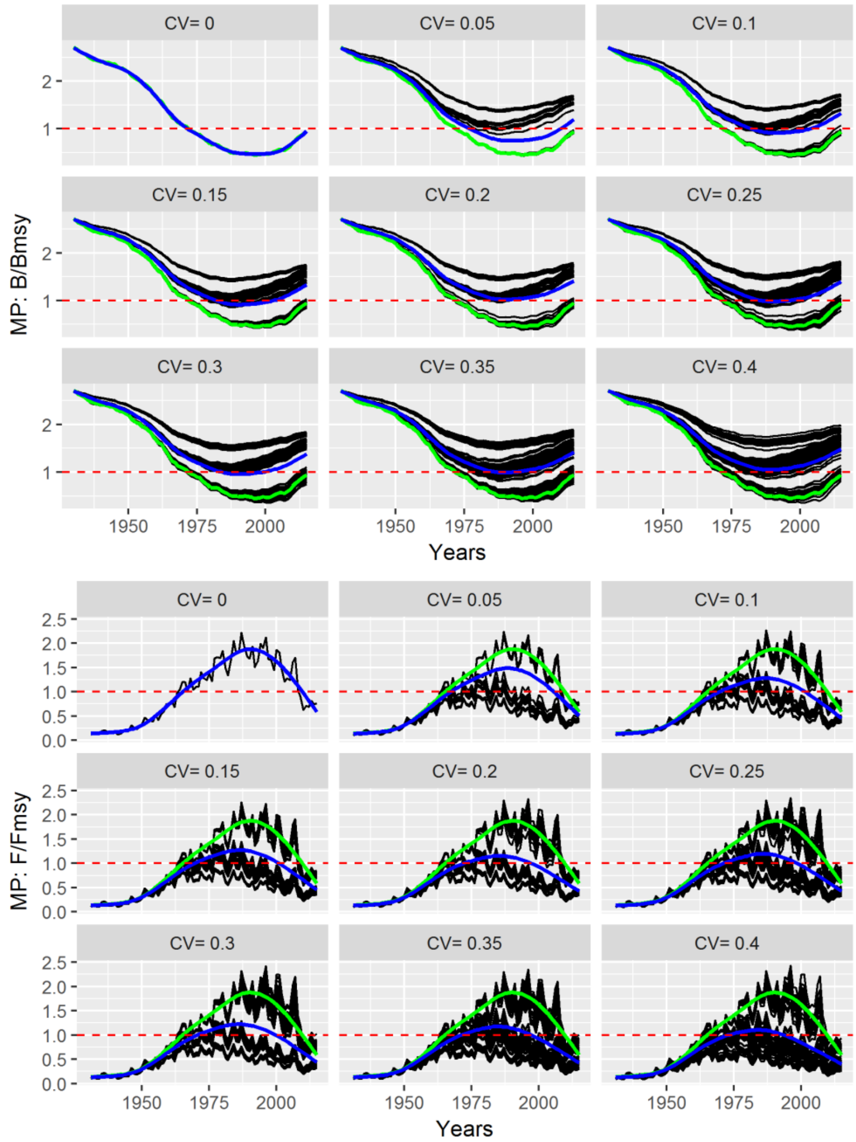

Figure 16. Fits to simulated indices for 2016 for different levels of CV.