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TECHNIQUES FOR VALIDATION OF OPERATING MODELS

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SUMMARY

The 2018 assessment for North Atlantic swordfish is used as a case-study to demonstrate a technique for validating operating models (OMs). The validation process follows three steps. First, the OMs are checked for convergence, and OMs that have not converged are eliminated from further analysis. Second the OMs are examined for estimated parameters that are at the specified bounds. OMs with parameters at the bounds can be identified and removed from the analysis if it is believed that the poorly estimated parameters make the OM unfit for inclusion in a management strategy evaluation. Finally, the model fits to the indices of abundance are plotted, and the statistical properties of the model fits used to identify criteria that can be used to eliminate unacceptable OMs.

RÉSUMÉ

L'évaluation de 2018 de l'espadon de l'Atlantique Nord sert d'étude de cas pour démontrer une technique de validation des modèles opérationnels (OM). Le processus de validation suit trois étapes. Tout d'abord, la convergence des OM est vérifiée et les OM qui n'ont pas convergé sont éliminés de l'analyse ultérieure. Ensuite, on examine les OM pour déterminer les paramètres estimés qui se situent aux limites spécifiées. Les OM avec des paramètres aux limites peuvent être identifiés et retirés de l'analyse si l'on estime que les paramètres mal estimés rendent l'OM inapte à être inclus dans une évaluation de la stratégie de gestion. Enfin, les ajustements du modèle aux indices d'abondance sont présentés sous forme de diagramme et les propriétés statistiques des ajustements du modèle sont utilisées pour identifier les critères qui peuvent être utilisés pour éliminer les OM inacceptables.

RESUMEN

La evaluación de 2018 del pez espada del Atlántico norte se utiliza como estudio de caso para demostrar una técnica de validación de modelos operativos (OM). El proceso de validación sigue tres pasos. En primer lugar, se comprueba la convergencia de los OM y los que no han convergido se eliminan de los análisis posteriores. En segundo lugar, se examinan los OM para determinar los parámetros estimados que se encuentran dentro de los límites especificados. Los OM con parámetros en los límites pueden identificarse y eliminarse del análisis si se cree que los parámetros mal estimados hacen que el OM no sea apto para ser incluido en una evaluación de estrategias de ordenación. Finalmente, los ajustes del modelo a los índices de abundancia se reflejan en un diagrama y se utilizan las propiedades estadísticas del ajuste del modelo para identificar los criterios que pueden utilizarse para eliminar los OM inaceptables.

KEYWORDS

Swordfish, management strategy evaluation, CPUE, statistics

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1. Introduction

Operating models (OMs) are intended to represent a plausible range of uncertainty in fishery system dynamics and are therefore central to the closed-loop simulation testing component of management strategy evaluation (MSE). Operating models are often specified by conditioning (fitting) them to data, in a process similar to conventional stock assessment.

Typical fishery data are not sufficiently informative to estimate certain aspects of population and fishery dynamics that are nonetheless considered important sources of uncertainty and can have large impacts on estimates of stock status and related reference points (e.g. BMSY, MSY). Typical examples of such parameters include recruitment compensation (steepness) and natural mortality rate (M). Instead of attempting to estimate these, such parameters are often fixed to point values for individual model runs. To encompass a credible range of uncertainty in these dynamics, multiple operating models are fitted with varying assumptions for model structure and parameter values. It is to be expected that not all of these OMs will be conditioned satisfactorily, either failing to numerically converge or provide estimates or fits to data that are considered unacceptable.

When only a small number of candidate OMs are produced, it may be possible to manually examine the properties of each OM and decide by group consensus to discard or keep the OM. However, in MSE processes that consider a large number of candidate OMs (which is the case for North Atlantic swordfish), it is necessary to develop a 'model validation' protocol to identify the OMs that are not considered suitable for inclusion in the MSE.

This paper describes possible inputs to such a protocol that can be used for OM validation, and demonstrates how the approach can be used to identify OMs that are considered suitable for inclusion in an MSE.

2. Methods

The 2018 North Atlantic swordfish assessment is used to demonstrate possible inputs to a model validation protocol. The 2018 swordfish assessment (hereafter assessment) was conducted with Stock Synthesis 3 (Methot and Wetzel, 2013) and included a base case assessment, and an uncertainty grid of 288 assessments with alternative assumptions including a range of assumed values for natural mortality, variance in recruitment deviations, and steepness of the stock-recruitment relationship, and other assumptions such as degree of observation error in the indices of abundance.

The validation process involves 3 steps:

(1) OMs are examined for convergence of the stock assessment model

(2) the remaining OMs are examined for estimated parameters that are at the prescribed bounds, indicating that the model has not adequately estimated these parameters.

(3) statistical properties of the model fits to indices of abundance are calculated.

2.1 Numerical Convergence

The first test of numerical convergence failure was by checking for a non-positive definite Hessian matrix. Note that a non-positive definite Hessian rules out numerical convergence but a positive-definite Hessian is not in itself sufficient to rule out non-convergence (that can be achieved for example if parameters hit their bounds). OMs with a non-positive definite Hessian matrix were identified and not included in the remaining OM validation steps.

2.2 Overparameterization

A common problem in fitting fishery models to data is the specification of overparameterized models for which there is insufficient information in the data to reliably estimate all parameters. In such cases the numerical optimizer may propose parameters values on the bounds of the specified distribution, effectively reducing the number of estimated parameters. Where two or more parameters are confounded, the model outputs can be chaotic, and provide radically differing estimates of stock status (for example) with varying initial values for parameters. In such circumstances model estimates may not be reproducible and it may not be possible to evaluate their credibility.

For the purposes of this demonstration protocol, all estimated parameters that were within 1% of the specified upper and lower estimation bounds were classified as 'at bounds', and an indicator of potential problems with OM conditioning.

The 2018 North Atlantic swordfish assessment model estimated 52 non-recruitment deviation parameters, with corresponding upper and lower bounds for all parameters. OMs with a large number of parameters at the bounds are eliminated from further analysis.

For the purposes of this analysis, all OMs with more than 1 parameter at the bounds were excluded from further consideration.

2.3 Statistical Properties of CPUE Indices

The 2018 North Atlantic swordfish assessment is fitted to CPUE indices of abundance for 9 fleets (SPN_1, US_2, CAN_LATE_4, CAN_ERLY_5, JPN_ERLY_5, JPN_MID_6, JPN_LATE_7, PORT_8 and MOR_10) and 5 age-classes (Age-1, Age-2, Age-3, Age-4, and Age-5). The statistical properties of the model fits to the indices were calculated in several ways.

First, the standard deviation and auto-correlation factor of the deviations from the fitted model was calculated for each index. Second, the correlation between observed and predicted values was also calculated for each index. Third, a standardized root-mean-squared error (RMSE) was calculated for each index by:

$$\mathrm{RMSE}_i = \frac{\sqrt{\frac{\sum_{y=1}^{n}\left(i_y - \hat{\imath}_y\right)^2}{n}}}{\sigma_i}$$

where *n* is the total number of years in index *i*, i_y is the observed index value in year *y*, $\hat{\imath}_y$ is the predicted index value in year *y*, and σ_i is the standard deviation of the observed index *i*. Standardizing by the standard deviation of the observed index has the useful property that RMSE values greater than 1 indicate variance in the predicted index that is greater than that in the observed index; that is, values greater than 1 indicate poor predictability.

Finally, the index deviations were examined with a runs-test to identify consistent patterns of over- and under-estimation in residuals of model fit.

The summary statistics of the model fits for each OM can be used to rank the OM and identify a cut-off point to exclude OMs that are not considered representative of the dynamics of the fishery. To aid in this process, figures were generated for each OM showing the observed and predicted indices for each year, as well as a barplot of the log deviations for each index to visually display the results of the runs-test. The mean and standard deviation of the RMSE for each index was calculated to represent the average predictability of each index.

3. Results

A total of 174 OMs (including the base-case OM and 173 OMs from the uncertainty grid) successfully converged (**Table 1**). The remaining 115 OMs were removed from further consideration. A factor analysis can be used to examine if a pattern exists in non-convergence (**Figure 1**).

With the exception of the base case OM, all of the OMs that successfully converged had a least one parameter close to or at the specified bounds (**Figure 2**). At total of 42 OMs had 1 parameter at the bounds. Of the remainder, 110 OMs had 2 parameters at bound, 20 OMs had 3, and 1 OM has 4 estimated parameters at the bounds (**Figure 2**).

The SPN_1 index had the poorest predictive power, and RMSE greater than 1 for all OMs and a mean RMSE across all OMs of 7.23 (**Table 2**). The Age-3 index had the lowest mean RMSE (0.629; **Table 2**).

Figure 3 and **Figure 4** show the operating model fits for the 5 age-class indices and the remaining 9 indices respectively for the base case OM. These plots can be used to visually identify indices that are considered acceptable for use in a management procedure, as well as determine the statistical properties of indices and OMs that are considered unacceptable.

While similar figures can be produced for all 43 OMs that passed the first two criteria (convergence and parameters at bounds), these results would be too numerous to include in the paper. Instead, as a demonstration of the process that can be used to visually inspect the OMs, the OMs with the lowest, median, and highest RMSE values for the Age-3 index were selected to demonstrate the properties of OMs with increasingly poor fits to this index.

Figure 5 and **Figure 6** show the operating model fits for the 5 age-class indices and the remaining 9 indices respectively for the OM with the lowest RMSE for the Age-3 index. These plots can be compared with the OM with median RMSE for Age-3 index (**Figure 7** and **Figure 8**), and the OM with the highest RMSE for Age-3 index (**Figure 9** and **Figure 10**).

4. Discussion

This paper has described inputs for a model validation protocol that can be applied to a large number of OMs to produce a reduced list of OMs that are considered suitable to include in an MSE analysis. The approach first eliminates OMs that have not converged. Secondly, the number of estimated parameters that are at the specified bounds is used to identity potentially problematic OMs, and to provide a metric to exclude OMs from consideration. In this example, OMs with more than 1 parameter at the bounds were not considered further.

The statistical properties of the model fits to the indices of population abundance were calculated for each of the remaining OMs, and summarized in table form as well as presented graphically. These plots provide statistics that can be identify criteria that are indicative of poor model fit and poor predictability of the indices. A working group can examine plots like those show in **Figure 3** to **Figure 10** to identify cut-off values for the summary statistics that indicate OMs with unacceptable properties. Once these cut-off values are agreed upon by group consensus, they can be used to filter the remaining OMs down to a list of OMs that are considered valid to include in the MSE analysis.

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6. References

Methot, R. D., & Wetzel, C. R. (2013). Stock synthesis: A biological and statistical framework for fish stock assessment and fishery management. *Fisheries Research*, *142*, 86–99. https://doi.org/10.1016/j.fishres.2012.10.012

Table 1. Convergence diagnostics for the base case OM and the 288 OMs from the uncertainty grid.

Stock Synthesis 3 Assessment	Converge?
base_case	TRUE
1-M0.1_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1_env-4_number1	FALSE
2-M0.2_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1_env-4_number2	FALSE
3-M0.3_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1_env-4_number3	FALSE
4-M0.1_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1_env-4_number4	FALSE
5-M0.2_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1_env-4_number5	FALSE
6-M0.3_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1_env-4_number6	FALSE
7-M0.1_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1_env-4_number7	FALSE
8-M0.2_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1_env-4_number8	FALSE
9-M0.3_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1_env-4_number9	FALSE
10-M0.1_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1_env-4_number10	FALSE
11-M0.2_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1_env-4_number11	FALSE
12-M0.3_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1_env-4_number12	FALSE
13-M0.1_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1_env-4_number13	FALSE
14-M0.2_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1_env-4_number14	FALSE
15-M0.3_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1_env-4_number15	FALSE
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20-M0.2_sigmaR0.2_steepness0.6_cpuecv0.6_ess2_llq1_env-4_number20	TRUE
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23-M0.2_sigmaR0.6_steepness0.6_cpuecv0.6_ess2_llq1_env-4_number23	TRUE
24-M0.3_sigmaR0.6_steepness0.6_cpuecv0.6_ess2_llq1_env-4_number24	TRUE
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42-M0.3_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1_env-4_number42	FALSE
43-M0.1_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1_env-4_number43	FALSE

Stock Synthesis 3 Assessment	**Converge?**
44-M0.2_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1_env-4_number44	TRUE
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46-M0.1_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1_env-4_number46	FALSE
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88-M0.1_sigmaR0.6_steepness0.9_cpuecv0.3_ess2_llq1.01_env-4_number88	FALSE

Stock Synthesis 3 Assessment	Converge?
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105-M0.3_sigmaR0.2_steepness0.9_cpuecv0.6_ess2_llq1.01_env-4_number105	TRUE
106-M0.1_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1.01_env-4_number106	TRUE
107-M0.2_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1.01_env-4_number107	TRUE
108-M0.3_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1.01_env-4_number108	TRUE
109-M0.1_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1.01_env-4_number109	FALSE
110-M0.2_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1.01_env-4_number110	FALSE
111-M0.3_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1.01_env-4_number111	TRUE
112-M0.1_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1.01_env-4_number112	FALSE
113-M0.2_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1.01_env-4_number113	FALSE
114-M0.3_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1.01_env-4_number114	FALSE
115-M0.1_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1.01_env-4_number115	FALSE
116-M0.2_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1.01_env-4_number116	TRUE
117-M0.3_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1.01_env-4_number117	TRUE
118-M0.1_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1.01_env-4_number118	FALSE
119-M0.2_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1.01_env-4_number119	FALSE
120-M0.3_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1.01_env-4_number120	FALSE
121-M0.1_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1.01_env-4_number121	TRUE
122-M0.2_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1.01_env-4_number122	TRUE
123-M0.3_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1.01_env-4_number123	TRUE
124-M0.1_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1.01_env-4_number124	FALSE
125-M0.2_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1.01_env-4_number125	FALSE
126-M0.3_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1.01_env-4_number126	FALSE
127-M0.1_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1.01_env-4_number127	TRUE
128-M0.2_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1.01_env-4_number128	TRUE
129-M0.3_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1.01_env-4_number129	TRUE
130-M0.1_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1.01_env-4_number130	TRUE
131-M0.2_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1.01_env-4_number131	TRUE
132-M0.3_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1.01_env-4_number132	TRUE
133-M0.1_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1.01_env-4_number133	TRUE

Stock Synthesis 3 Assessment	**Converge?**
134-M0.2_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1.01_env-4_number134	TRUE
135-M0.3_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1.01_env-4_number135	TRUE
136-M0.1_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1.01_env-4_number136	TRUE
137-M0.2_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1.01_env-4_number137	TRUE
138-M0.3_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1.01_env-4_number138	TRUE
139-M0.1_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1.01_env-4_number139	TRUE
140-M0.2_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1.01_env-4_number140	TRUE
141-M0.3_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1.01_env-4_number141	TRUE
142-M0.1_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1.01_env-4_number142	TRUE
143-M0.2_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1.01_env-4_number143	TRUE
144-M0.3_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1.01_env-4_number144	TRUE
145-M0.1_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1_env4_number145	FALSE
146-M0.2_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1_env4_number146	FALSE
147-M0.3_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1_env4_number147	FALSE
148-M0.1_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1_env4_number148	FALSE
149-M0.2_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1_env4_number149	FALSE
150-M0.3_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1_env4_number150	FALSE
151-M0.1_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1_env4_number151	FALSE
152-M0.2_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1_env4_number152	FALSE
153-M0.3_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1_env4_number153	FALSE
154-M0.1_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1_env4_number154	FALSE
155-M0.2_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1_env4_number155	FALSE
156-M0.3_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1_env4_number156	FALSE
157-M0.1_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1_env4_number157	FALSE
158-M0.2_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1_env4_number158	FALSE
159-M0.3_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1_env4_number159	FALSE
160-M0.1_sigmaR0.6_steepness0.9_cpuecv0.3_ess2_llq1_env4_number160	FALSE
161-M0.2_sigmaR0.6_steepness0.9_cpuecv0.3_ess2_llq1_env4_number161	FALSE
162-M0.3_sigmaR0.6_steepness0.9_cpuecv0.3_ess2_llq1_env4_number162	FALSE
163-M0.1_sigmaR0.2_steepness0.6_cpuecv0.6_ess2_llq1_env4_number163	TRUE
164-M0.2_sigmaR0.2_steepness0.6_cpuecv0.6_ess2_llq1_env4_number164	TRUE
165-M0.3_sigmaR0.2_steepness0.6_cpuecv0.6_ess2_llq1_env4_number165	TRUE
166-M0.1_sigmaR0.6_steepness0.6_cpuecv0.6_ess2_llq1_env4_number166	TRUE
167-M0.2_sigmaR0.6_steepness0.6_cpuecv0.6_ess2_llq1_env4_number167	TRUE
168-M0.3_sigmaR0.6_steepness0.6_cpuecv0.6_ess2_llq1_env4_number168	TRUE
169-M0.1_sigmaR0.2_steepness0.75_cpuecv0.6_ess2_llq1_env4_number169	TRUE
170-M0.2_sigmaR0.2_steepness0.75_cpuecv0.6_ess2_llq1_env4_number170	TRUE
171-M0.3_sigmaR0.2_steepness0.75_cpuecv0.6_ess2_llq1_env4_number171	TRUE
172-M0.1_sigmaR0.6_steepness0.75_cpuecv0.6_ess2_llq1_env4_number172	TRUE
173-M0.2_sigmaR0.6_steepness0.75_cpuecv0.6_ess2_llq1_env4_number173	TRUE
174-M0.3_sigmaR0.6_steepness0.75_cpuecv0.6_ess2_llq1_env4_number174	TRUE
175-M0.1_sigmaR0.2_steepness0.9_cpuecv0.6_ess2_llq1_env4_number175	TRUE
176-M0.2_sigmaR0.2_steepness0.9_cpuecv0.6_ess2_llq1_env4_number176	TRUE
177-M0.3_sigmaR0.2_steepness0.9_cpuecv0.6_ess2_llq1_env4_number177	TRUE
178-M0.1_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1_env4_number178	TRUE

Stock Synthesis 3 Assessment	Converge?
179-M0.2_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1_env4_number179	TRUE
180-M0.3_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1_env4_number180	TRUE
181-M0.1_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1_env4_number181	TRUE
182-M0.2_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1_env4_number182	TRUE
183-M0.3_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1_env4_number183	TRUE
184-M0.1_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1_env4_number184	FALSE
185-M0.2_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1_env4_number185	FALSE
186-M0.3_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1_env4_number186	FALSE
187-M0.1_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1_env4_number187	TRUE
188-M0.2_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1_env4_number188	TRUE
189-M0.3_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1_env4_number189	TRUE
190-M0.1_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1_env4_number190	FALSE
191-M0.2_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1_env4_number191	FALSE
192-M0.3_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1_env4_number192	FALSE
193-M0.1_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1_env4_number193	TRUE
194-M0.2_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1_env4_number194	TRUE
195-M0.3_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1_env4_number195	TRUE
196-M0.1_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1_env4_number196	FALSE
197-M0.2_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1_env4_number197	FALSE
198-M0.3_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1_env4_number198	FALSE
199-M0.1_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1_env4_number199	TRUE
200-M0.2_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1_env4_number200	TRUE
201-M0.3_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1_env4_number201	TRUE
202-M0.1_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1_env4_number202	TRUE
203-M0.2_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1_env4_number203	TRUE
204-M0.3_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1_env4_number204	TRUE
205-M0.1_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1_env4_number205	TRUE
206-M0.2_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1_env4_number206	TRUE
207-M0.3_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1_env4_number207	TRUE
208-M0.1_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1_env4_number208	TRUE
209-M0.2_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1_env4_number209	TRUE
210-M0.3_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1_env4_number210	TRUE
211-M0.1_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1_env4_number211	TRUE
212-M0.2_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1_env4_number212	TRUE
213-M0.3_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1_env4_number213	TRUE
214-M0.1_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1_env4_number214	TRUE
215-M0.2_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1_env4_number215	TRUE
216-M0.3_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1_env4_number216	TRUE
217-M0.1_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1.01_env4_number217	FALSE
218-M0.2_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1.01_env4_number218	FALSE
219-M0.3_sigmaR0.2_steepness0.6_cpuecv0.3_ess2_llq1.01_env4_number219	FALSE
220-M0.1_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1.01_env4_number220	FALSE
221-M0.2_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1.01_env4_number221	FALSE
222-M0.3_sigmaR0.6_steepness0.6_cpuecv0.3_ess2_llq1.01_env4_number222	FALSE
223-M0.1_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1.01_env4_number223	FALSE

Stock Synthesis 3 Assessment	Converge?
224-M0.2_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1.01_env4_number224	FALSE
225-M0.3_sigmaR0.2_steepness0.75_cpuecv0.3_ess2_llq1.01_env4_number225	FALSE
226-M0.1_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1.01_env4_number226	FALSE
227-M0.2_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1.01_env4_number227	FALSE
228-M0.3_sigmaR0.6_steepness0.75_cpuecv0.3_ess2_llq1.01_env4_number228	FALSE
229-M0.1_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1.01_env4_number229	FALSE
230-M0.2_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1.01_env4_number230	FALSE
231-M0.3_sigmaR0.2_steepness0.9_cpuecv0.3_ess2_llq1.01_env4_number231	FALSE
232-M0.1_sigmaR0.6_steepness0.9_cpuecv0.3_ess2_llq1.01_env4_number232	FALSE
233-M0.2_sigmaR0.6_steepness0.9_cpuecv0.3_ess2_llq1.01_env4_number233	FALSE
234-M0.3_sigmaR0.6_steepness0.9_cpuecv0.3_ess2_llq1.01_env4_number234	FALSE
235-M0.1_sigmaR0.2_steepness0.6_cpuecv0.6_ess2_llq1.01_env4_number235	TRUE
236-M0.2_sigmaR0.2_steepness0.6_cpuecv0.6_ess2_llq1.01_env4_number236	TRUE
237-M0.3_sigmaR0.2_steepness0.6_cpuecv0.6_ess2_llq1.01_env4_number237	TRUE
238-M0.1_sigmaR0.6_steepness0.6_cpuecv0.6_ess2_llq1.01_env4_number238	TRUE
239-M0.2_sigmaR0.6_steepness0.6_cpuecv0.6_ess2_llq1.01_env4_number239	TRUE
240-M0.3_sigmaR0.6_steepness0.6_cpuecv0.6_ess2_llq1.01_env4_number240	TRUE
241-M0.1_sigmaR0.2_steepness0.75_cpuecv0.6_ess2_llq1.01_env4_number241	TRUE
242-M0.2_sigmaR0.2_steepness0.75_cpuecv0.6_ess2_llq1.01_env4_number242	TRUE
243-M0.3_sigmaR0.2_steepness0.75_cpuecv0.6_ess2_llq1.01_env4_number243	TRUE
244-M0.1_sigmaR0.6_steepness0.75_cpuecv0.6_ess2_llq1.01_env4_number244	TRUE
245-M0.2_sigmaR0.6_steepness0.75_cpuecv0.6_ess2_llq1.01_env4_number245	TRUE
246-M0.3_sigmaR0.6_steepness0.75_cpuecv0.6_ess2_llq1.01_env4_number246	TRUE
247-M0.1_sigmaR0.2_steepness0.9_cpuecv0.6_ess2_llq1.01_env4_number247	TRUE
248-M0.2_sigmaR0.2_steepness0.9_cpuecv0.6_ess2_llq1.01_env4_number248	TRUE
249-M0.3_sigmaR0.2_steepness0.9_cpuecv0.6_ess2_llq1.01_env4_number249	TRUE
250-M0.1_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1.01_env4_number250	TRUE
251-M0.2_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1.01_env4_number251	TRUE
252-M0.3_sigmaR0.6_steepness0.9_cpuecv0.6_ess2_llq1.01_env4_number252	TRUE
253-M0.1_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1.01_env4_number253	TRUE
254-M0.2_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1.01_env4_number254	TRUE
255-M0.3_sigmaR0.2_steepness0.6_cpuecv0.3_ess20_llq1.01_env4_number255	TRUE
256-M0.1_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1.01_env4_number256	FALSE
257-M0.2_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1.01_env4_number257	FALSE
258-M0.3_sigmaR0.6_steepness0.6_cpuecv0.3_ess20_llq1.01_env4_number258	FALSE
259-M0.1_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1.01_env4_number259	TRUE
260-M0.2_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1.01_env4_number260	TRUE
261-M0.3_sigmaR0.2_steepness0.75_cpuecv0.3_ess20_llq1.01_env4_number261	TRUE
262-M0.1_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1.01_env4_number262	FALSE
263-M0.2_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1.01_env4_number263	FALSE
264-M0.3_sigmaR0.6_steepness0.75_cpuecv0.3_ess20_llq1.01_env4_number264	FALSE
265-M0.1_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1.01_env4_number265	TRUE
266-M0.2_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1.01_env4_number266	TRUE
267-M0.3_sigmaR0.2_steepness0.9_cpuecv0.3_ess20_llq1.01_env4_number267	TRUE
268-M0.1_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1.01_env4_number268	FALSE

Stock Synthesis 3 Assessment	Converge?
269-M0.2_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1.01_env4_number269	FALSE
270-M0.3_sigmaR0.6_steepness0.9_cpuecv0.3_ess20_llq1.01_env4_number270	FALSE
271-M0.1_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1.01_env4_number271	TRUE
272-M0.2_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1.01_env4_number272	TRUE
273-M0.3_sigmaR0.2_steepness0.6_cpuecv0.6_ess20_llq1.01_env4_number273	TRUE
274-M0.1_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1.01_env4_number274	TRUE
275-M0.2_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1.01_env4_number275	TRUE
276-M0.3_sigmaR0.6_steepness0.6_cpuecv0.6_ess20_llq1.01_env4_number276	TRUE
277-M0.1_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1.01_env4_number277	TRUE
278-M0.2_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1.01_env4_number278	TRUE
279-M0.3_sigmaR0.2_steepness0.75_cpuecv0.6_ess20_llq1.01_env4_number279	TRUE
280-M0.1_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1.01_env4_number280	TRUE
281-M0.2_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1.01_env4_number281	TRUE
282-M0.3_sigmaR0.6_steepness0.75_cpuecv0.6_ess20_llq1.01_env4_number282	TRUE
283-M0.1_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1.01_env4_number283	TRUE
284-M0.2_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1.01_env4_number284	TRUE
285-M0.3_sigmaR0.2_steepness0.9_cpuecv0.6_ess20_llq1.01_env4_number285	TRUE
286-M0.1_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1.01_env4_number286	TRUE
287-M0.2_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1.01_env4_number287	TRUE
288-M0.3_sigmaR0.6_steepness0.9_cpuecv0.6_ess20_llq1.01_env4_number288	TRUE

Table 2. Mean and standard deviation of the root-mean-squared-error for the 14 indices from the 43 OMs that converged and had less than 2 parameters at the bounds.

Index	Mean RMSE	Standard deviation RMSE
Age-1	0.86	0.1
Age-2	0.724	0.175
Age-3	0.629	0.186
Age-4	0.889	0.156
Age-5+	0.659	0.149
CAN_ERLY_5	0.914	0.00593
CAN_LATE_4	1.27	0.258
JPN_ERLY_5	0.836	0.0328
JPN_LATE_7	0.888	0.0163
JPN_MID_6	0.901	0.0112
MOR_10	0.896	0.124
PORT_8	1.03	0.108
SPN_1	7.23	1.78
US_2	1.07	0.0747

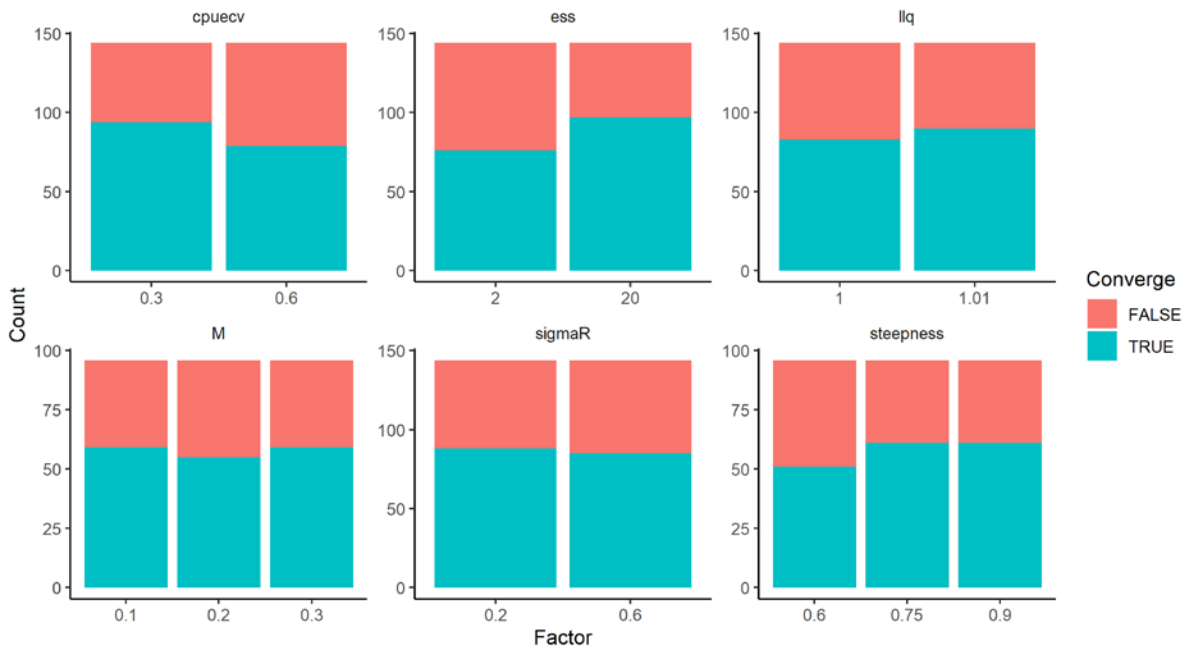

Figure 1. Factor analysis showing the convergence rate for the 6 variables included in the 288 operating models from the uncertainty grid.

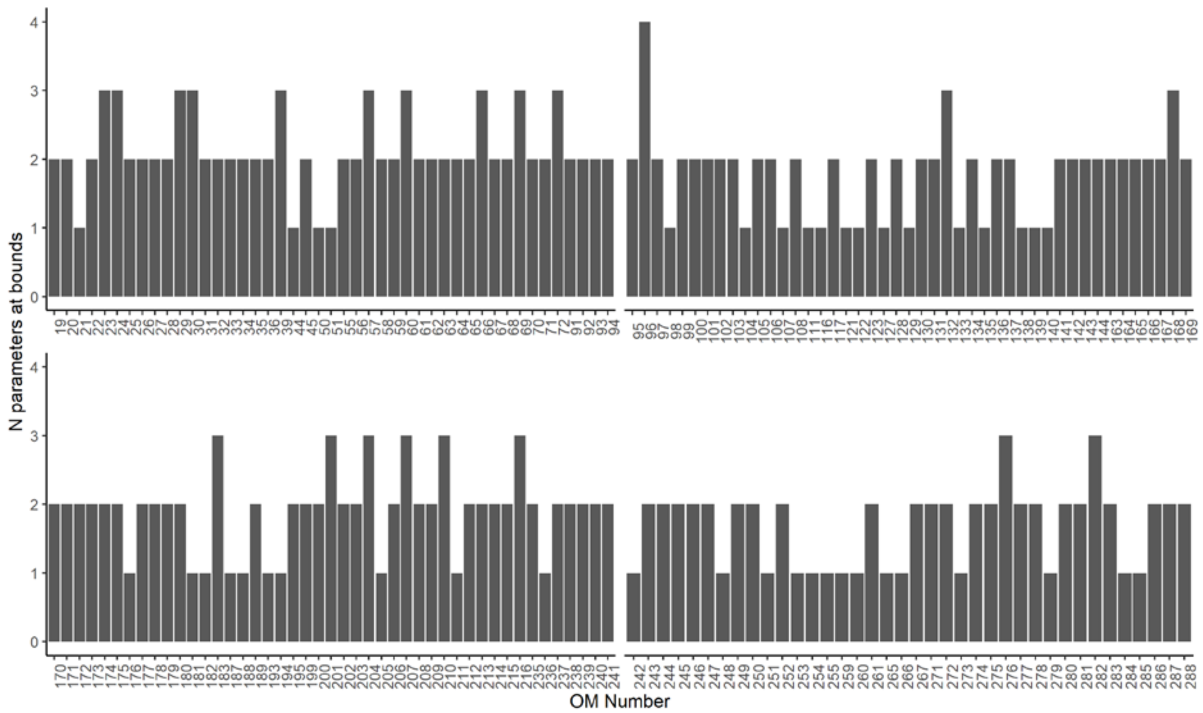

Figure 2. Barplots showing the number of estimated parameters, out of a total 52, that were within 1% of the specified bounds for the 173 OMs that converged but had at least 1 parameter close to the bounds.

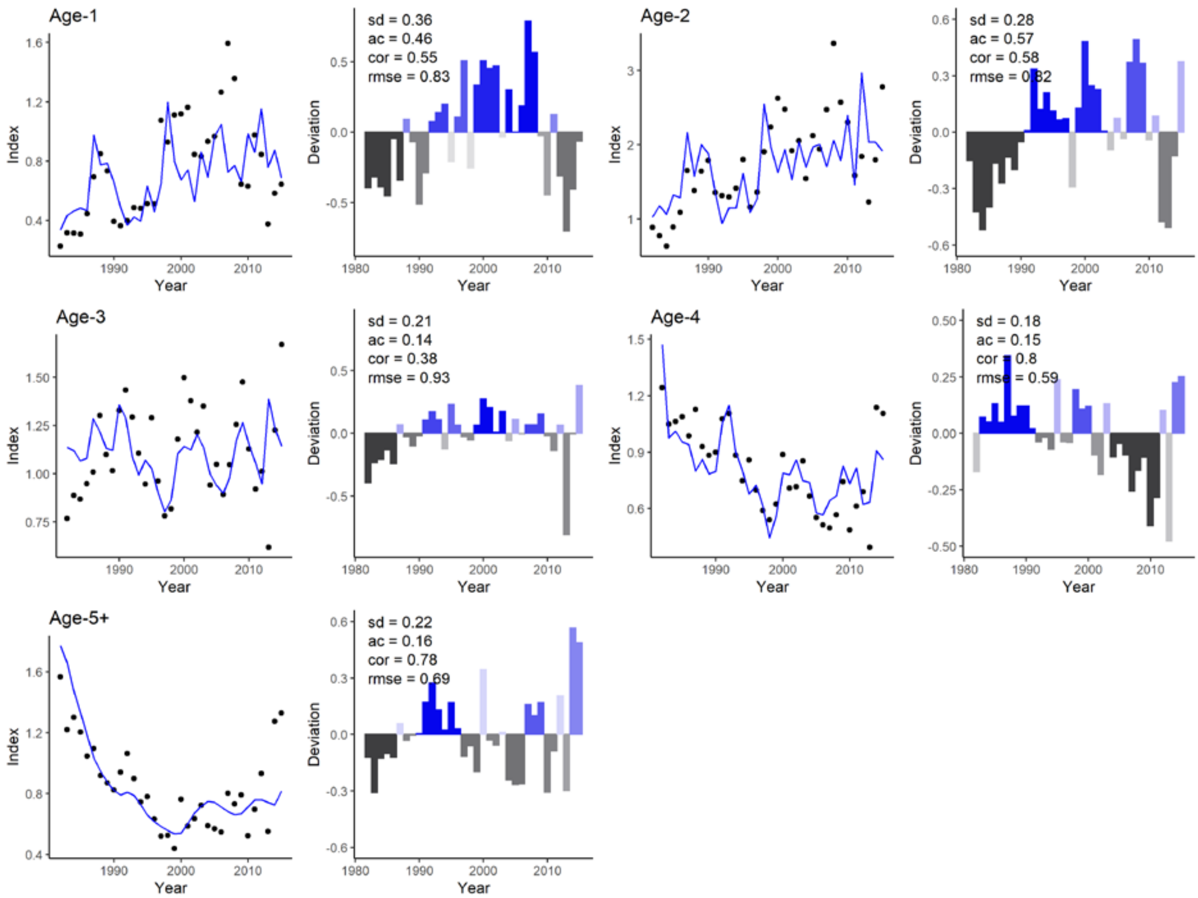

Figure 3. Operating model fits to for the 5 age-class indices for the base case OM. The left-hand panel for each plot shows the observed (black dots) and model predicted (blue line) indices. The right-hand panels for each plot show the log deviations (the observation model is log-normal) including the residual standard deviation (sd) and lag-1 autocorrelation in residuals (ac), correlation (cor), and standardized root-mean-square-error (rmse). Runs of increasing length for positive residuals are filled with increasingly darker shade of blue. Runs of increasing length for negative residuals are filled with increasingly darker shade of grey.

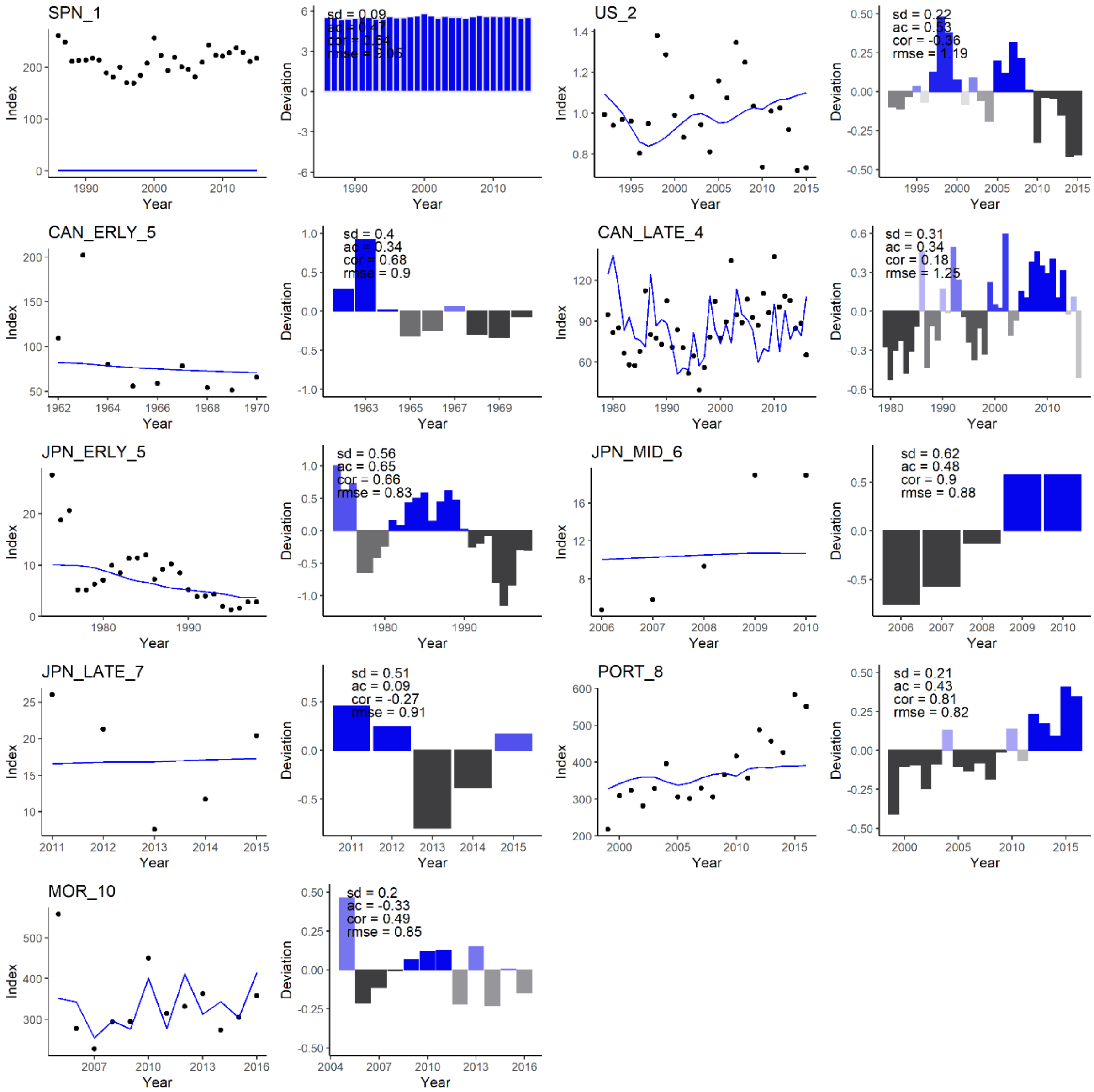

Figure 4. Operating model fits to for the 9 remaining indices for the base case OM. The left-hand panel for each plot shows the observed (black dots) and model predicted (blue line) indices. The right-hand panels for each plot show the log deviations (the observation model is log-normal) including the residual standard deviation (sd) and lag-1 autocorrelation in residuals (ac), correlation (cor), and standardized root-mean-square-error (rmse). Runs of increasing length for positive residuals are filled with increasingly darker shade of blue. Runs of increasing length for negative residuals are filled with increasingly darker shade of grey.

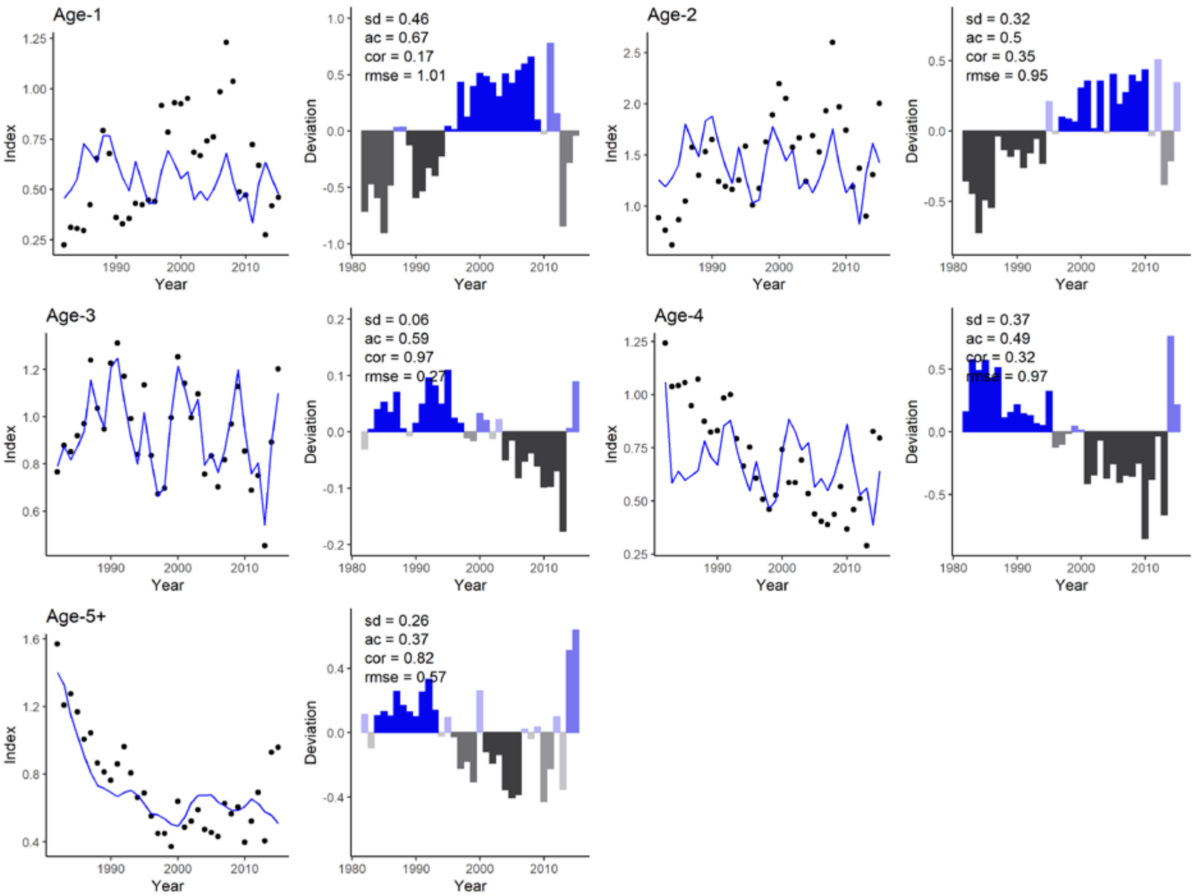

Figure 5. Operating model fits to for the 5 age-class indices for the OM with the lowest RMSE for the Age-3 index. The left-hand panel for each plot shows the observed (black dots) and model predicted (blue line) indices. The right-hand panels for each plot show the log deviations (the observation model is log-normal) including the residual standard deviation (sd) and lag-1 autocorrelation in residuals (ac), correlation (cor), and standardized root-mean-square-error (rmse). Runs of increasing length for positive residuals are filled with increasingly darker shade of blue. Runs of increasing length for negative residuals are filled with increasingly darker shade of grey.

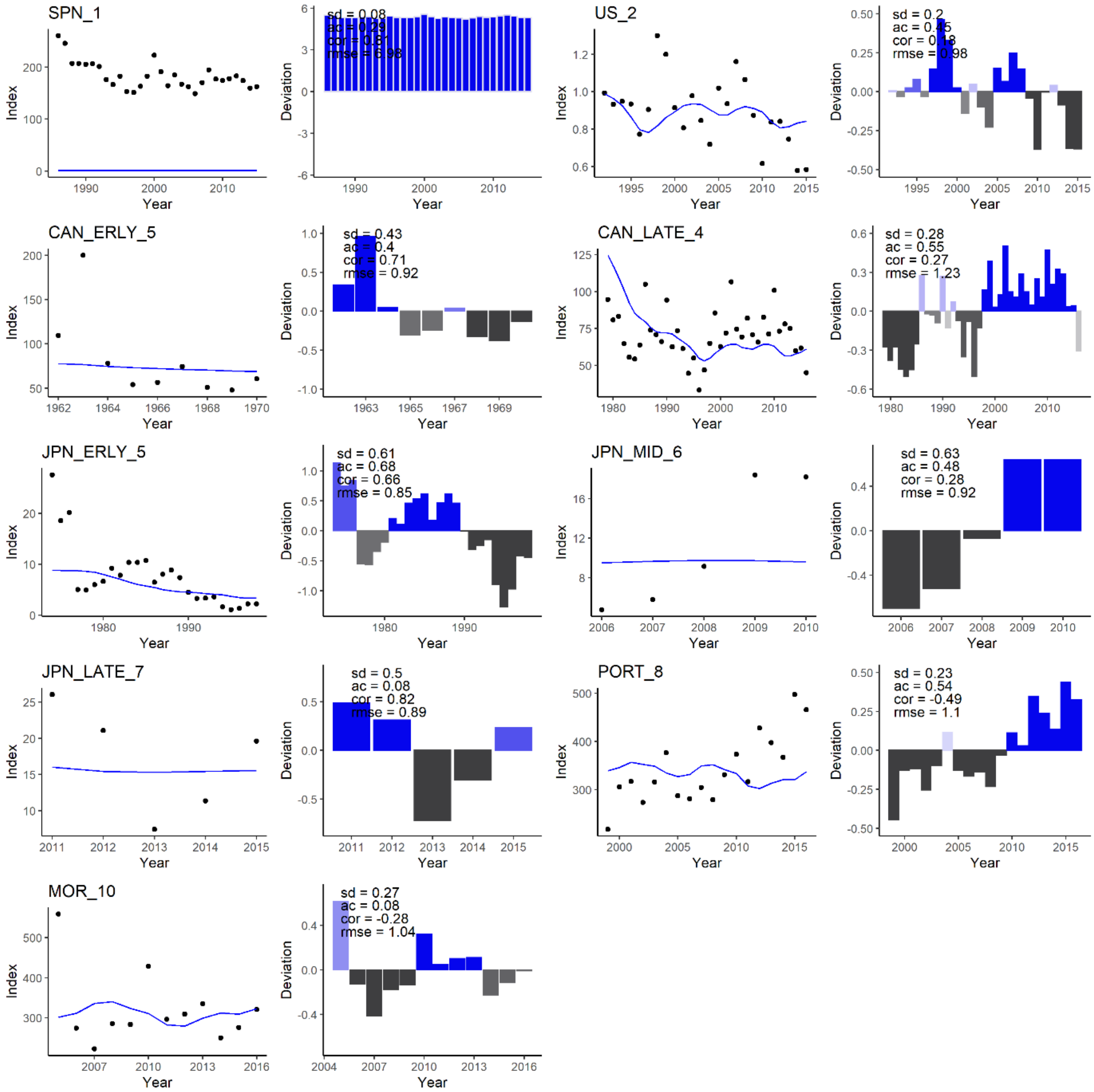

Figure 6. Operating model fits to for the 9 remaining indices for the OM with the lowest RMSE for the Age-3 index. The left-hand panel for each plot shows the observed (black dots) and model predicted (blue line) indices. The right-hand panels for each plot show the log deviations (the observation model is log-normal) including the residual standard deviation (sd) and lag-1 autocorrelation in residuals (ac), correlation (cor), and standardized root-mean-square-error (rmse). Runs of increasing length for positive residuals are filled with increasingly darker shade of blue. Runs of increasing length for negative residuals are filled with increasingly darker shade of grey.

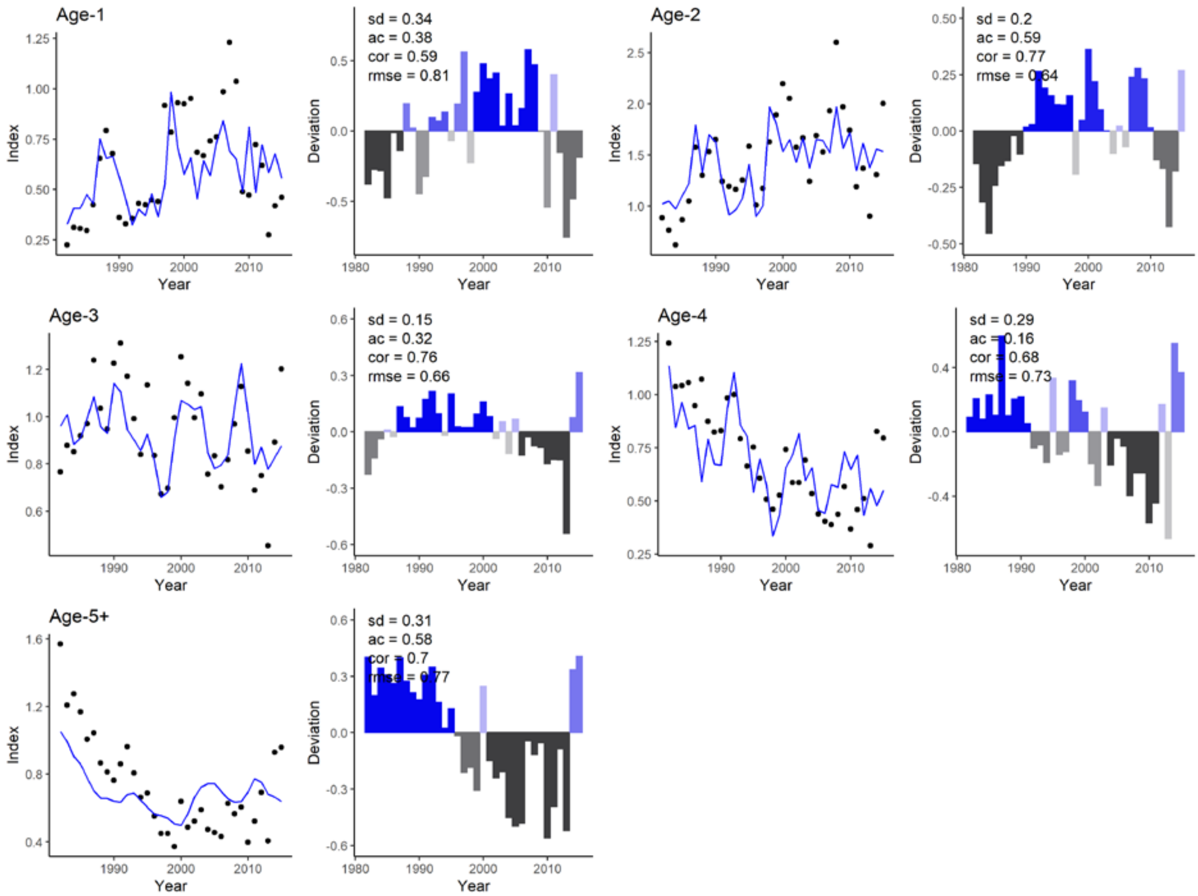

Figure 7. Operating model fits to for the 5 age-class indices for the OM with the median RMSE for the Age-3 index. The left-hand panel for each plot shows the observed (black dots) and model predicted (blue line) indices. The right-hand panels for each plot show the log deviations (the observation model is log-normal) including the residual standard deviation (sd) and lag-1 autocorrelation in residuals (ac), correlation (cor), and standardized root-mean-square-error (rmse). Runs of increasing length for positive residuals are filled with increasingly darker shade of blue. Runs of increasing length for negative residuals are filled with increasingly darker shade of grey.

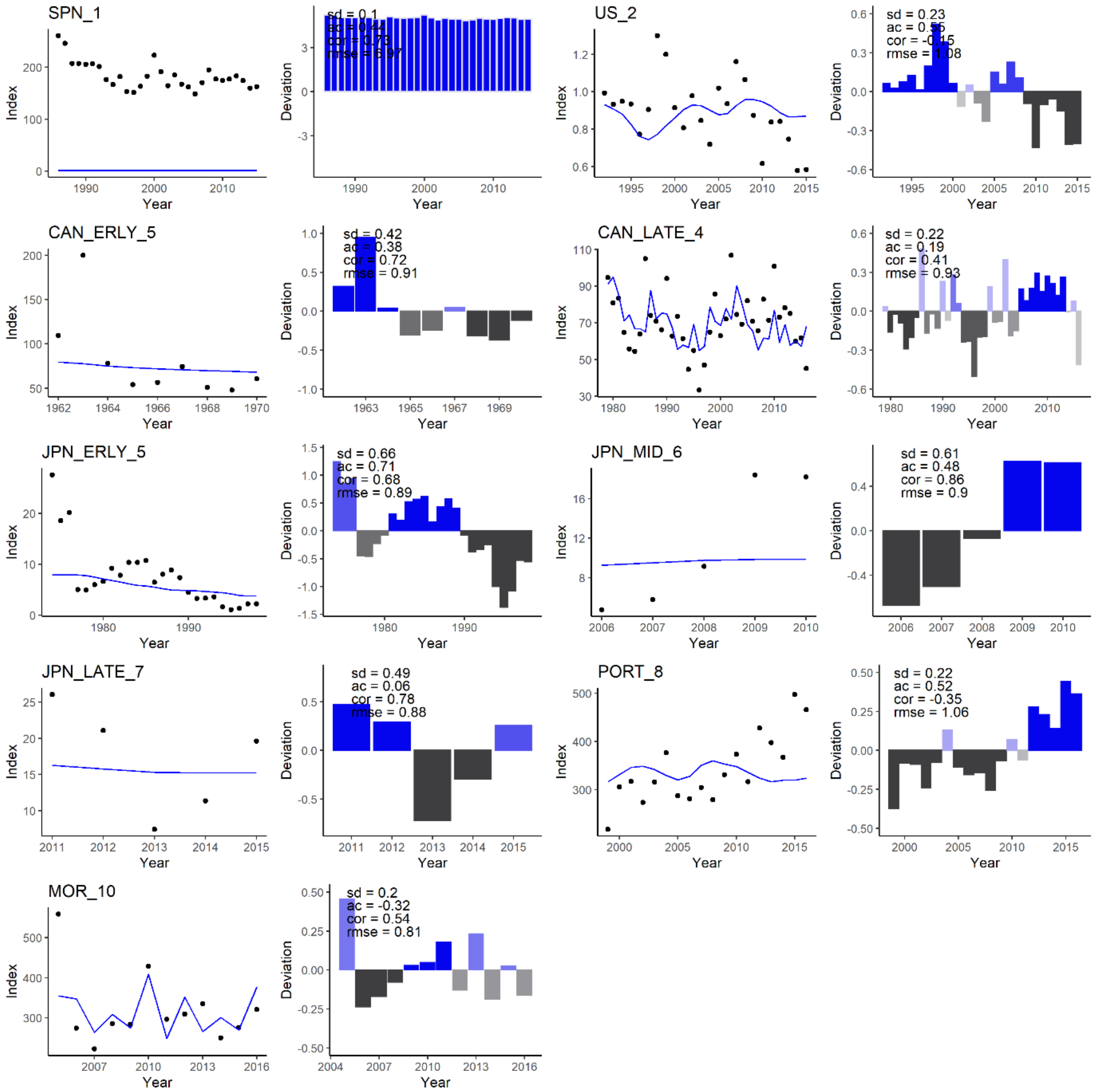

Figure 8. Operating model fits to for the 9 remaining indices for the OM with the median RMSE for the Age-3 index. The left-hand panel for each plot shows the observed (black dots) and model predicted (blue line) indices. The right-hand panels for each plot show the log deviations (the observation model is log-normal) including the residual standard deviation (sd) and lag-1 autocorrelation in residuals (ac), correlation (cor), and standardized root-mean-square-error (rmse). Runs of increasing length for positive residuals are filled with increasingly darker shade of blue. Runs of increasing length for negative residuals are filled with increasingly darker shade of grey.

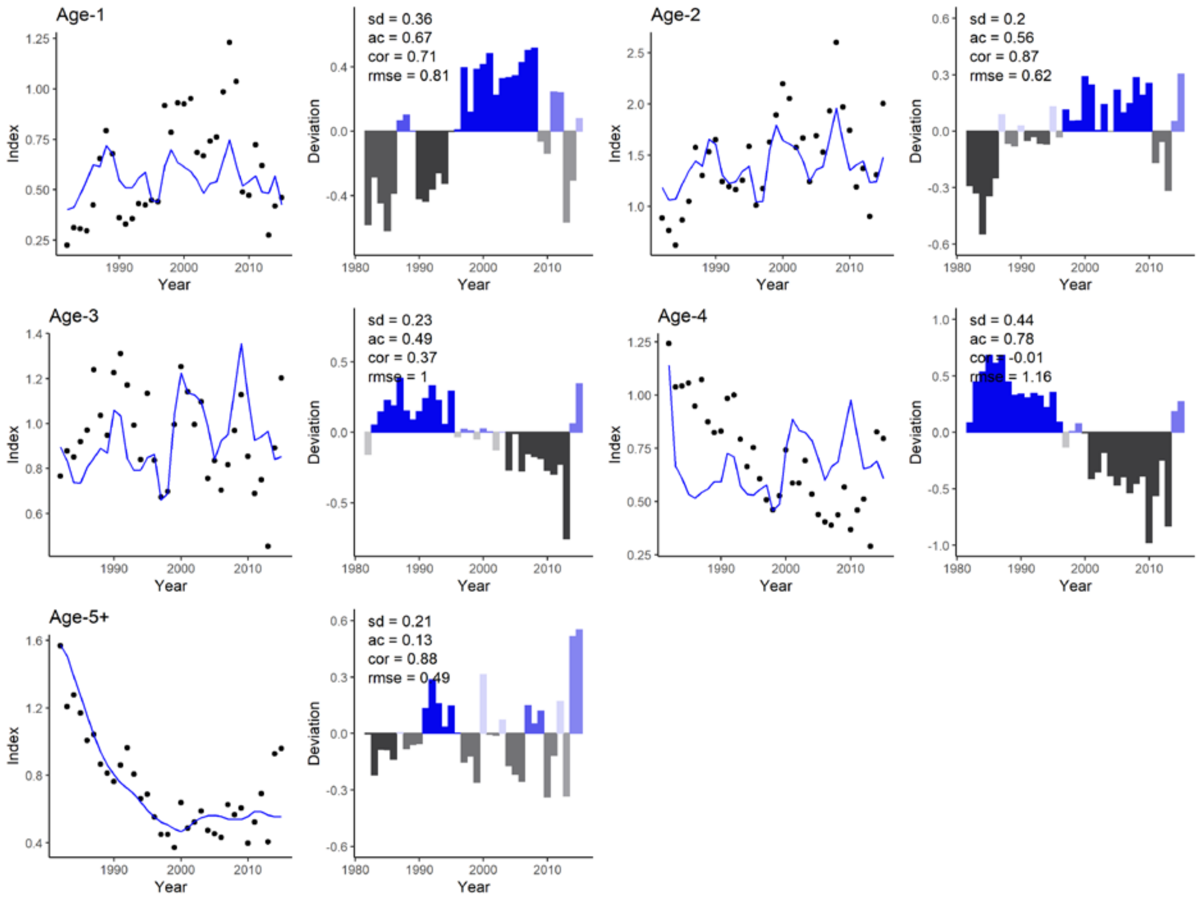

Figure 9. Operating model fits to for the 5 age-class indices for the OM with the highest RMSE for the Age-3 index. The left-hand panel for each plot shows the observed (black dots) and model predicted (blue line) indices. The right-hand panels for each plot show the log deviations (the observation model is log-normal) including the residual standard deviation (sd) and lag-1 autocorrelation in residuals (ac), correlation (cor), and standardized root-mean-square-error (rmse). Runs of increasing length for positive residuals are filled with increasingly darker shade of blue. Runs of increasing length for negative residuals are filled with increasingly darker shade of grey.

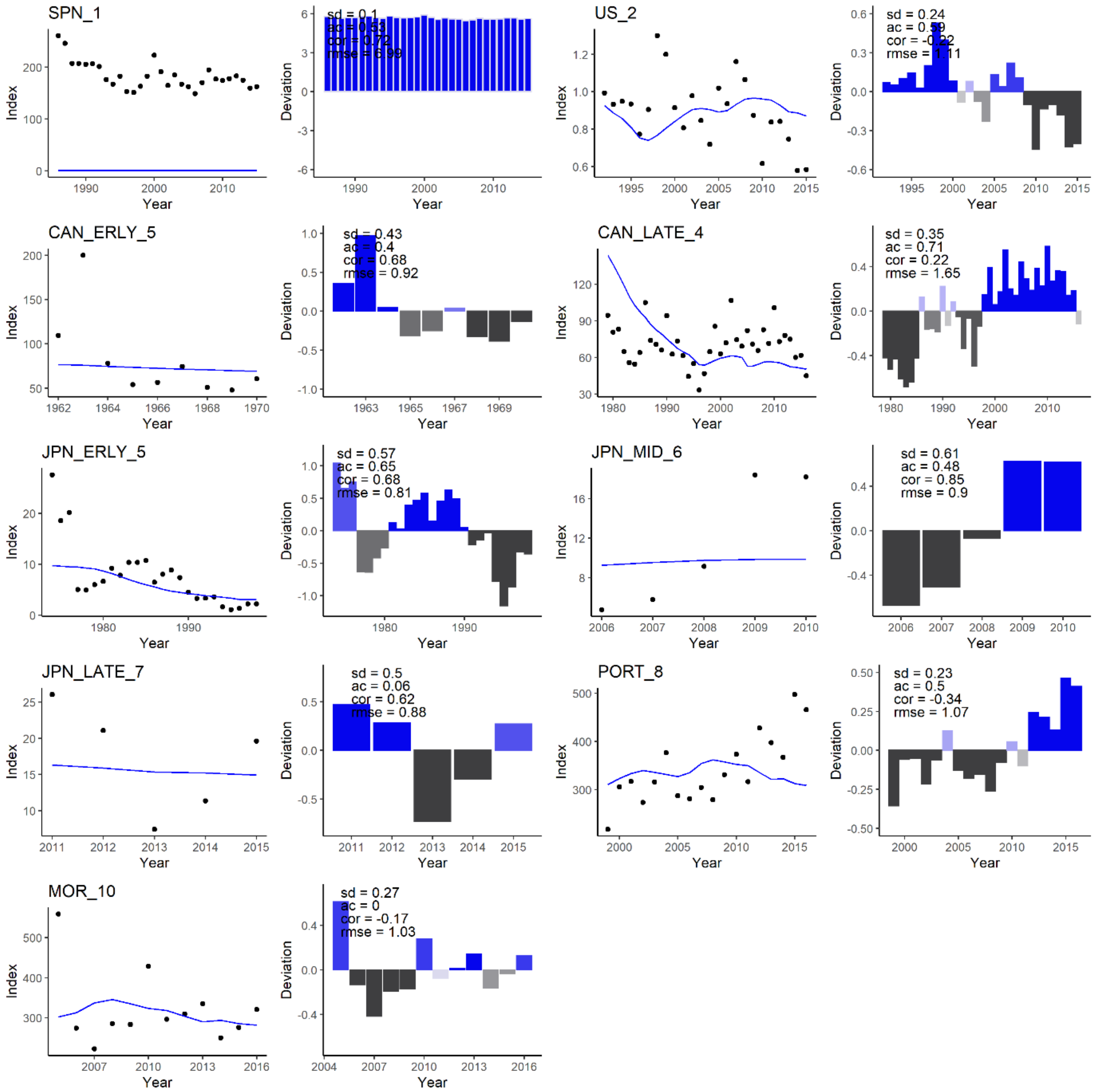

Figure 10. Operating model fits to for the 9 remaining indices for the OM with the highest RMSE for the Age-3 index. The left-hand panel for each plot shows the observed (black dots) and model predicted (blue line) indices. The right-hand panels for each plot show the log deviations (the observation model is log-normal) including the residual standard deviation (sd) and lag-1 autocorrelation in residuals (ac), correlation (cor), and standardized root-mean-square-error (rmse). Runs of increasing length for positive residuals are filled with increasingly darker shade of blue. Runs of increasing length for negative residuals are filled with increasingly darker shade of grey.