

Universidad de Concepción Dirección de Postgrado Facultad de Ciencias Naturales y Oceanográficas Programa de Magíster en Ciencias con Mención en Pesquerías

# Evaluación del efecto de la incorrecta determinación de la edad en un modelo de evaluación edad estructurado y sus implicancias para el manejo pesquero: un caso de estudio en Bacalao de profundidad



Tesis para optar al grado de Magíster en Ciencias con Mención en Pesquerías

# VANIA PATRICIA HENRÍQUEZ TRIBIÑOS CONCEPCIÓN-CHILE 2015

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Dedicada a mi familia

### Agradecimientos

Agradezco a cada una de las personas que contribuyeron en el desarrollo de este trabajo. Principalmente a mi profesor guía Luis Cubillos, gracias por recibirme en EPOMAR y por todas las oportunidades que me ha dado siendo parte de su equipo de trabajo. Agradezco también a Cristián Canales de IFOP, por sus consejos, buena voluntad y aportes durante el desarrollo de esta tesis. Quiero agradecer enormemente el apoyo del profesor Sean Cox de SFU, por todo el tiempo que me dedicó en SFU durante mi pasantía, porque la mayoría de las ideas nuevas que aumentaron la calidad de este estudio, surgieron del trabajo realizado durante mi estadía en SFU. Agradezco a la comisión evaluadora Cristian Canales y Sergio Neira, por el tiempo invertido en la revisión de este trabajo. Agradezco también a Juan Carlos Quiroz de IFOP, por su disposición y apoyo en los primeros meses del desarrollo de este trabajo.

Agradezco a mi amiga Sonia, por su apoyo incondicional y por ser mi gran compañera en Concepción.

A mis compañeros de Magíster: José, María Cristina, Sandra, Jaime y a mis compañeros de EPOMAR: Claudio, Caro, Sandra y María Cristina, por todos los momentos compartidos. A mis compañeras y amigas de la Cabina 10: Cote y Sandra M.

Quiero agradecer especialmente a mi familia, principalmente a mi mamá Mónica, por su apoyo incondicional, por su amor, por creer siempre en mi y en mis capacidades, por ser el mejor ejemplo que tengo a seguir. A mis hermanos Sebastián y Nicolás, por el amor y la paciencia y por aguantar mi mal genio en los momentos de stress, que no fueron pocos. Quiero agradecer al gordo, mi compañero y amigo, por creer en mi, y por hacerme sentir que me las puedo cuando sentía que esto se volvía un poco interminable.

Estoy muy agradecida de este trabajo, ha sido un trabajo muy lindo, de muchas cosas nuevas, un desafío diario y de mucho aprendizaje.

### Agradecimientos Institucionales

Quiero agradecer a las instituciones que permitieron el desarrollo de esta tesis. En primer lugar agradezco enormemente a la Comisión Nacional de Ciencia y Tecnología de Chile (CONICYT) por el financiamiento otorgado para el desarrollo del Magíster. Sin el soporte económico de la beca CONICYT, difícilmente hubiese podido realizar un postgrado. Agradezco también al Programa Canada-Chile Leadership Exchange Scholarships del Gobierno de Canadá, por financiar mi pasantía en Simon Fraser University. Agradezco al Programa COPAS Sur Austral, por la beca otorgada para el financiamiento parcial de este trabajo. Agradezco a la Dirección de Postgrado, a la Facultad de Ciencias Naturales y Oceanográficas, y al Programa COPAS Sur Austral de la Universidad de Concepción, por el apoyo financiero otorgado para la asistencia a congresos. Finalmente estoy muy agradecida del Instituto de Fomento Pesquero y de la Subsecretaría de Pesca por la facilitación de los datos de la pesquería de Bacalao de profundidad.



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### RESUMEN

La edad es información clave en el manejo y evaluación de poblaciones explotadas, debido a que los parámetros determinados a partir de ésta subyacen en los modelos de dinámica poblacional utilizados en evaluación de stock. Determinaciones incorrectas de la edad pueden afectar la calidad de una evaluación de stock y la recomendación científica derivada de ésta. En las evaluaciones de pesquerías que utilizan modelos edad estructurados, los errores de lecturas de edades dentro de los datos de composición de edades pueden conducir a estimaciones sesgadas de las tasas de mortalidad y de la fuerza de las clases anuales. Estos errores pueden ser intensificados aun más cuando los datos de la composición de edades dependientes de la pesquería son influenciados por cambios temporales de selectividad, capturabilidad o por una incorrecta especificación de la selectividad.

Este trabajo utiliza el stock de bacalao de profundidad (*Dissostichus eleginoides* Smitt, 1898) de la Patagonia austral de Chile como caso de estudio. La composición de edades de las capturas de bacalao de profundidad presenta diferencias debido al uso de dos estructuras duras (escamas y otolitos) en la determinación de la edad. La composición de edades de las capturas de esta pesquería está dividida en dos conjuntos de datos basados en lecturas de escamas (1989-2006) y otolitos (2007-2012), donde las lecturas de escamas muestran un claro efecto de truncamiento a partir de aproximadamente los 13 años de edad. Las edades determinadas a partir de escamas fueron subestimadas por efecto de la sobreposición de anillos en el borde de éstas. Sumado a la inconsistencia en la composición de edades de las capturas, el stock de bacalao de profundidad se encuentra en un estado de sobreexplotación y sobrepesca, con niveles críticos de biomasa y mortalidad por pesca que han excedido los puntos de referencia límites.

Este estudio aplicó un enfoque de simulación - estimación para evaluar el desempeño de un modelo estadístico de captura a la edad (SCA) bajo diferentes escenarios, particularmente, donde existe una incorrecta determinación de la composición de edades y cuándo parámetros tiempo variantes (selectividad y capturabilidad) comúnmente esperados en pesquerías que sólo cuentan con información dependiente de la pesquería, y una incorrecta especificación de la selectividad son incluidos o no en el procedimiento de simulación-estimación. Este trabajo evalúa la influencia de estos factores en parámetros de importancia para la evaluación de stock y para el manejo pesquero, tales como el reclutamiento virginal promedio ( $R_0$ ), la depleción ( $D_{final}$ ) y la mortalidad por pesca en el ultimo año ( $F_{terminal}$ ). Por otra parte, el estado actual de sobreexplotación y sobrepesca del bacalao de profundidad, así como el posible sesgo en la estimación de puntos de referencia para el manejo producto del error de lecturas de edades, hizo necesario plantearse preguntas acerca de qué procedimientos de manejo podrían ser más efectivos para recuperar el stock en el mediano a largo plazo y mostrar las consecuencias de procedimientos de manejo (MP) alternativos. Esto último fue abordado a través de un enfoque de Evaluación de Estrategias de Manejo (MSE).

La simulación de estrategias de manejo es una herramienta útil para evaluar el desempeño de distintos MPs contra objetivos económicos y de conservación. MPs exitosos son necesarios no sólo para la conservación de las poblaciones explotadas, sino también para fortalecer la capacidad de recuperación económica de las pesquerías. Se utilizaron simulaciones de estrategias de manejo para explorar MP candidatos destinados a la recuperación del stock de bacalao de profundidad del sur de Chile y para examinar el equilibrio entre la viabilidad de la pesca y la conservación de los peces. Las reglas de control (HCR) que conformaron los MP simulados consistieron de: (1) un objetivo o target de recuperación que representó el tamaño del stock desovante deseado (TSSB) correspondiente a  $B_{MSY}$  (biomasa desovante en el máximo rendimiento sostenible) o a los proxy  $0.45B_0 \circ 0.4B_0$  (45% o 40% de la biomasa desovante en estado virginal); (2) un punto límite (LSSB) que representó el tamaño límite permitido del stock desovante, correspondiente a múltiplos de  $B_{MSY}$  ó  $B_0$  (e.g.  $0.5B_{MSY}$ ); y (3) una tasa de mortalidad por pesca objetivo (*target*) correspondiente a múltiplos de  $F_{MSY}$  (mortalidad por pesca que maximiza el rendimiento total en equilibrio) or  $F_{SPR45\%}$  (mortalidad por pesca que reduce la biomasa desovante por recluta a un 45% de su nivel en estado virginal). Se utilizó un modelo de excedentes de producción en la simulación de la evaluación de stock para estimar la biomasa explotable anual junto con las HCR antes mencionadas. Veinte MPs fueron testeados contra un modelo operativo edad estructurado que imitó la población y pesquería del bacalao de profundidad durante el periodo 1989 a 2012.

El error de lecturas de edades generó estimaciones imprecisas y positivamente sesgadas de  $R_0$  (rango 19 a >200%),  $D_{final}$  (rango -27 a >200%) y  $F_{terminal}$  (rango -33 a >200%). El sesgo sobre  $D_{final}$  y  $R_0$  fue más severo cuando una selectividad con forma de domo fue utilizada. Selectividades tiempo variantes (asintótica y con forma de domo) incrementaron el sesgo sobre  $D_{final}$  y  $F_{terminal}$ , pero disminuyeron el sesgo sobre  $R_0$ . El efecto del error de edad fue mas severo o fue enmascarado con la incorrecta especificación de la selectividad. Generalmente, el error de edad condujo a percepciones más optimistas del actual estado de la pesquería. Una corrección de la incorrecta especificación de la edad dentro del SCA fue realizada a través de la multiplicación de la proporción a la edad predicha por la matriz transpuesta a partir de la cual el error de edad

fue generado. La corrección mejoró la utilidad de los datos de composición de edades, generando estimaciones de parámetros más precisas e insesgadas.

Las estimaciones de MSE concluyen que el stock de bacalao de profundidad no se recuperará en el corto plazo (es decir, en los primeros 9 años de la estrategia de manejo). Si la mortalidad por pesca se mantiene en el status quo (mortalidad por pesca actual), el stock se enfrentará a un gran riesgo de agotamiento en el corto plazo. Los mejores MPs incluyeron HCRs con (i) LSSB =  $0.5B_{MSY}$ , TSSB =  $B_{MSY}$ , y  $F_{MSY}$ , (ii) LSSB =  $0.2B_0$ , TSSB =  $0.45B_0$ , y  $0.5F_{spr45\%}$ , y (iii) F<sub>MSY</sub>. constante. Los mejores MPs demuestran que el Bacalao de profundidad podría recuperarse de su actual estado de sobrepesca a niveles mayores que  $0.25B_0$  dentro de los años 2022 a 2038. Sin embargo tal recuperación costaría al menos una reducción de 36 - 40% en la captura anual (~ 400 toneladas).

Los resultados de esta tesis destacan que podría existir un mal entendimiento del actual estado de la pesquería de bacalao de profundidad en Chile. En particular, las estimaciones de biomasa y otras medidas de importancia para el manejo han estado probablemente sesgadas por efecto de la inconsistencia en la determinación de la edad, conduciendo a capturas mas optimistas y menos efectivas para la conservación.

Palabras claves: Error de lecturas de edades, Enfoque de simulación - estimación, Modelo estadístico edad estructurado, Selectividad tiempo variante, Incorrecta especificación de la selectividad, Evaluación de estrategias de manejo.

### ABSTRACT

The age is a key point in the management and evaluation of exploited populations, because the parameters determined from the age underlie the population dynamics models used in stock assessment. Incorrect age determinations may affect the quality of the stock assessment and scientific advice derived from it. In age-structured fisheries stock assessments, ageing errors within age composition data can lead to biased mortality rate and year-class strength estimates. These errors may be further compounded where fishery-dependent age composition data are influenced by temporal changes in fishery selectivity, catchability or by selectivity misspecification.

This study uses the Patagonian toothfish (*Dissostichus eleginoides* Smitt, 1898) stock from Southern Chile as case study. The Patagonian toothfish fishery from southern Chile is affected from ageing errors due to the use of two hard structures, scales and otoliths, for ageing. Age composition data used to assess this fishery are split into two sets based on scale (1989-2006) and otolith (2007-2012) readings, where the scale readings show clear age-truncation effects from 13 years old. Ages determined from scales were underestimated due to the overlapping of rings at the edge. In addition to the incorrect age determination, the Patagonian toothfish stock is in overfishing and overfished status, with critical levels of biomass and fishing mortality that have exceeded the limit reference points.

This study applied a simulation-estimation approach to evaluate the performance of an statistical catch-at-age analysis (SCA) under different scenarios, particularly where there is an incorrect determination of the age composition and when time-varying parameters (selectivity and catchability) commonly expected in fisheries that only have fishery-dependent data and selectivity misspecification, are or not included in the simulation-estimation procedure. This paper evaluates the influence of these factors on important parameters for stock assessment and fisheries management, such as the average virgin recruitment ( $R_0$ ), spawning stock depletion ( $D_{final}$ ), and fishing mortality in the terminal year ( $F_{terminal}$ ).

Moreover, the current overfishing and overfished status of this resource, as well as, the possible bias in the estimation of reference points for the management as result of the incorrect age determination, arise also questions about what management procedures (MPs) could be more effective to rebuild the stock and yield sustainable catches. This last was evaluated through a management strategy evaluation (MSE). Management strategy simulation is a useful tool for evaluating expected performance MPs against economic and conservation objectives. Successful

MPs are necessary not only for conservation of exploited stocks, but also for strengthening economic resilience of fisheries. We used management strategy simulations to explore MP candidates aimed at rebuilding the Patagonian toothfish stock from Southern Chile and to examine trade-offs between fishery viability and fish conservation. The harvest control rules (HCR) components of simulated management procedures consisted of (1) a rebuilding target (TSSB) corresponding to  $B_{MSY}$  (stock size that can produce the maximum sustainable yield) or  $0.45B_0$  or  $0.4B_0$  proxy (45% or 40% of unfished spawning biomass); (2) limits (LSSB) corresponding to multiples of  $B_{MSY}$  or  $B_0$  (e.g.  $0.5B_{MSY}$ ); and (3) target fishing mortality rates corresponding to multiples of  $F_{MSY}$  (fishing mortality that maximizes equilibrium total yield) or  $F_{SPR45\%}$  (fishing mortality that reduces spawning stock biomass-per-recruit to 45% of the unfished level). We used a surplus production model in simulated stock assessments to estimate annual exploitable biomass along with the harvest control rule components given above. Twenty MPs were tested against an age-structured operating model that mimicked the Patagonian toothfish population and fishery over the period 1989 to 2012.

Ageing error generated imprecise and positively biased estimates of  $R_0$  (range 19 to >200%),  $D_{final}$  (range -27 to >200%) y  $F_{terminal}$  (range -33 to >200%). The bias on  $D_{final}$  and  $R_0$  was more severe when the dome-shaped selectivity was used. Time-varying selectivity (asymptotic and dome-shaped) increased the bias on  $D_{final}$  and  $F_{terminal}$ , but decreased the bias on  $R_0$ . The effect of ageing error was more severe or was masked with selectivity misspecification. Generally, ageing error led to overly optimistic perceptions of current fishery status relative to historical reference points A correction of the age misspecification inside the SCA was performed by multiplying the predicted age proportion by the transposed matrix from which the ageing error was generated. The correction improved the utility of age composition data produced more precise and unbiased parameters.

The MSE estimates demonstrate that the current stock status of Patagonian toothfish will not recover in the short term (i.e. the first 9 years of management strategy). If the fishing mortality is maintained in the status quo, the stock will be in big risk of collapse in the short term. The best MPs included HCRs with (i) LSSB =  $0.5B_{MSY}$ , TSSB =  $B_{MSY}$ , and  $F_{MSY}$ , (ii) LSSB =  $0.2B_0$ , TSSB =  $0.45B_0$ , and  $0.5F_{spr45\%}$ , and (iii) constant  $F_{MSY}$ . The best MPs demonstrate that Patagonian toothfish could recover from its current over-fished state to levels greater than  $0.25B_0$ within the years 2022 to 2038; however, such recovery would cost at least 36-40% reduction in annual catch (~ 400 tonnes). The results of this thesis point out that there may be a misunderstanding of the current status of Patagonian toothfish fishery in Chile. In particular, estimates of biomass and other measures of importance to the fishery management has probably been biased due to age-reading errors, leading to more optimistic quotas and less effective for conservation.

Keywords: Age-reading errors, Simulation-estimation approach, Statistical Catch-at-Age model, Time-varying selectivity, Selectivity misspecification, Management Strategy Evaluation.



## **INTRODUCCIÓN**

Estimaciones precisas y confiables de la composición de edad son información clave en la evaluación de stock de peces. La información proveniente de la edad constituye la base para las estimaciones en los modelos edad estructurados, debido a que la edad es utilizada para seguir las cohortes de la población a través del tiempo (Richards *et al.*, 1992). Las estimaciones de edad no sólo son importantes en la determinación de la abundancia y en las estimaciones de biomasa, sino que también juegan un rol crucial en la estimación de otras medidas claves para el manejo pesquero, derivadas de los modelos de evaluación de stock (Tyler *et al.*, 1989; Bradford, 1991). Por lo tanto, determinaciones incorrectas de la edad pueden conducir a tomar medidas de manejo inapropiadas para un recurso pesquero.

Estimaciones de edad incorrectas ocurren cuando existe una diferencia sistemática entre la edad obtenida a partir de la lectura de estructuras duras (por ejemplo, otolitos y escamas) y la verdadera edad del pez, conduciendo a sesgo e imprecisión. En el análisis estadístico de captura a la edad (SCA), por ejemplo, la información de la edad (obtenida a partir de cruceros o de la pesquería) es usada para inferir la composición de edad de la población, y para modelar procesos como la madurez y el crecimiento. La información de la captura a la edad, es la base para la estimación de tasas de mortalidad y para medir la variación año a año de la fuerza del reclutamiento en la población (Maunder & Punt, 2013). Por lo tanto, un error sistemático en la determinación de la edad, y por consiguiente en los datos de captura a la edad, puede conducir a sesgo e imprecisión en las estimaciones de biomasa desovante y reclutamiento. Estimaciones sesgadas de edad pueden conducir también a sobreestimar las tasas de crecimiento y mortalidad, comprometiendo el entendimiento de la fuerza de las clases anuales (Mills & Beamish, 1980; Richards et al., 1992; Yule et al., 2008), haciendo que años con fuertes clases anuales parezcan más débiles y que años con débiles clases anuales parezcan más fuertes de lo que son en realidad (Fournier & Archibald, 1982; Kimura & Lyons 1991; Richards et al., 1992). Por otra parte, el error de la edad puede introducir considerable sesgo y autocorrelación en las series de tiempo del reclutamiento (Bradford, 1991). Reeves (2003) encontró que el error en la edad afectó las estimaciones de biomasa del stock desovante y el nivel absoluto de mortalidad en el bacalao del norte (Gadus morhua) del Báltico oriental. Esto condujo a una captura total permisible (TAC) demasiado optimista y menos efectiva para la conservación del stock. Por otra parte, Yule et al., (2008) postularon que el colapso de Cisco (Coregonus artedi) de Great Lakes estuvo relacionado en parte a la subestimación sistemática de la edad debido a que ésta fue determinada a partir de lecturas realizadas en escamas.

En desmedro de nuestro entendimiento de la producción de una población de peces, los errores de lecturas de edades también reducen la calidad de una evaluación de stock e incrementan el riesgo asociado con estrategias futuras de manejo (Fournier & Archibald, 1982; Richards *et al.*, 1992; Punt *et al.*, 2008).

La selectividad también juega un rol crítico dentro del SCA, pero en general las evaluaciones de stock no exploran su influencia (Sampson, 2014). Los resultados del SCA pueden ser sensibles a la especificación incorrecta de la selectividad, lo que puede ocurrir cuando asumimos una forma incorrecta en la función de selectividad, o cuando cambios temporales de la selectividad no son tomados en cuenta de manera apropiada en la evaluación de stock (Linton & Bence, 2010). Una selectividad tiempo-variante debería ser esperada en la mayoría de las pesquerías, principalmente cuando utilizan datos dependientes de la pesquería. La selectividad es función de la edad y de la dinámica espacio-temporal del recurso y la pesquería. En consecuencia, es improbable que la dinámica tanto del recurso como de la pesquería sean homogéneas a través del espacio y del tiempo. La razón, es que la selectividad para las pesquerías comerciales es altamente influenciada por la selección específica del arte de pesca, por las características de las flotas y sus niveles de esfuerzo, por la distribución espacial del esfuerzo y por el movimiento de los peces (Sampson, 2014).

Las evaluaciones de stock deberían explorar regularmente los cambios en la selectividad de la pesquería, debido a que es altamente probable que ésta cambie a lo largo del tiempo. Suponer que la selectividad es constante, puede sesgar los resultados de una evaluación. Maunder & Piner (2015), enfatizan que los puntos de referencia que son determinados típicamente a través del uso de modelos de evaluación de stock y evaluados utilizando los resultados de la evaluación de stock, no sólo son sensibles a los parámetros biológicos, tales como steepness (parámetro de escarpamiento), mortalidad y crecimiento, sino que también son altamente sensibles a la selectividad del arte de pesca. Goodyear (1996), mostró cómo la estimación del máximo rendimiento sostenible (MSY) en número y en peso varió cuando la edad máxima de selectividad cambió. Por lo tanto, ignorar cambios en la selectividad a través del tiempo puede producir estimaciones sesgadas de las cantidades de importancia para el manejo, de los puntos de referencia biológicos y subestimar la incertidumbre.

Aunque varios estudios examinan la influencia del error en la determinación de la edad en la evaluación de stock y en el asesoramiento científico derivado de ésta (Fournier & Archibald, 1982; Coggins & Quinn, 1998; Bradford, 1991; Rivard, 1989; Restrepo & Powers, 1990; Reeves, 2003; Bertignac & Pontual, 2007; Punt *et al.*, 2008; Dorval *et al.*, 2013; Liao *et al.*, 2013), no hay estudios que evalúen cómo los errores en la determinación de la edad y la selectividad se combinan para afectar la credibilidad de un modelo de evaluación de stock.

Las interacciones entre el error en la determinación de la edad y la selectividad tiempovariante son importantes debido a que cada uno de estos factores puede tener efectos independientes sobre las estimaciones de reclutamiento, la percepción del estado del stock y la mortalidad por pesca.

Para muchos stocks, la subestimación sistemática de la edad de los peces es aún un problema, debido a que estimaciones de edad más precisas requieren técnicas más complicadas y costosas (Cardinale & Arrhenius, 2004; Begg *et al.*, 2005). A diferencia de la selectividad, la cual es difícil de medir independientemente, es posible corregir el error en la determinación de la edad dentro del modelo de evaluación de stock, lo que permite mejorar la utilidad de los datos de composición de edades.

Este trabajo utiliza el stock de bacalao de profundidad (*Dissostichus eleginoides*) de la Patagonia austral de Chile como caso de estudio.

El bacalao de profundidad soporta una de las pesquerías más lucrativas que se desarrolla en aguas Antárticas y Sub - Antárticas del cono sur de América de Sur, con capturas que son rentables incluso a bajos rendimientos, debido a su alto valor comercial en los mercados extranjeros (US\$25/kg). En Chile, la pesquería de bacalao de profundidad de la Patagonia austral, es desarrollada por una flota industrial de espinel que opera desde los 47° S a 57° S. El bacalao de profundidad es una especie demersal que se distribuye en el hemisferio sur, principalmente entre los 40°S a 60°S y en la región circumpolar – Antártica (Laptikhovsky & Brickle, 2005). El bacalao de profundidad se caracteriza por ser una especie longeva, con individuos que alcanzan sobre los 50 años de edad (Horn, 2002; Belchier, 2004), por presentar un crecimiento lento y una madurez sexual tardía, alcanzando la talla de primera madurez sexual aproximadamente a los 89.8 cm en hembras y 81.3 cm en machos, lo que corresponde aproximadamente a 14 años (Arana, 2009). Actualmente el stock chileno de bacalao de profundidad se encuentra en un estado de sobreexplotación con riesgo de colapso, con niveles críticos de biomasa y mortalidad por pesca que han excedido los puntos de referencia límites (Tascheri & Canales, 2015).

La pesquería de bacalao de profundidad es clasificada como una pesquería de información moderada (Restrepo & Powers, 1999), con varias limitaciones que subvacen en la evaluación de stock, principalmente que sólo cuenta con información dependiente de la pesquería. La composición de edades usada en la evaluación de stock muestra un claro error en las lecturas de edades como consecuencia del uso de diferentes estructuras en la determinación de la edad. Hasta ahora, no se ha desarrollado ninguna metodología que tenga como finalidad corregir este problema. En particular, lecturas en escamas fueron usadas para determinar la edad los primeros años de la pesquería (1989 - 2006), mientras que durante los últimos años (2007 - presente), la edad ha sido determinada a partir de cortes transversales realizados en otolitos. En general, existen diferencias significativas en la determinación de la edad cuando las lecturas son realizadas utilizando escamas u otolitos. La principal razón es debido a la baja resolución de los grupos de edad más viejos con el método de lectura en escamas, producto de una sobreposición de anillos en el borde de la escama (Tyler *et al.*, 1989). Una de las consecuencias es que agrupa ejemplares viejos en edades más jóvenes y subestima el aporte de ejemplares viejos a las capturas. De hecho, en la composición de edad de la pesquería de la Patagonia austral, la máxima edad estimada usando escamas ha sido 23 años de edad, mientras que utilizando otolitos se ha determinado edades de 30 años o más (Ashford et al., 2001).

Estos hechos revelan que puede existir un mal entendimiento del estado actual de la pesquería de bacalao de profundidad. Particularmente, las estimaciones de biomasa y otras medidas de manejo han estado probablemente sesgadas por el efecto de la incorrecta determinación de la composición de edades.

El actual estado de sobrepesca y sobreexplotación de este recurso, conlleva a plantearse también preguntas acerca de qué procedimientos de manejo (MP) podrían ser más efectivos para recuperar el stock y producir capturas sostenibles. Una herramienta útil para evaluar procedimientos de manejo considerando tanto objetivos de conservación como económicos es la Evaluación de Estrategias de Manejo (MSE), llamado también closed loop simulation o Procedimientos de Manejo (de la Mare, 1998; Smith, 1993; Cooke, 1999; Punt and Smith, 1999; Butterworth, 2007). MSE involucra la construcción de (1) un modelo operativo que represente toda la información y supuestos del stock y de la pesquería. Este modelo operativo es usado para

simular datos de la dinámica poblacional y del proceso de recolección de datos pesqueros; (2) estos datos son usados por un modelo de estimación que evalúa el estatus del stock; (3) entonces, se aplica una regla de decisión (HCR) para determinar capturas límites en términos de TAC, o de esfuerzo de pesca permitido (A'mar *et al.*, 2008); y, finalmente, (4) se comparan diferentes estrategias de manejo para determinar cuáles de éstas cumplen con los objetivos deseados.

MPs exitosos son necesarios no sólo para la conservación de las poblaciones explotadas, sino también para fortalecer la capacidad de recuperación económica de las pesquerías. La simulación de estrategias de manejo permite explorar MP candidatos destinados a la recuperación de los stocks y examinar el equilibrio entre la viabilidad de la pesca y la conservación de los peces.

En este estudio, se utilizó un enfoque de simulación estimación para investigar (i) cómo los parámetros estimados por el modelo SCA son afectados por el error de edad presente en los datos de composición de edades, tipo de selectividad (asintótica o con forma de domo), incorrecta especificación de la selectividad y selectividades tiempo variantes y (ii) bajo qué condiciones una corrección del error de edad dentro del modelo de estimación SCA conduce a una mejora substancial en el desempeño del modelo de evaluación de stock. Una de las ventajas de evaluar el desempeño de métodos de evaluación a través del uso de simulación es que los valores verdaderos de los parámetros y el verdadero estado de la población son conocidos exactamente (Smith, 1993; Butterworth & Punt, 1999; Wetzel & Punt, 2011). El modelo operativo utilizado en la simulación fue parametrizado utilizando las características biológicas y de la pesquería de bacalao de profundidad del sur de Chile [Capitulo II (Tabla 1)]. Finalmente, se utilizó un enfoque MSE para evaluar iii) qué procedimientos de manejo podrían ser más efectivos para recuperar el stock en el mediano a largo plazo y cuáles son las consecuencias de estos procedimientos de manejo alternativos.

### **OBJETIVO GENERAL**

 El objetivo general de este trabajo es evaluar el desempeño de un modelo estadístico de captura a la edad (SCA) bajo diferentes escenarios a través de un enfoque de simulación estimación, específicamente cuando existe una incorrecta determinación de la composición de edades, cuando existe una incorrecta especificación de la selectividad y cuándo parámetros tiempo variantes son incluidos o no en el procedimiento de simulaciónestimación.

## **OBJETIVO ESPECÍFICOS**

- Implementar un modelo operativo edad estructurado que simule la dinámica poblacional y la pesquería de bacalao de profundidad desarrollada en la Patagonia austral de Chile, generando composiciones de edades que den cuenta del uso de diferentes estructuras duras (escamas y otolitos) en la determinación de la edad.
- Evaluar el efecto del error en la determinación de la edad sobre el sesgo y la precisión de parámetros de importancia para la evaluación de stock y el manejo pesquero.
- Analizar el efecto del error en la determinación de la edad y su interacción con parámetros tiempo variantes comúnmente descritos en pesquerías de datos dependientes, tales como selectividad y capturabilidad y con selectividades incorrectamente especificadas.
- Determinar la factibilidad de corregir el error en la composición de edades dentro del modelo de estimación (SCA).
- Evaluar qué procedimientos de manejo podrían ser más efectivos para recuperar el stock de bacalao de profundidad en el mediano a largo plazo y cuáles son las consecuencias de procedimientos de manejo (MP) alternativos, a través de un enfoque MSE,.

# HIPÓTESIS

Las hipótesis de trabajo consideran que:

# Capítulo I

El uso de lecturas de edades basadas en escamas y otolitos no altera las estimaciones de los parámetros de importancia para la evaluación de stock y el manejo pesquero de bacalao de profundidad, estimados por el modelo estadístico de captura a la edad (SCA).

# Capítulo II

Una estrategia de pesca constante, basada en la mortalidad por pesca en el máximo rendimiento sostenible  $F_{MSY}$  o en un proxy de  $F_{MSY}$ , permite la recuperación del stock de bacalao de profundidad en el mediano a largo plazo.



Capítulo I

Interactions between ageing error and selectivity in statistical catch-at-age models: simulations and implications for assessment of the Chilean Patagonian toothfish fishery



# Interactions between ageing error and selectivity in statistical catch-at-age models: simulations and implications for assessment of the Chilean Patagonian toothfish fishery

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### Abstract

In age-structured fisheries stock assessments, ageing errors within age composition data can lead to biased mortality rate and year-class strength estimates. These errors may be further compounded where fishery-dependent age composition data are influenced by temporal changes in fishery selectivity and selectivity misspecification. In this study, we investigated how ageing error within age composition samples interacts with time-varying fishery selectivity and selectivity misspecification to affect estimates of average unfished recruitment ( $R_0$ ), spawning stock depletion ( $D_{final}$ ), and fishing mortality in the terminal year ( $F_{terminal}$ ) derived from a statistical catch-at-age (SCA) model that used fishery-dependent data. The Patagonian toothfish (Dissostichus eleginoides) fishery in southern Chile was used as a case study. Age composition data used to assess this fishery are split into two sets based on scale (1989-2006) and otolith (2007-2012) readings, where the scale readings show clear age-truncation effects. We used a simulation-estimation approach to examine the bias and precision of parameter estimates under various combinations of ageing error, selectivity type (asymptotic or dome-shaped), selectivity misspecification and variation in selectivity over time. Generally, ageing error led to overly optimistic perceptions of current fishery status relative to historical reference points. Ageing error generated imprecise and positively biased estimates of  $R_0$  (range -19% to >200%),  $D_{final}$  (range -27% to >200%), and  $F_{terminal}$  (range -33% to >200%). The bias in  $D_{final}$  and  $R_0$  was more severe when selectivity was dome-shaped. Time-varying selectivity (both asymptotic and dome-shaped) increased the bias in  $D_{\text{final}}$  and  $F_{\text{terminal}}$ , but decreased the bias in  $R_0$ . The effect of ageing error was more severe or was masked with selectivity misspecification. Correcting the ageing error inside the SCA reduced bias and improved precision of estimated parameters.

**Keywords:** Ageing errors, selectivity misspecification, simulation-estimation approach, statistical catch-at-age model, stock assessment, time-varying selectivity.

### Introduction

Age-dependent processes of growth, mortality, and reproduction are critical in fisheries science, extending everywhere from the general theory of fishing to specific harvest advice derived from fisheries stock assessments (Tyler *et al.*, 1989; Bradford, 1991). In statistical catchat-age analysis (SCA), for instance, age information (from surveys or fisheries) is used to model maturity and growth schedules, natural mortality rates, and year-to-year variation in recruitment to fish populations (Maunder and Punt, 2013). Unfortunately, systematic underestimation of age remains a problem for many fish stocks because obtaining precise age estimates is expensive and time-consuming (Cardinale and Arrhenius, 2004; Begg *et al.*, 2005).

Fish ages determined via low-resolution methods, such as scales or whole-otoliths, may lead to biased perceptions of the population age structure and, therefore, imprecise stock assessment estimates of spawning biomass, recruitment, and fish population productivity (Mills and Beamish, 1980; Richards *et al.*, 1992; Yule *et al.*, 2008). For example, ageing error affected spawning stock biomass and fishing mortality estimates of Atlantic cod (*Gadus morhua*) from the Eastern Baltic, leading to overly optimistic Total Allowable Catch (TAC) and ineffective conservation measures (Reeves, 2003). Similarly, Yule *et al.*, (2008) postulated that the collapse of cisco (*Coregonus artedi*) in the Great Lakes was linked in part to a systematic underestimation of fish ages determined from scales. For recruitment, in particular, biased age estimates cause strong year-classes to appear weaker and weak year-classes to appear stronger (Fournier and Archibald, 1982; Kimura and Lyons, 1991; Richards *et al.*, 1992), leading to biased inferences from stock-recruit analyses, as well as mistaken appearance of auto-correlation in recruitment time-series (Bradford, 1991). By degrading our understanding of fish production, ageing errors also reduce the quality of risk assessments associated with future management strategies (Fournier and Archibald, 1982; Richards *et al.*, 1992; Punt *et al.*, 2008).

Fishery selectivity also plays a critical role in SCA. However, in general, there is little fisheries stock assessment research exploring selectivity (Sampson, 2014), or how it might interact with other assumptions built into stock assessment models. SCA models can be sensitive to misspecification of selectivity, which can occur, for instance, when using an incorrect shape (asymptotic versus dome-shaped) or by incorrectly assuming that selectivity is constant over time (Linton and Bence, 2010). Time-varying selectivity should be expected in fishery-dependent data because selectivity is highly influenced by the fishing gear, characteristics of the fleet, effort levels, spatial distribution of effort, and movement of the fish (Sampson, 2014). Ignoring changes in selectivity over time can lead to biased estimates of management quantities, biological reference points, and estimates of uncertainty (Maunder and Piner, 2015; Goodyear, 1996).

Although several studies examine the influence of ageing errors on stock assessments and fisheries advice (Fournier and Archibald, 1982; Coggins and Quinn, 1998; Bradford, 1991; Rivard, 1989; Restrepo and Powers, 1990; Reeves, 2003; Bertignac and Pontual, 2007; Punt *et al.*, 2008; Dorval *et al.*, 2013; Liao *et al.*, 2013), few studies evaluate how ageing errors and selectivity combine to affect stock assessment model reliability. Interactions between ageing error and time-varying fishing selectivity are important because each can have independent effects on

recruitment estimates and perceptions of stock status and fishing mortality. Unlike selectivity, which is difficult to measure independently, it is possible to use ageing error correction estimates to improve the utility of age composition data.

In this study, we used a simulation-estimation approach to investigate (1) how SCA model parameter estimates are affected by ageing error in the age composition data, selectivity type (asymptotic or dome-shaped), selectivity misspecification, and selectivity variation over time, and (2) under what conditions correcting the ageing error inside the SCA estimation model led to improvements in stock assessment model performance. One advantage of evaluating the performance of assessment methods via simulation is that the true parameter values and the true status of the population are known exactly (Smith, 1993; Butterworth and Punt, 1999; Wetzel and Punt, 2011). The operating model used in the simulation step was parameterized using the biological and fishery characteristics of the Chilean Patagonian toothfish fishery (Table 1).

### The Chilean Patagonian toothfish fishery

The Patagonian toothfish supports one of the most lucrative fisheries operating in Antarctic and Sub Antarctic waters off the southern cone of South America between 47°S and the limit of Chile's Exclusive Economic Zone. The Patagonian toothfish is a deep-water species with slow growth, late maturity, and great longevity, often living to greater than 50 years (Horn, 2002; Belchier, 2004). Current estimates of spawning stock biomass for the Chilean Patagonian toothfish are below the limit reference point and the fishing mortality rate is higher than the limit reference value (Tascheri and Canales, 2015).

Age composition data for the Patagonian toothfish fishery off southern Chile contains ageing errors due to the use of two hard structures, scales and otoliths, for ageing in two different periods. Therefore, it is an ideal case study for testing the effects of ageing error and selectivity assumptions in stock assessments.

Age composition for Patagonian toothfish were obtained from scale readings between 1989 and 2006; since then, age composition has been determined from thin transverse sections of otoliths. Significant differences exist between ages determined from scales and otoliths. Overlapping rings on the scale edge led to low resolution in older ages of fish aged from scales (Tyler *et al.*, 1989), causing old fish to appear younger and underestimating the contribution of older fish to the catch. Switching to otolith readings raised the maximum estimated age from 23 to over 30 years (Ashford *et al.*, 2001). Therefore, biomass estimates and other management quantities have probably been biased by these differences.

### Methods

Overview

The general simulation-estimation framework consisted of four main steps. (1) Simulate, for a period of 24 years, the true population and fishery dynamics with process errors in recruitment, process errors in selectivity (if applicable), and observation errors in fishery catch-per-unit-effort (CPUE), catchability, and age-composition data. Parameters for each operating model were obtained by conditioning the model to one of 4 cases as defined below. (2) Apply the SCA estimation model to the simulated data. (3) Repeat steps (1) and (2) 100 times. (4) Calculate performance statistics for the relevant fishery and management parameters against their true values from the operating model (OM) (Figure 1).

### The Operating Model (OM)

Parameter definitions and equations used to describe the OM are presented in Table 1 and Appendix A (Table A.1). The base model was a single-sex, age-structured population dynamics model with instantaneous fishing mortality [Equation (A.3.1)]. Annual recruitment of age-1 fish followed a Beverton–Holt stock-recruitment relationship [Equation (A.3.2)] with multiplicative lognormal random deviates [ $w_t$ , Equation (A.3.2)] affecting recruitment each year, as well as the initial abundances in Year 1 [Equation (A.4.1)].

Four fishery selectivity cases in the OM were defined by combining logistic and double logistic types with time-invariant and time-varying dynamics (Figure 2). Time-invariant logistic selectivity was modeled as shown in equation (A.5.1). For the time-varying logistic selectivity function, the age-at-50% selectivity ( $\Omega_1$ ) varied year-to-year following an auto-correlated random walk [Equation (A.5.2)]. The time-invariant double-logistic function was modeled as presented in equation (A.5.3). The term *MAX<sub>a</sub>(num<sub>a</sub>)* indicates the maximum value of the numerator. This term normalized the age-specific selectivity, so that fully selected individuals had a value of 1.0. For the time-varying selectivity function, the inflexion 1 ( $\Omega_3$ ) and inflexion 2 ( $\Omega_4$ ) parameters varied over time following an autocorrelated random walk [Equation (A.5.4)].

The catch-at-age in numbers was calculated using the Baranov equation [Equation (A.6.1)]. Catch-at-age matrices were obtained for the first eighteen years of the fishery using age compositions derived from scale-based age readings and, for the final six years, using age compositions was derived from otolith-based age readings. Age compositions were then transformed to proportions-at-age using equations A.6.3-A.6.6. Observed catch-at-age data were simulated using random draws from a multinomial distribution with a sample size of 800. Bias

caused by ageing error was then introduced to the observed proportions-at-age (A.6.3-6.4). The term P(a'|a) is an age-reading error probability matrix that mimics the age-reading error for scale reading [Equation (A.6.3)], while E(a'|a) represents the age-reading error probability for otolith readings [Equation (A.6.4)]. Both P(a'|a) as E(a'|a) were generated following the same procedure. However, E(a'|a) was generated using a minimal systematic bias as was reported by Welsford *et al.* (2012) for Patagonian toothfish. The bias for E(a'|a) was generated by including a constant standard error (SE) equal to 0.15. Details of the P(a'|a) term are given in the ageing error procedure section.

Fishery catch-per-unit-effort (CPUE) in the OM included observation error as lognormal random deviates corrected for lognormal bias [Equation (A.7.1)]. The catchability coefficient [Equations (A.7.3 - A.7.5)] was a constant parameter (q) or a time-varying random walk ( $q_t$ ) depending on the cases and scenarios [see Fishery-dependent information section in Appendix A (A.7)].

Ageing error procedure

The OM generated age composition data with and without ageing error. The ageing error was represented with an age-reading error matrix P(a'|a) with rows and columns corresponding to scale ages a' and otoliths ages a (true ages), respectively. Matrix P(a'|a) specifies the probability that a fish with true age a, from otoliths, was assigned a different age a', from scales, P(a'|a). This probability matrix had constraints  $P(a'|a) \ge 0$  and  $\sum_{a=1}^{A} P(a'|a) = 1$  for each a. An

example age-reading error matrix can be found in the Supplementary material (Table S1).

Matrix P(a|a) was obtained via a reproducibility experiment carried out in 2006 at the Chilean Fisheries Institute (IFOP), in which both scales and otoliths were read from the same fish (n=392) by the same reader experienced in reading hard structures of the Patagonian toothfish. The data, unfortunately, did not cover the whole range of older ages. Nevertheless, the available data followed the same pattern found for otoliths and scales of Patagonian toothfish from South Georgia (Ashford *et al.*, 2001), which clearly demonstrated that ages estimated using scales were younger than ages assigned from otoliths.

Matrix P(a/a) values were modeled as functions of true ages (X), observed scale ages (Y), and the standard deviation ( $\sigma_{sa}$ ) of age readings about the predicted value. We fit a logistic model of the form  $Y = y_{max}(1 - e^{-mX})$  to the true otolith ages (X) and the observed scale age (Y), where  $y_{max}$  and *m* are the regression maximum predicted age and slope, respectively. Values of P(a'|a) were then generated assuming a normal distribution around the predicted ages, i.e.,  $P(a'|a) \sim Normal(y_{max}(1 - e^{-mX}), \sigma_{sa}^2)$ , where the standard error of the scale age,  $\sigma_{sa}$ , varied as a power function of the true otolith age i.e.,  $\sigma_{sa} = a_1 * X^{b1}$ .

We used a Bayesian approach to estimate parameters  $y_{max}$  and m. Uninformative priors were used for  $y_{max}$  and m and the Metropolis-Hastings algorithm in the R package MCMCpack (Martin *et al.*, 2011) was used to approximate the posterior distribution. For the simulationestimation experiments, we sampled 100 ( $y_{max}$ , m) pairs from the joint posterior distribution of parameter samples to obtain a different P(a/a) for each simulation (Supplementary Figure S1).

The OM was implemented in the statistical software R (R Core Team, 2014). Full details on the population dynamics model and equations can be found in Appendix A.

### Statistical catch-at-age estimation Model

The estimation model was a statistical catch-at-age model (SCA) with estimated parameters  $R_0$  (average unfished recruitment), a time-series of deviations around average recruitment, the fishery selectivity parameters, and the yearly fishing mortalities. Under some scenarios, selectivity was also allowed to vary over time in a random walk fashion. All other parameters, such as those for natural mortality, fecundity, the length-weight relationship, and steepness, were fixed at their true values in the SCA (Table 1). The catchability parameter was also estimated in the SCA as a time-invariant parameter, but this parameter was time-invariant or time-varying in the OM. The parameters were estimated using a penalized maximum likelihood procedure implemented in AD Model Builder (Fournier *et al.*, 2012). Full details of the SCA can be found in Appendix B.

### Ageing error correction procedure

The P(a/a) matrix, with the maximum likelihood estimates of  $y_{max}$  and m, was used inside the SCA to correct the ageing errors obtained from scale readings. The predicted age-proportion in the SCA was [Equation (B.2.1)] multiplied by the transpose of the P(a/a) matrix to obtain predicted scale-based age compositions. This "corrected" age composition matrix was then input into the multinomial likelihood of the SCA [see the Ageing error correction procedure section in Appendix B (B.2)].

### **Simulation cases**

Four general simulation-estimation cases were created to explore SCA performance in the presence of ageing error, as well as time-varying selectivity and catchability parameters. In each case, selectivity in the OM and SCA were identical, except that the true parameters were unknown in the SCA. The selectivity functions were time-invariant logistic (TI-L), time-invariant double logistic (TI-DL), time-varying logistic (TV-L), and time-varying double logistic (TV-DL). For each of these selectivity cases, we generated data from the operating model under the following six scenarios combining ageing error with catchability (AE-1), and ageing error with constant catchability (NAE-1), ageing error with constant catchability (AE-1). Time-varying catchability scenarios are labeled similarly, except a "2" is used in place of "1". A description of cases and scenarios is given in Table 2.

Additionally, we explored SCA performance under four cases with both ageing error and selectivity misspecification. In each case, selectivity differed between the OM and SCA. The case configurations were: i) time-invariant logistic selectivity in the OM and time-invariant double logistic selectivity in the SCA (TI-L\_TI-DL); ii) time-invariant double logistic selectivity in the SCA (TI-L\_TI-DL); iii) time-invariant double logistic selectivity in the OM and time-invariant logistic selectivity in the SCA (TI-DL\_TI-L); iii) time-varying logistic selectivity in the OM and time-invariant logistic selectivity in the SCA (TV-L\_TI-L), and iv) time-varying double logistic selectivity in the OM and time-invariant double logistic selectivity in the EM (TV-DL\_TI-DL). For each of these cases, the data were generated under the following four scenarios combining ageing error with or without time-varying catchability: no ageing error with constant catchability (NAE-1), ageing error with constant catchability (AE-1), no ageing error with time-varying catchability (AE-2). A description of these cases and scenarios is given in Table 3 and Table 4.

### **Performance statistics**

Estimation performance for the SCA was evaluated against the true OM values for each of the 6 scenarios corresponding to each of the cases with selectivity correctly specified (4 cases), and for each of the 4 scenarios corresponding to each of the misspecified selectivity cases (4 cases). Performance measures were computed for parameters  $R_0$ ,  $D_{final}$ , and  $F_{terminal}$  because these are most closely related to management reference points.  $R_0$  is the unexploited recruitment level before starting the fishery.  $D_{final}$  is the spawning biomass depletion or ratio between the spawning biomass from a given year and the unexploited spawning biomass.  $F_{terminal}$  is the fishing mortality rate in the most recent year. Bias and precision of the EM were determined by calculating the relative error (RE) and the median absolute relative error (MARE) for each trial relative to the OM values. This resulted in 100 RE and MARE values for each scenario-case combination. The RE and MARE were calculated as:

$$RE_{i,j} = 100 * \frac{E_{i,j} - T_{i,j}}{T_{i,j}}$$
(1)

$$MARE_{i,j} = 100 * \left( \left| \frac{E_{i,j} - T_{i,j}}{T_{i,j}} \right| \right)$$
(2)

where  $E_{i,j}$  is the estimated value for parameter *i* for simulation *j*, and  $T_{i,j}$  is the true value for parameter *i* for simulation *j*. Changes in model performance among scenarios were evaluated by comparison of the *RE* and *MARE* values.

#### Results

### Effect of ageing error on stock assessment and management parameters

A strong positive bias in  $D_{final}$  was found for all time-invariant (TI) and time-varying (TV) selectivity scenarios in which ageing errors (i.e., AE scenarios) were present (Figure 3) independent of both the OM selectivity pattern and whether constant or time-varying catchability was used.

In the presence of ageing error, median *RE* of  $D_{final}$  was sometimes greater than 50% (e.g., TV-DL-AE-1 and TV-DL-AE-2). On the contrary, in the base scenario (TI-L-NAE-1) and in those scenarios where ageing error was absent (i.e., NAE scenarios) or present, but corrected (i.e., AEC scenarios) in the SCA, *RE* values were close to the true values (Figure 3), except in TV-DL-NAE-1 and TV-DL-NAE-2. Higher *MARE* values indicated that  $D_{final}$  estimates were significantly less precise in all the scenarios with ageing error, compared to those scenarios where ageing error was absent or present, but corrected in the SCA (Table 2). The greatest imprecision occurred in scenarios with double logistic selectivity (i.e., TI-DL-AE-1, TI-DL-AE-2, TV-DL-AE-1, and TV-DL-AE-2), where *MARE* values were sometimes >50% (TV-DL-AE-1, and TV-DL-AE-2). Scenarios with logistic selectivities (TI-L-AE-1, TI-L-AE-2, TV-L-AE-1, and TV-L-AE-2) also showed higher imprecision, but *MARE* values did not exceed 36%. In the base scenario or those without ageing error or corrected ageing error, *MARE* values were less than 19% (Table 2).

 $R_0$  estimates also showed a significant positive bias in the presence of ageing error. However, a higher inter-quartile range for *RE* was found in comparison with  $D_{final}$  (Figure 3). The positive bias in  $R_0$  was very high for all time-invariant (TI) and time-varying (TV) selectivity scenarios in which ageing error (AE) was present (Figure 3), with median *RE* values near or above to 100%.  $R_0$  even showed a positive bias in some scenarios where ageing error was absent (NAE) or was corrected in the SCA (AEC). However, in these scenarios, the median of the *RE* values was generally less than 25% (Figure 3).

Precision of the  $R_0$  estimates was generally poor (*MARE* > 80%) in all scenarios in which ageing error was present. In scenarios without ageing error (NAE) or with ageing error corrected (AEC), the *MARE* values ranged from 14% to 26%, and did not show a much difference among scenarios (Table 2).

 $F_{terminal}$  exhibited similar trends to  $D_{final}$  and  $R_0$  in the ageing error present scenarios. Scenarios with logistic selectivity (TI-L-AE-1, TV-L-AE-2, TV-L-AE-1, and TV-L-AE-2) showed a higher overestimation of  $F_{terminal}$  than the double logistic scenarios (TI-DL-AE-1, TI-DL-AE-2, TV-DL-AE-1, and TV-DL-AE-2).  $F_{terminal}$  estimates were close to the true values for scenarios in which ageing error was absent or was present, but corrected in the SCA, except in the base case (TI-L-NAE-1) (Figure 3).

Precision of  $F_{terminal}$  estimates was slightly lower (*MARE* > 30%) than  $D_{final}$  (except in TI-DL-AE-2, TV-DL-AE-1 and TV-DL-AE-2)and better than  $R_0$  in the scenarios with ageing error. Even in the scenarios where logistic selectivity was used (TI-L-AE-1, TV-L-AE-1, and TV-L-AE-2), *MARE* values near and above 50% were found. In those scenarios where ageing error was absent or was corrected in the SCA, precision of  $F_{terminal}$  was high, with low *MARE* values ranging between 12% and 24% (Table 2).

### Interactions between ageing error, selectivity, and catchability

Positive bias of  $D_{final}$  generated by ageing errors increased for scenarios in which timevarying selectivity was present (TV-L-AE-1, TV-L-AE-2, TV-DL-AE-1, and TV-DL-AE-2) rather than absent (TI-L-AE-1, TI-L-AE-2, TI-DL-AE-1, and TI-DL-AE-2). The highest positive bias occurred in scenarios with time-varying double logistic selectivity. In these scenarios, median *RE* was always greater than 50%. Additionally, positive bias of  $D_{final}$  increased marginally in those scenarios that combined ageing error with time-varying catchability in the OM (TI-L-AE-2, TI-DL-AE-2, TV-L-AE-2, and TV-DL-AE-2) (Figure 3). In general,  $D_{final}$  was close to the true value for scenarios in which ageing error was absent or was corrected in the SCA and time-varying
selectivity was present (i.e., in both the OM and SCA; Figure 3). In these scenarios, the use of time-varying catchability in the OM generally resulted in more biased  $D_{final}$  estimates (except in TV-DL-AEC-2).  $D_{final}$  was highly imprecise (*MARE* > 50%) when time-varying double logistic selectivity was present in both the OM and SCA (TV-DL-AE-1 and TV-DL-AE-2) (Table 2). Poor precision also occurred for the scenarios with time-varying logistic selectivity (TV-L-AE-1 and TV-L-AE-2), although *MARE* values were only around 30%. In general, precision in simulations with time-varying selectivity and ageing error (TV-L-AE-1, TV-L-AE-2, TV-DL-AE-1, and TV-DL-AE-2) depended on whether a time-invariant or time-varying catchability was used in the OM. In scenarios without ageing error, or with ageing error corrected in the SCA, there was no significant difference among the  $D_{final}$  *MARE* values when time-varying catchability was incorporated into the OM (Table 2).

In the scenarios with ageing error,  $R_0$  had marginally lower positive bias when timevarying selectivity was present (TV-L-AE-1, TV-L-AE-2, TV-DL-AE-1, and TV-DL-AE-2), than when selectivity was constant (TI-L-AE-1, TI-L-AE-2, TI-DL-AE-1, and TI-DL-AE-2). For logistic selectivity, the positive bias was slightly lower in the time-varying scenario (TV-L-AE-1) compared to time-invariant (TI-L-AE-1). In contrast, a considerably higher positive bias was found for  $R_0$  in the cases with time-invariant double logistic selectivity (TI-DL-AE-1 and TI-DL-AE-2) compared to time-varying double logistic selectivity (TV-DL-AE-1 and TV-DL-AE-2). When time-varying catchability was combined with time-invariant or time-varying selectivity (logistic or double logistic), the median *RE* for  $R_0$  increased marginally, exhibiting a slightly greater positive bias (Figure 3). The precision of  $R_0$  was marginally better when time-varying selectivity was present (TV-L-AE-1, TV-DL-AE-1, and TV-DL-AE-2) compared to absent (TI-L-AE-1, TI-DL-AE-1, and TI-DL-AE-2). Finally, time-varying catchability in the OM generated higher imprecision in  $R_0$  in all the scenarios with ageing error (TI-L-AE-2, TI-DL-AE-2, TV-L-AE-2, and TV-DL-AE-2).

In scenarios without or with ageing error corrected in the SCA, there was no significant difference among the median RE for  $R_0$  when time-varying selectivity (logistic and double logistic) and constant catchability were used in the OM. However, the double logistic selectivity (time-invariant and time-varying) generated slightly less bias in  $R_0$  estimates (except in TI-DL-NAE-1). The time-varying catchability generated more biased  $R_0$  estimates in cases with time-invariant and time-varying selectivity (logistic and double logistic). The imprecision in  $R_0$  in the scenarios without or with ageing error corrected in the SCA was marginally higher with the time-varying logistic selectivity and even greater when there was time-varying catchability and time-

varying logistic selectivity. Time-varying double logistic generated more precise  $R_0$  estimates than time-invariant double logistic (except in TV-DL-NAE-2) when ageing error was absent or was corrected in the SCA.

Overestimation of  $F_{terminal}$  in the presence of ageing error was higher in almost all scenarios in which time-varying selectivity was also present (TV-L-AE-1, TV-L-AE-2 and TV-DL-AE-1), except TV-DL-AE-2. The highest positive bias and broadest inter-quartile range for  $F_{terminal}$  occurred for scenarios in which time-varying logistic selectivity was present (TV-L-AE-1 and TV-L-AE-2). This difference was less marked when time-invariant (TI-DL-AE-1 and TI-DL-AE-2) versus time-varying (TV-DL-AE-1 and TV-DL-AE-2) double logistic selectivity, where the positive bias in  $F_{terminal}$  was only slightly higher in the time-varying scenario TV-DL-AE-1 (Figure 3). Time-varying catchability and ageing error (TI-L-AE-2, TI-DL-AE-2, TV-L-AE-2, and TV-DL-AE-2) produced a consistent pattern of bias in  $F_{terminal}$ . In particular, these scenarios presented a marginally lower positive bias compared with those scenarios where the catchability was constant (Figure 3). In most of the scenarios with correct age estimates or age correction in the SCA, the  $F_{terminal}$  estimates were closely to the true value (bias lower than 19%), except the base scenario (TI-L-NAE-1). However, in some scenarios with time-varying catchability and time-varying selectivities (TV-L-AEC-2, TV-DL-NAE-2, and TV-DL-AEC-2) F<sub>terminal</sub> was moderately underestimated (Figure 3). The precision of the  $F_{terminal}$  estimates was lower in the scenarios with ageing error and decreased further when time-varying selectivities were incorporated, except in scenario TV-DL-AE-2. However, in those scenarios with time-varying selectivity, the precision improved marginally when time-varying catchability was incorporated (TV-L-AE-2 and TV-DL-AE-2) (Table 2).

In the scenarios where ageing error was absent or was corrected in the SCA, precision of  $F_{terminal}$  decreased when time-varying logistic selectivity (TV-L-AEC-1, TV-L-NAE-2, and TV-L-AEC-2) was present. On the contrary, the precision was very similar between time-invariant and time-varying double logistic selectivity in the scenarios where ageing error was absent or was corrected. In these scenarios, the precision of  $F_{terminal}$  was not affected by invariant or time-varying catchability.

# Correcting ageing error inside the estimation model

The ageing error correction decreased the positive bias and improved the precision of all parameter estimates (Figure 3, Table 2). In most scenarios, including an ageing-error correction

(i.e., AEC scenarios) in the SCA resulted in similar levels of bias and precision (*MARE* values were less than 26%) in estimates of  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$ , as the scenarios without ageing error (i.e., NAE scenarios). The ageing-error correction had beneficial effects under both time-invariant and time-varying selectivity scenarios (logistic and double logistic). Estimates of  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$  were less biased in some cases than scenarios in which ageing error was absent (Figure 3).

In scenarios with logistic selectivity (time-invariant and time-varying),  $D_{final}$  was unbiased across all scenarios (TI-L-AEC-1, TI-L-AEC-2, TV-L-AEC-1, and TV-L-AEC-2). The positive bias for  $D_{final}$  decreased from values near and above 25% (ageing error) to values near to zero. The  $D_{final}$  estimates improved (less biased and more precise) further when time-varying catchability was present in the OM and the time-invariant logistic selectivity was used (TI-L-AEC-2) (Figure 3, Table 2). On contrary, when the time-invariant double logistic selectivity was used,  $D_{final}$  was marginally underestimated (TI-DL-AEC-1, and TI-DL-AEC-2); however, the accuracy improved with median *RE* values close to zero when the selectivity was time-varying double logistic (TV-DL-AEC-1 and TV-DL-AEC-2).  $D_{final}$  was slightly less biased when the ageing-error correction was applied and the time-varying catchability was used. In contrast, adding time-varying catchability decreased marginally SCA precision in the presence of timevarying selectivity (logistic and double logistic) in scenarios with ageing-error correction (Table 2).

 $R_0$  was also less biased in scenarios with logistic selectivity (TI-L-AEC-1, TI-L-AEC-2, TV-L-AEC-1, and TV-L-AEC-2) and the positive bias decreased from near 100% in the presence of ageing error to less than 25% when the ageing-error correction was applied. When the ageing-error correction interacted with time-varying catchability, a slightly increase in the positive bias was found. When ageing error was corrected,  $R_0$  showed no great differences in bias between time-invariant (TI-DL-AEC-1 and TI-DL-AEC-2) and time-varying (TV-DL-AEC-1 and TV-DL-AEC-2) double logistic selectivity scenarios. As in the scenarios with logistic selectivity, scenarios with double logistic selectivity (TI-DL-AEC-1, TI-DL-AEC-2, TV-DL-AEC-1, and TV-DL-AEC-2) generally showed a low positive bias in  $R_0$  that increased when time-varying catchability was used in the OM (Figure 3).

Ageing error correction in the SCA also improved precision of  $R_0$  estimates (i.e., lower MARE values), mainly in the presence of time-invariant (logistic and double logistic) and time-varying double logistic selectivity. In these scenarios, *MARE* values  $R_0$  were similar to the

scenarios with correct age composition. When time-varying catchability and the ageing correction process in the EM were applied, the precision decreased (Table 2).

 $F_{terminal}$  estimates in some ageing error correction scenarios (TI-L-AEC-1, TI-L-AEC-2, TV-L-AEC-1, and TV-DL-AEC-2) were less biased than scenarios where the ageing error was absent. Time-varying catchability in the OM also generated less biased parameter estimates with the time-invariant logistic selectivity (TI-L-AEC-2). In general,  $F_{terminal}$  was less biased when the ageing error correction was applied to scenarios with time-invariant selectivity (logistic and double logistic) and time-varying catchability (TI-L-AEC-2 and TI-DL-AEC-2) or when the ageing error correction was applied to scenarios with time-varying selectivity (logistic and double logistic) and time-invariant catchability (TV-L-AEC-1 and TV-DL-AEC-1) (Figure 3). However, the scenario with time-invariant logistic selectivity and time-invariant catchability (TV-L-AEC-1) and time-varying logistic selectivity and time-invariant catchability (TV-DL-AEC-1) was less biased than the scenario without ageing error (TV-DL-NAE-1).

Precision of  $F_{terminal}$  estimates was similar for scenarios in which ageing errors were corrected within the SCA to no ageing error, but mainly under time-invariant double logistic (TI-DL-AEC-2), and time-varying logistic (TV-L-AEC-1 and TV-L-AEC-2) and double logistic (TV-DL-AEC-1) selectivity. Time-varying catchability in the OM had no effect on  $F_{terminal}$  precision when the ageing correction was applied in the SCA (Table 2).

# Misspecification of selectivity without ageing error

In the absence of ageing error, misspecification of selectivity changed the bias and precision of  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$ , when compared with the parameters estimated when the same selectivity was used in both the OM and the SCA.

 $D_{final}$  exhibited a marginally higher positive bias under the misspecified selectivity scenario. In this scenario, the OM used time-invariant logistic selectivity and the SCA used time-invariant double logistic selectivity (TI-L\_TI-DL-NAE-1), as compared to the scenario with correctly specified selectivity, where the SCA used the same time-invariant logistic selectivity as the OM (TI-L\_TI-DL-NAE-1(\*), Figure 4). The precision was slightly better in the misspecified scenario (Table 3).  $R_0$  and  $F_{terminal}$  showed lower bias and higher precision under the misspecified

selectivity scenario than when selectivity was correctly specified (Figure 4, Table 3). However,  $R_0$  was slightly negatively biased compared to the correct selectivity specification. Moreover,  $D_{final}$ ,  $R_0$  and  $F_{terminal}$  even exhibited marginally lower bias when the data were generated with time-varying catchability in the misspecified selectivity scenario (TI-L\_TI-DL-NAE-2), in comparison with the scenario with time-invariant catchability and misspecified selectivity (TI-L\_TI-DL-NAE-2). NAE-1) (Figure 4, Table 3).Only  $F_{terminal}$  had slightly higher precision in TI-L\_TI-DL-NAE-2.

 $D_{final}$ ,  $R_0$  and  $F_{terminal}$  estimates were positively biased under the misspecified selectivity scenario (TI-DL\_TI-L-NAE-1). In this scenario, the OM had time-invariant double logistic selectivity and the SCA had time-invariant logistic selectivity, whereas the correctly specified scenario (TI-DL\_TI-L-NAE-1(\*)), had time-invariant double logistic selectivity in both the OM and SCA (Figure 4). The positive bias and imprecision were higher in  $R_0$  and  $F_{terminal}$ . MARE values for  $R_0$  increased from 15%, with selectivity correctly specified (TI-DL\_TI-L-NAE-1(\*)), to 30%, under selectivity misspecification (TI-DL\_TI-L-NAE-1).  $F_{terminal}$  was 5% less precise under the misspecified selectivity scenario (TI-DL\_TI-L-NAE-1), than the correctly specified scenario TI-DL\_TI-L-NAE-1(\*) (Table 3). The use of time-varying catchability in the OM generated even higher positive bias and lower precision, in  $D_{final}$  and  $R_0$  under the misspecified selectivity (TI-DL\_TI-L-NAE-2) than the scenario with time-invariant catchability and misspecified selectivity (TI-DL\_TI-L-NAE-1).  $R_0$  was highly imprecise, with a MARE value near 42%. On the contrary,  $F_{terminal}$  was less biased in TI-DL\_TI-L-NAE-2, but also was less precise (Figure 4, Table 3).

The misspecified selectivity scenario (TV-L\_TI-L-NAE-1), where the OM selectivity was time-varying logistic and the SCA selectivity was time-invariant logistic, generated large interquartile variability in  $D_{final}$ ,  $R_0$  and  $F_{terminal}$ . Interquartile variability was lower in scenario TV-L\_TI-L-NAE-1(\*), where the selectivity was correctly specified (time-varying logistic in the OM and the SCA).  $D_{final}$  was marginally positively biased,  $R_0$  was underestimated and  $F_{terminal}$  had a median *RE* value near to zero, but with the biggest interquartile range. All the parameter estimates were less precise when selectivity was misspecified, than when correctly specified (Figure 4, Table 3). Having time-varying catchability in the OM, improved the precision and accuracy of  $R_0$  estimates in the misspecified selectivity and time-invariant catchability (TV-L\_TI-L-NAE-1). On the contrary,  $D_{final}$  and  $F_{terminal}$  were more imprecise, although  $F_{terminal}$  exhibited lower interquartile variability in TV-L\_TI-L-NAE-2 (Figure 4, Table 3).

Finally, for the misspecified selectivity scenario (TV-DL\_TI-DL-NAE-1), where the OM selectivity was time-varying double logistic and the SCA selectivity was time-invariant double logistic, bias in the estimates of  $D_{final}$  were similar to the scenario with correctly specified selectivity (TV-DL\_TI-DL-NAE-1(\*)), where the OM and the SCA had time-varying double logistic selectivity. However,  $D_{final}$  was more imprecise in the misspecified selectivity scenario.  $R_0$  was marginally less biased and  $F_{terminal}$  was slightly underestimated in the misspecified selectivity scenario, compared to the correctly specified one. Also,  $F_{terminal}$  showed higher interquartile variability and was more imprecise (Figure 4, Table3). Using time-varying catchability in the OM, together with misspecified selectivity (TV-DL\_TI-DL-NAE-2), generated marginally more unbiased and precise  $D_{final}$  estimates, compared to the misspecified one that used time-invariant catchability (TV-DL\_TI-DL-NAE-1). In contrast,  $R_0$  was slightly more positively biased and imprecise.  $F_{terminal}$  showed less interquartile variability when selectivity was misspecified and catchability was time-varying (TV-DL\_TI-DL-NAE-2).

# Misspecification of selectivity with ageing error

In scenarios with ageing error, misspecification of the selectivity either intensified the effects of ageing error or masked them with the outcome depending on the selectivity used in the OM and the selectivity specified in the SCA. For example, the misspecified selectivity scenario in which the selectivity in the OM was time-invariant logistic and the SCA selectivity was time-invariant double logistic (TI-L\_TI-DL-AE-1), triggered a higher positive bias and lower precision in  $D_{final}$ , compared to TI-L\_TI-DL-AE-1(\*), where the OM and the SCA both had time-invariant logistic selectivity. Conversely, for  $R_0$  and  $F_{terminal}$ , the ageing error effect was masked in the misspecified selectivity scenario (i.e., a lower positive bias and higher imprecision) (Figure 5, Table 4). Generally, the use of time-varying catchability in the OM, with misspecified selectivity (TI-L\_TI-DL-AE-2), resulted in more positively biased and imprecise  $D_{final}$  and  $R_0$  estimates, but less biased and more precise  $F_{terminal}$  estimates, when compared to the scenario with misspecified selectivity and time-invariant catchability (TI-L\_TI-DL-AE-1) (Figure 5, Table 4).

The misspecified selectivity scenario in which selectivity in the OM was time-invariant double logistic and the SCA selectivity used time-invariant logistic (TI-DL\_TI-L-AE-1), resulted in similar estimates of  $D_{final}$ , in terms of bias and precision, to the scenario with correctly specified selectivity, where both the OM and the SCA used time-invariant double logistic

selectivity (TI-DL\_TI-L-AE-1(\*), Figure 5). By contrast, the selectivity misspecification (TI-DL\_TI-L-AE-1) intensified the ageing error effect on  $R_0$  and  $F_{terminal}$ , with a higher positive bias and imprecision (Figure 5, Table 4). The use of time-varying catchability in the misspecified selectivity scenario (TI-DL\_TI-L-AE-2), marginally decreased the positive bias and imprecision of  $R_0$  and  $F_{terminal}$  (Figure 5, Table 4).

When selectivity was misspecified via time-varying logistic selectivity in the OM and time-invariant logistic selectivity in the SCA (TV-L\_TI-L-AE-1), ageing error generate more positive bias and decreased precision on  $D_{final}$  compared to the correct selectivity specification (TV-L\_TI-L-AE-1(\*)). In contrast, for  $R_0$  and  $F_{terminal}$ , the ageing error effect was diminished in the misspecified selectivity scenario (Figure 5). Here, both parameters showed a decrease in their positive bias and imprecision (lower MARE values) (Table 4). In general, the use of time-varying catchability, in the OM with misspecified selectivity (TV-L\_TI-L-AE-2), increased the positive bias in all the parameter estimates ( $D_{final}$ ,  $R_0$  and  $F_{terminal}$ ), in comparison to the scenario with time-invariant catchability (TV-L\_TI-L-AE-1) (Figure 5, Table 4).

Finally, the use of time-varying double logistic selectivity in the OM, along with the assumption of time-invariant double logistic selectivity in the SCA (TV-DL\_TI-DL-AE-1), masked the ageing error effect, generating an important decrease (more than 15%) in the positive bias of  $D_{final}$ ,  $R_0$  and  $F_{terminal}$  compared to the correctly specified scenario (TV-DL\_TI-DL-AE-1(\*)) (i.e., time-varying double logistic selectivity in the OM and in the SCA) (Figure 5). Also, the MARE values for  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$  were lower (higher precision) in the misspecified selectivity scenario (Table 4). Using time-varying catchability increased the precision of  $D_{final}$  and  $F_{terminal}$  in the misspecified selectivity scenario (TV-DL\_TI-DL-AE-2), but increased the positive bias and imprecision of  $R_0$ , in comparison to the scenario with misspecified selectivity and time-invariant catchability (TV-DL\_TI-DL-AE-1).

## Discussion

#### The effect of the ageing error on stock assessment and management parameters

Age composition data and fishery selectivity are key components within contemporary age-structured assessments, yet there is little research examining how ageing error and fishery selectivity assumptions interact to affect the quality of advice derived from stock assessment models.

The incorrect age determination for Patagonian toothfish likely affects SCA performance, generating bias and imprecision in the parameter estimates. Our results showed a significant bias in  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$  in the presence of ageing error regardless of selectivity type. Most importantly, our results showed that ageing errors result in more optimistic estimates of population status ( $D_{final}$ ) from a range of SCA models, which could lead to more optimistic TAC determination.

Between the three management quantities we examined, average unfished recruitment  $R_0$  was the most positively biased, imprecise, and showed the highest interquartile variability when ageing error was present.  $R_0$  is a scale population parameter; therefore, when this parameter is estimated with bias, it could compromise all the stock assessment estimates. Similar to  $D_{final}$  and  $R_0$ , the effect of the incorrect age determination also generated a positive bias and low precision in estimating  $F_{terminal}$ . These results agreed with those reported by Liao *et al.* (2013), who found that  $F_{terminal}$  was overestimated by 19% in the presence of ageing-error. In output control management strategies, the  $F_{terminal}$  estimates are important to set catch limits and recovery plans.

## Effect of selectivity type and time-varying selectivity in the absence of ageing error

In the absence of ageing error, performance of the SCA depended on assumptions about selectivity. In general,  $D_{final}$  was better estimated in scenarios where logistic selectivity occurred in both operating and estimation models. Scenarios with double logistic selectivity (time-invariant and time-varying) tended to show positive bias in  $D_{final}$ , generating more optimistic results, but mainly in the time-varying scenarios. Probably, because double logistic selectivity can lead to biomass estimates with greater uncertainty, where the estimated proportion of older fishes may not reflect the observations of the fishery (Maunder and Piner, 2014).

In the absence of ageing error,  $R_0$  showed a similar level of bias between the timeinvariant logistic and double logistic selectivity, with estimates centered on the true values. When estimates from scenarios with time-varying selectivity (logistic and double logistic) were compared,  $R_0$  exhibited a higher positive bias with logistic selectivity (<15%), although it showed similar precision (MARE values) among scenarios.

Time-invariant selectivity (logistic and double logistic) without ageing error produced a positive bias in  $F_{terminal}$  estimates, mainly with the logistic selectivity function. The time-varying selectivities generated very unbiased and more precise estimates, probably because time-varying selectivities are more flexible and allow for a better fit to the age compositions.

#### Interaction between ageing error and time-invariant or time-varying selectivity

Performance of the SCA varied depending on the selectivity type and presence of ageing error. The SCA performed poorest in estimating  $D_{final}$  when ageing error was combined with time-invariant double logistic selectivity.

Conversely,  $F_{terminal}$  estimates were slightly more precise and less biased when timeinvariant double logistic selectivity was used and the age was incorrectly determined. These differences were less pronounced in estimating  $R_0$ .

Double logistic selectivity, in which the availability of older fish to the fishing gear decreases after some peak selectivity age, accentuates problems arising from ageing errors because low presence of old fish in the age composition data - resulting from negatively biased ageing errors – cannot be separated from low selectivity by the fishing gear. As a result, the stock assessment frequently over-estimates biomass and stock status, while the  $F_{terminal}$  overestimation decreases slightly.

Time-varying selectivity was included in the OM to evaluate how the ageing error interacts with realistic models of fishery-dependent data. These sources of variability are expected to occur in most fisheries where CPUE is the only abundance index, such as the Chilean Patagonian toothfish fishery. The time-varying selectivities (logistic and double logistic) with the incorrect age determination generated a higher positive bias and a lower precision in estimating  $D_{final}$ . This was most pronounced with the double logistic function. While the difference in bias and precision may not be large, the absolute values of  $D_{final}$  can generate a false perception of a less depleted stock. For example, the absolute values for  $D_{final}$  ranged between ~10% to 20% when a time-varying selectivity with ageing error was used. This range of values is enough to change the status of the fishery (Supplementary Figure S3). This shows the importance of including time-varying selectivities in management strategy evaluation (e.g., closed-loop simulations) to establish sustainable exploitation rates.

Time-varying selectivities generated a similar effect when estimating  $F_{terminal}$ . Conversely,  $R_0$  showed lower bias and higher precision when time-varying selectivities interacted with an incorrectly determined age composition. This resulted in better estimates of  $R_0$ , likely because the time-varying selectivity absorbs some of the noise from the ageing errors, while time-invariant selectivity can not.

Using time-varying selectivity within a stock assessment has advantages and disadvantages. It provides a greater flexibility to accommodate uncertainty, but it considerably increases the number of parameters to be estimated. This could increase the relative error and

imprecision for the  $D_{final}$  and  $F_{terminal}$  estimates. Martell and Stewart (2014) suggest that in the absence of knowledge about selectivity, a time-varying selectivity should be assumed. However, it is difficult to determine objectively when the selectivity changes in a fishery. Thus, in the absence of reliable information about changes in selectivity for the Patagonian toothfish fishery, this study used a random walk in the selectivity function to provide more realistic scenarios.

It is important to note that in the double logistic selectivity function (time-invariant and time-varying), the parameters that determine the right side of the curve (i.e.,  $\Omega_3$  and  $\Omega_5$ ) generated a significant bias when allowed to vary over time. Thus, they were fixed in the estimation model. This suggests that the age composition data was probably not informative enough to fit a double logistic selectivity or the selectivity does not follow a dome-shaped function. Either way, estimating the descending side of the curve is particularly problematic. The choice made about how to handle the descending side of the curve can significantly affect the results of an evaluation (Linton and Bence, 2011).

# Interaction between ageing error and time-varying catchability

The SCA performance was also evaluated when the data were generated with timevarying catchability and error in age determination. Overall, the results showed that under these conditions the SCA performance decreased.  $R_0$  and  $D_{final}$  showed a marginal increase in positive bias and in the lack of precision, compared to when catchability was time-invariant. However, the opposite effect occurred in  $F_{terminal}$  estimates. When time-varying catchability was used with the incorrect age determination, the  $F_{terminal}$  estimates were less biased and more precise. This implies that when the catchability varies over time, the effect of an incorrect age determination on  $D_{final}$ and  $R_0$  can be more severe than on  $F_{terminal}$ .

Time-varying catchability is common and should be expected in most fishery-dependent data (Winters and Wheeler, 1985; Wilberg *et al.*, 2010). Each data point for the relative index is a sample of the abundance, not a census, so it contains some random sampling error (Maunder and Piner, 2015). Factors such as changes in abundance, the area inhabited by the stock, the environment, fish behavior or fishing gear, and management regulations, among others, may induce catchability to be time-varying (Wilberg *et al.*, 2010).

Here, variability in catchability was also generated through a random walk. Random walks have been used to model gradual changes in catchability over time in age-structured models (e.g., Fournier *et al.*, 1998; Wilberg *et al.*, 2005; Wilberg *et al.*, 2010). As with time-varying selectivity, it is difficult to determine when catchability changes in a fishery. Only a small

variation in catchability was allowed in the OM. If the variability had been higher, the SCA performance with time-varying catchability and ageing-error could have been lower.

## Correcting ageing error inside the estimation model

Applying an ageing error correction matrix within the SCA likelihood reduced the average bias for all three management quantities.

The results of this study suggest that when there is not enough information to quantify the bias in ageing error (i.e., empirical data of scales and otoliths readings), it is still possible to perform a correction in the SCA. In general, incorrect age determination derived from scales and otolith readings can be corrected (e.g., Liao *et al.*, 2013). Both structures from the same fish can be compared to correct for the bias produced by scale readings. However, it is not always possible. For example, in the Patagonian toothfish fishery, the sampling program only collected scales during the beginning of the fishery and then changed to otoliths, with no overlap in collection.

We believe that the matrix from which the ageing error was simulated and corrected, represented real errors in the age determination of the Patagonian toothfish population. This procedure has not yet been applied in current stock assessments of Patagonian toothfish. Here we applied this correction to a variety of scenarios through a simulation-estimation framework in order to test its performance. We believe that the age-reading error matrix can be used to correct the ageing error problem in this fishery. As shown in this study, the ageing error can produce a more optimistic stock status than if the stock was evaluated without any ageing correction.

#### Misspecification of selectivity in the absence of ageing error

We evaluated the effect of incorrect selectivity specification in scenarios with and without ageing error. Our results showed that the selectivity misspecification affected the SCA performance in the scenarios without ageing error. The effect depended on the selectivity shape and if time-varying or time-invariant selectivity was used in the OM and the SCA. For example, when the data were generated with time-invariant logistic selectivity and the SCA assumed time-invariant double logistic selectivity,  $D_{final}$  did not change much, but  $R_0$  and  $F_{terminal}$  were more precise and less biased.  $R_0$  did show a slight negative bias.  $D_{final}$  was relatively robust to selectivity misspecification. This is similar to the results reported by He *et al.* (2010), who found that depletion was unbiased even when the selectivity was incorrectly specified (i.e. logistic in

the simulations and double logistic in the assessment model and vice versa). The positive effect of selectivity misspecification on  $R_0$  and  $F_{terminal}$  probably results because double logistic selectivity can absorb some observation error in the age-composition for older fish. Double logistic selectivity also has a different fishing mortality for older fish than logistic selectivity. Therefore, the SCA selectivity (double logistic) can not buffer for the presence of older fish in the catch (logistic) and the fishing mortality decreases.

The opposite result was found when time-invariant double logistic selectivity was used in the OM and time-invariant logistic was used in the SCA. In this misspecified selectivity scenario, a higher positive bias and higher imprecision was found in all the parameter estimates. Misspecification of the selectivity alone could generate a misunderstanding of the stock status  $(D_{final})$ .  $R_0$  was overestimated around 30% and was less precise than in other scenarios with selectivity misspecification (i.e. logistic in the OM and double logistic in the SCA). Similarly, Wang *et al.* (2014) found a greater gradient of  $R_0$  likelihood profiles (for *Thunnus obesus*), indicating high imprecision when the selectivity was double logistic in the data and the assessment assumed a logistic function. However, their model was more complex than ours and only used length composition data. The increased positive bias in  $F_{terminal}$  also suggests that the SCA offsets the lack of older fish in the catch with an increase in the fishing mortality.

When we generated data from a time-varying selectivity (logistic or double logistic), but we used a time-invariant selectivity (logistic or double logistic) in the SCA, the precision in all parameter estimates decreased and the interquartile range increased.  $D_{final}$  and  $R_0$  were the most affected.  $D_{final}$  showed a higher positive bias than in the other misspecified selectivity scenarios.  $R_0$  was negatively biased with logistic selectivity (time-varying logistic in the OM and time-invariant logistic in the SCA) and was almost unbiased with double logistic selectivity (time-varying double logistic in the OM and time-invariant double logistic in the SCA). Furthermore,  $F_{terminal}$  had the highest interquartile range with the logistic selectivity scenario (time-varying logistic in the OM and time-invariant logistic in the SCA). Misspecified selectivity affected the perception of the stock status, generating overly optimistic conditions that could affect the estimation of reference points for management. Thus, using time-invariant selectivity when selectivity is actually time-varying can affect the decisions made in fisheries management. Crone *et al.* (2013) suggest the use of a more flexible selectivity function, because ignoring temporal changes in selectivity can produce biased estimates of management quantities and underestimate uncertainty.

### Misspecification of selectivity with ageing error

The effect of incorrect age determination on the parameters of interest may be exacerbated by an incorrect assumption about selectivity; i.e. assuming selectivity is time-invariant, when it is actually time-varying, or using an inappropriate selectivity function to represent the age-specific fishing mortality. In some cases, the interaction between the ageing error and selectivity misspecification increased the ageing error effect, but in others it masked the ageing error effect.

When the selectivity was specified incorrectly and ageing error was included, the bias and precision of all the parameters were affected. For example, when the data came from time-invariant logistic selectivity and the SCA assumed time-invariant double logistic selectivity,  $D_{final}$  exhibited a markedly higher positive bias due to the interaction between misspecified selectivity and ageing error. Punt *et al.* (2002), Yin and Sampson (2004) and Martell and Stewart (2014) all indicate that an incorrect assumption about the selectivity can lead to biased estimates of the spawning biomass and depletion. We found that logistic selectivity in the OM and double logistic selectivity in the SCA can lead to even higher bias and imprecision when ageing error was included. While the bias and imprecision in  $D_{final}$  were not extremely high, the impact on the absolute values can be very important. In contrast, the ageing error effect on  $R_0$  and  $F_{terminal}$  estimates was masked (less biased positively), probably because the ageing error present in an OM with time-invariant logistic selectivity is offset by time-invariant double logistic selectivity in the SCA, since the SCA assumes that there are no older fish in the catch. Again, the impact on  $R_0$  can affect the estimation of biological reference points. Changes in the maximum age of selectivity can impact the estimation of biological reference points (Goodyear, 1996).

When the selectivity was time-invariant double logistic in the OM and time-invariant logistic in the SCA, we observed the opposite effect to the previous scenario. Here, the effect of ageing error was slightly masked in  $D_{final}$ , but it was accentuated in  $R_0$  and  $F_{terminal}$ . The interaction between misspecified selectivity and the ageing error particularly increased the positive bias in  $R_0$  (median RE values > 200%).

Assuming that the selectivity (logistic and double logistic) is time-invariant (SCA) when it is actually time-varying (OM) generally masked the of effects of ageing error on the parameter estimates.  $D_{final}$ ,  $R_0$  and  $F_{terminal}$  exhibited lower positive bias and higher imprecision with ageing error, when the OM had time-varying selectivity and SCA assumed time-invariant selectivity.

Time-varying catchability, combined with misspecified selectivity, also affected the estimates of  $D_{final}$  and  $R_0$ , whether ageing error was present or not. However, these effects were

more accentuated when ageing error was present. In general, the interaction between timevarying catchability and misspecified selectivity led to an increase in the positive bias and imprecision of  $D_{final}$  and  $R_0$ . On the contrary, the  $F_{terminal}$  estimates were less biased and more precise with and without ageing error.

#### **Implications for management**

The incorrect age determination generated significant error and imprecision in the estimated parameters, spawning biomass and fishing mortality trajectories. This affected the understanding of the current status of the fishery. Considering the current status of Chilean Patagonian toothfish, using double logistic selectivity in the stock assessment for this fishery is not recommended, because tended to show a higher positive bias in  $D_{final}$ , generating more optimistic results. Adding time-varying parameters (selectivity and catchability) in the presence of ageing error, generally increased the bias and imprecision in the parameter estimation.

Our results show that the current Patagonian toothfish stock assessment in Chile is not robust to the problem of age underestimation. In fact, the difference in age composition data between scale and otolith readings has not been accounted for in the stock assessment. The current  $D_{final}$  for Patagonian toothfish is below 15%, so even a small change in the depletion value could mean a change in the fishery status from overfishing and overfished to collapsed.

Generally, selectivity misspecification produced a more severe bias when combine the ageing error. Some parameters had an increased positive bias while others strangely showed decreased bias because the misspecified selectivity offset the bias generated by ageing error, thus masking its effect.

We applied our ageing correction to the real fishery data and obtained improved parameter estimates, with less bias and more precision.

Considering that fishery selectivity is unknown in most cases, our results show that using time-varying logistic selectivity in the fishery assessment results in less biased parameter estimates and more conservative results. An erroneous selectivity assumption can affect the perceived stock status and the parameter estimates used in fisheries management. Additionally, we showed that time-varying catchability also produces bias in the estimated parameters when the only available abundance index is the CPUE. Including both time-varying selectivity and catchability increases the number of parameters estimated. Nevertheless, once our correction is applied to the age composition data, the age composition data becomes more useful and informative, which allows more parameters to be estimated.

The parameters we examined are key to determining catch limits and evaluating management strategies. Faced with declining fish stocks, as in the Patagonian toothfish population, it is necessary to have the most reliable information possible for the stock assessment (Richards and Megrey, 1994). A better understanding of the behavior of assessment models could lead to better estimates of stock status and thus, to better management of the fishery.

# Supplementary material

Supplementary material is available at the ICESJMS online version of the manuscript.

## Acknowledgements

This work was funded by a CONICYT scholarship (Master program of Fisheries Science), supported by the Ministry of Education in Chile, a Canada-Chile Leadership Exchange Scholarship, supported by Government of Canada, and a Program COPAS Sur-Austral PFB-31, supported by Universidad de Concepción, Chile. R. Licandeo was supported by CONICYT (Becas Chile program). We thank the Instituto de Fomento Pesquero de Chile (IFOP) and Subsecretaría de Pesca de Chile (SUBPESCA) for providing the fishery data. We also thank Cristian Canales from IFOP for help and comments that improved the development of this work and Juan Carlos Quiroz from IFOP for his help starting this research. We are very grateful to Shannon Obradovich for editing the language in earlier versions of the manuscript.

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# Figures



Figure 1. General conceptual scheme of the simulation-estimation procedure (modified from

Wetzel and Punt, 2011).





**Figure 2.** Selectivity curves of one random simulation used by the operating model to generate data. a) logistic selectivity; b) time-varying logistic selectivity; c) double logistic selectivity, and d) time-varying double logistic selectivity.



**Figure 3.** Median relative errors (black dots) and the central 90% confidence interval (gray line), for  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$ , for the 4 cases - 6 scenario combinations. Time-invariant logistic (TI-L), time-invariant double logistic (TI-D), time-varying logistic (TV-L), and time-varying double-logistic (TV-DL). The cases and scenarios descriptions are given in Table 2.



**Figure 4.** Results for misspecified selectivity models in the SCA. Median relative errors (black dots) and the central 90% confidence interval (gray line), for  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$ , for the 4 cases and 8 scenarios, where the selectivity was misspecified. NAE, indicates that the data were generated without ageing error in the OM, and the number 1 and number 2 indicates a time-invariant and time-varying catchability in the OM, respectively (see Table 3 for cases and scenario names). The asterisks in brackets, represent the scenarios with correct selectivity specification (i.e., the selectivity function used in the OM was maintained in the SCA), given in brackets in Table 3.



**Figure 5.** Results for misspecified selectivity models in the SCA. Median relative errors (black dots) and the central 90% confidence interval (gray line), for  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$ , for the 4 cases and 8 scenarios, where the selectivity was misspecified. AE, indicates that the data were generated with ageing error in the OM, and the number 1 and number 2 indicates a time-invariant and time-varying catchability in the OM, respectively (see Table 4 for cases and scenario names). The asterisks in brackets, represent the scenarios with correct selectivity specification (i.e., the selectivity function used in the OM was maintained in the SCA), given in brackets in Table 4.

# Tables

**Table 1.** Description and values for abundance index, structural parameters, state variables,

 derived variables and stochastic deviation used in the Patagonian toothfish population dynamics,

operating, and estimation model.

Index variablesImage: Constraint of the second	Symbols	Description	Value	Estimation model
i         Annual time step 7 = 24 (0989 - 2012)         [1, 2,, A]         [1, 2,, A]           Structure J         Age-class in years where A = 30         II. 2,, A]         [1, 2,, A]           Structure J         Growth coefficient (year')         0021         0021           k         Growth coefficient (year')         0021         0021           c         Mean asymptotic size (ump')         14.17         14.17           d         Instantic source in a structure construction (the coefficient of cach-per-interify)         0.15         14.17           d         Structure (the construction of cach-per-interify)         0.16         0.15         14.17           d         Structure (the construction of cach-per-interify)         0.16         0.16         0.16           d         Structure (the construction of cach-per-interify)         0.16         0.16         0.16           d         Structure (the construction of cach-per-interify)         0.16         0.16         0.16           d         Structure (the construction of cach per-inter	Index variables	*		
a         Age-class in years where A = 30         (1, 2,, A)         (1, 2,, A)           Number of parameter         Number of parameter         (1, 2,, A)         (1, 2,, A)           L         Mean symptotic size (mm) <sup>n</sup> 2021         0.021         0.021           ac         Growth coefficient (year) <sup>n</sup> -2.390         -2.390         -2.390           ac         Age-ar 50% matriny <sup>n</sup> - age-ar 50% matriny <sup>n</sup> 11.5         0.15         0.15           ac         Age-ar 50% matriny <sup>n</sup> - age-ar 50% matriny <sup>n</sup> 11.5         11.7         11.7           Age-ar 50% matriny <sup>n</sup> - age-ar 50% matriny <sup>n</sup> 0.15         0.6         11.6           Age-ar 50% matriny <sup>n</sup> - age-ar 50% matriny <sup>n</sup> 0.15         0.6         11.6           Add deviation for the recuitment deviations         0.60         1.6         11.6           Age         Standard deviation for the recuitment deviations         0.6         6         12.0070         1.5         11.6         1.6           Age         Cancetakine versing cancetaking versing consists (vg cort <sup>n</sup> )         0.14         1.5         1.6         1.6         1.6         1.6         1.6         1.6         1.6         1.6         1.6         1.6         1.6         1.6         1	t	Annual time step $T = 24$ (1989 - 2012)	$\{1, 2, \ldots, T\}$	$\{1, 2, \ldots, T\}$
Structure         Vertical set of the set of	а	Age-class in years where $A = 30$	$\{1, 2, \ldots, A\}$	$\{1, 2, \ldots, A\}$
l, ω         Mean a symptotic size (mm) <sup>4</sup> 271         2871           k         Growth coefficient (qern) <sup>4</sup> 0.021         0.021         0.021           a <sub>0</sub> Mean length-sit-age (yern) <sup>4</sup> -2.390         -2.289         -2.289           a <sub>1</sub> Scaling constant for weight-sit-length (mm tonnes) <sup>4</sup> Allometric factor <sup>4</sup> 2.59e-12 - 3.00         2.99e-12 - 3.00           m <sub>1</sub> Mean signation constant for weight-sit-length (mm tonnes) <sup>4</sup> Allometric factor <sup>4</sup> 2.59e-12 - 3.00         2.99e-12 - 3.00           M         Instantances stantant mortality (yern <sup>7</sup> )         0.15         0.15         0.15           K         Steppess         0.60         0.54         0.54           R         Cancabulty (yerd) <sup>4</sup> / <sup>2</sup> 0.20         0.20           Growth (yerd) conflication for CPUE         0.9         0.54         0.54           Growth (yerd) conflication for CPUE         0.9         0.54         0.54           Growth (yerd) (yerd) (yerd) (yerd) (yerd)         10 - 14         Stimated (0, and 0.)           Growth (yerd) (yerd) (yerd) (yerd)         0.9         -         0.54           Growth (yerd) (yerd) (yerd) (yerd) (yerd)         0.9         -         0.54           Growth (yerd) (yerd) (yerd) (yerd) (yerd) (y	Structural parameters		-	-
k         Growth coefficient (year ')*         0.021         0.021           a_a         Meen length-aise at zon ag (year)*         -4.289         -4.289         -4.289           c - d         Scaling constant for weight-ai-length (unn to tones)* - Allonetric factor         2.59-12 - 3.206         2.50-12 - 3.206           m - m, - m, - Maga-3-06 mattright - ages 4-58 mattright	$l_{\infty}$	Mean asymptotic size (mm) <sup>a</sup>	2871	2871
a <sub>g</sub> Mean length-at-gapt (marto to nons) <sup>*- A</sup> lometric factor <sup>*</sup> 2-4289     -4289       m <sub>1</sub> - m <sub>1</sub> Age-at-50% maturity <sup>*-</sup> age-at-95% maturity <sup>*</sup> 14 + 17     14 + 17       M     Instantances naturi a morphy maturity <sup>*-</sup> 0.15     0.15       F     Average fishing mortality rate     0.60     -       R <sub>0</sub> Unfished transmin     0.60     -       R <sub>0</sub> Unfished transmin     0.60     -       R <sub>0</sub> Catability coefficients for the resultment divisions     0.60     -       Q <sub>1</sub> Catability coefficients for the resultment divisions     0.60     -       Q <sub>1</sub> Catability coefficient for the resultment divisions     0.61     -       Q <sub>1</sub> Catability coefficient for the resultment divisions     0.02     0.2       Q <sub>1</sub> Catability coefficient for the result of QCUE     0.02     -       Q <sub>1</sub> Catability coefficient for the result of Queble logistic selectivity     0.9     -       Q <sub>1</sub> Catability coefficient for the age-at-50% (objistic selectivity)     10 - 14     Estimated       Q <sub>1</sub> Catability coefficient for the age-at-50% (objistic selectivity)     7     -       Q <sub>1</sub> Catability coefficient for the age-at-50% (objistic selectivity)     10 - 14     Estimated       Q <sub>1</sub> Catability Catability of Queble objistic selectivi	k	Growth coefficient (year <sup>-1</sup> ) <sup>a</sup>	0.021	0.021
$c \cdot d$ Scaling constant for weight-at-length (mm to tomes)* Allometric factor*259:-12 - 3.206259:-12 - 3.2	$a_0$	Mean length-at-age at zero age (year) <sup>a</sup>	-4.289	-4.289
	c - d	Scaling constant for weight-at-length (mm to tonnes) <sup>a</sup> - Allometric factor <sup>a</sup>	2.59e-12 - 3.206	2.59e-12 - 3.206
MInstantaneous natural mortality (year')0.150.15FAverage fishing mortality (year')0.60-hSteepness0.60-RoUnfished recruitment12100700Estimated $a_{i}$ Standard deviation for the recruitment deviations0.600.6 $a_{i}$ Standard deviation for the recruitment deviations0.610.6 $a_{i}$ Standard deviation for the CPUE0.0154Estimated $a_{i}$ Standard deviation for the readow valk (vop for q $a_{i}$ Correlation coefficient for the re for $q$ 0.9- $a_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity)10 - 14Estimated $D_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity0.9- $a_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity0.9- $a_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity0.9- $a_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity0.9- $a_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity0.9- $a_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity0.9- $a_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity0.9- $a_{i}$ Correlation coefficient for the re vin the inne-varying logistic selectivity1- <t< td=""><td><math>m_1 - m_2</math></td><td>Age-at-50% maturity<sup>b</sup> - age-at-95% maturity<sup>b</sup></td><td>14 - 17</td><td>14 - 17</td></t<>	$m_1 - m_2$	Age-at-50% maturity <sup>b</sup> - age-at-95% maturity <sup>b</sup>	14 - 17	14 - 17
$P$ Average hshing montality rateIstimated $h_{1}$ Seeposss0.6- $R_{1}$ Unfished recruitment deviations0.60.6 $q$ Sandad deviation for the recruitment deviations0.60.6 $q$ Catchability coefficient for carch-perunit-effort (CPUE)0.212.2 $q$ Sandad deviation for the rendom valk (w) for $q$ $q$ Coefficient for the args - 30% and age-a95% (logistic selectivity)10 - 14Estimated $\beta_{1}$ $\Omega_{2}$ Coefficients for the args - 30% and age-a95% (logistic selectivity)10 - 8 - 0.65 - 0.09Estimated ( $\Omega_{2}$ and $\Omega_{2}$ ) $\beta_{1}$ $\Omega_{2}$ Coefficients for the args - 45% (logistic selectivity)10 - 8 - 0.65 - 0.09Estimated ( $\Omega_{2}$ and $\Omega_{2}$ ) $\beta_{1}$ $\Omega_{2}$ Coefficient for the rev for the time-varying parameter vector of subject selectivity)79- $\alpha_{1}$ Time-varying parameter vectors inflexible selectivity)79- $\alpha_{2}$ Coefficient for the rev (logistic selectivity)79- $\alpha_{2}$ $\alpha_{2}$ $\alpha_{3}$ $\alpha_{2}$ Coefficient for the rev (logistic selectivity)0.9 $\alpha_{2}$ $\alpha_{3}$ $\alpha_{3}$ $\alpha_{3}$ Coefficient for the rev (logistic selectivity)0.9 $\alpha_{3}$ Coefficient for the rev (logistic selectivity)0.9 $\alpha_{3}$ Coefficient for the rev (logistic selectivity)0.9 $\alpha_{3}$ Coefficient for the	M	Instantaneous natural mortality (year <sup>-1</sup> )	0.15	0.15
nSeepness $0.000$ - $R_p$ Unfished recruitment1210070Estimated $a_k$ Standad deviation for the cremitment deviations $0.6$ $0.6$ $a_i$ Catchability coefficient for catch-per-unit-effort (CPUE) $0.154$ Estimated $a_i$ Standard deviation for the CPUE $0.2$ $0.2$ $a_i$ Time-varying catchability coefficients for CPUE $  a_i$ Correlation coefficient for the vir $0$ of $q$ $0.9$ $ B_i$ , $\Omega_i$ Coefficients for the age-at-50% and age-at-95% (logistic selectivity) $10.14$ Estimated $\Omega_i$ , $\Omega_i$ Coefficients for the age-at-50% and age-at-95% (logistic selectivity) $10.14$ Estimated $\Omega_i$ Standard deviation for the vir for the varying logistic selectivity) $10.14$ Estimated $\Omega_i$ Standard deviation for the vir for the varying logistic selectivity $7$ $ \Omega_0$ Correlation coefficient for the vir for the severativing logistic selectivity $7$ $ \Omega_0$ Lower and upper bounds (se selectivity) $7$ $ \Omega_0$ Correlation coefficient for the vir (double logistic selectivity) $7$ $ \Omega_0$ Correlation coefficient for the vir (double logistic selectivity) $7$ $ \Omega_0$ Correlation coefficient for the vir double logistic selectivity) $0.9$ $ \Omega_0$ Correlation coefficient for the vir double logistic selectivity) $  \Omega_0$ Correlation coefficient for the vir double logistic selectivity) $-$	F	Average fishing mortality rate	0.50	Estimated
$R_{0}$ Character continuentLature deviation for the recruitment deviationsLature deviation for deviation for the recruitment deviations deviation for the recruitment deviation deviat	h	Steepness	0.60	-
$ \begin{array}{ccc} & & & & & & & & & & & & & & & & & &$	$R_0$	Unfished recruitment	1210070	Estimated
$q'$ Calculation of element for $(a + c) = prime transmitted (CPCE)00154Estimatedq'Standard deviation for the CPUE   q'Standard deviation for the random walk (w) for q   p'Corelicients for the gave abs/bs and geat-95% (logistic selectivity)10 \cdot 14Estimated\Omega_1, \Omega_2, \Omega_2, \Omega_6Inflection 1. inflection 2. slope 1. and slope 2 (double logistic selectivity)10 \cdot 8 \cdot 0.65 \cdot 0.09Estimated\Omega_1, \Omega_1, \Omega_2, \Omega_6, D_6Inflection 1. inflection 2. slope 1. and slope 2 (double logistic selectivity)7Estimated\Omega_1, \Omega_1, \Omega_2, \Omega_6, D_6Inflection 1. inflection 2. slope 1. and slope 2 (double logistic selectivity)7Estimated\Omega_1, \Omega_2, \Omega_6, D_6Inflection 1. inflection 2. slope 1. and slope 2 (double logistic selectivity)77\Omega_1, \Omega_2, \Omega_6, D_6Inflection 1. double for the reversing inflection 2 (double logistic selectivity)77\Omega_1, \Omega_4, \Omega_6, D_6Intervarying parameter vectors inflection 1. adouble logistic selectivity)77\Omega_1, \Omega_4, \Omega_6, D_6Intervarying parameter vectors inflection 1. adouble logistic selectivity)77\Omega_1, \Omega_4, \Omega_4, \Omega_4, \Omega_4, \Omega_4, \Omega_4, \Omega_4, \Omega_4$	$\sigma_R$	Standard deviation for the recruitment deviations	0.0	U.6 Estimated
$D_{1}$ Statustical derivation for the CPUE $0.2$ $0.2$ $q_{1}$ Time-varying catchability coefficients for CPUE $a_{1}$ $\Omega_{1}$ Correlation coefficient for the random walk (w) for $q$ 0.9 $\Omega_{1}$ $\Omega_{2}$ Coefficients for the gae-at-50% and age-at-95% (logistic selectivity)10-14Estimated $\Omega_{1}$ $\Omega_{2}$ Coefficients for the age-at-50% (logistic selectivity)10-14Estimated $\Omega_{10}$ Standard deviation for the vor for the ine-varying logistic selectivity)7Estimated $\Omega_{10}$ Standard deviation for the vor for the ine-varying logistic selectivity)7- $\Omega_{10}$ Lower and upper bounds for the age-at-50% selectivity0.9- $\Omega_{10}$ Lower and upper bounds for the age-at-50% selectivity)0.9- $\Omega_{20}$ Lower and upper bounds for the vor double logistic selectivity)0.9- $\Omega_{20}$ Lower and upper bounds for $\Omega_{20}$ and $\Omega_{10}$ 4-11- $\Omega_{20}$ Lower and upper bounds for $\Omega_{20}$ and $\Omega_{10}$ 4-11- $\Omega_{20}$ Lower and upper bounds for $\Omega_{20}$ and $\Omega_{10}$ $N_{20}$ Lower and upper bounds for $\Omega_{20}$ $N_{20}$ Lower and upper bounds for $\Omega_{20}$ $\Omega_{20}$ Lower and upper bounds for $\Omega_{20}$ $\Omega_{20}$ Lower and upper bound or taility $N_{20}$ Lower and upper bounds for $\Omega_{20}$ $N_{20}$ <td><i>q</i></td> <td>Standard deviation for the CDUE</td> <td>0.0154</td> <td></td>	<i>q</i>	Standard deviation for the CDUE	0.0154	
$q_q$ Interval pig calculation (p) control (p) (p) $  q_q$ Sandal deviation (p) the random walk (rs) for $q$ 0.9 $ p_q$ Correlation coefficients for the row for $q$ 0.9 $ \Omega_1 \cdot \Omega_2$ Coefficients for the gas 41.5% (h) (or g) (s) its eslectivity)10 - 8 - 0.55 - 0.09Estimated $\Omega_1 \cdot \Omega_2$ Sandard deviation (or the raw for $q$ ges 41.5%) $0.9$ $  \Omega_1 \cdot \Omega_2$ Sandard deviation (or the raw for $q$ ges 41.5%) $0.9$ $  \Omega_1$ Correlation coefficient for the age-at-50% solectivity $0.9$ $  \Omega_3 \cdot \Omega_4$ Correlation coefficient for the raw in the time-varying logistic selectivity $7$ $  \Omega_3 \cdot \Omega_4$ Tune-varying parameter vectors, inflection 1 and inflection 2 (d) hole logistic selectivity) $7$ $  \Omega_3 \cdot \Omega_4$ Tune-varying parameter vectors, inflection 1 and inflection 2 (d) hole logistic selectivity) $1$ $  \Omega_2 \cdot \Omega_4$ Tune-varying parameter vector of slope 1 (d) hole logistic selectivity) $1$ $  \Omega_3 \cdot \Omega_4$ Tune-varying parameter vector of slope 1 (d) hole logistic selectivity) $0.9$ $  \Omega_4 \cdot \Omega_4$ Tune-varying parameter vector of slope 1 (d) hole logistic selectivity) $1$ $  \Omega_4 \cdot \Omega_4$ Tune-varying parameter vector of slope 1 (d) hole logistic selectivity) $0.9$ $  \Omega_4 \cdot \Omega_4$ Tune-varying parameter vector of slope 1 (d) hole logistic selectivity) $  -$ <t< td=""><td>0<sub>1</sub></td><td>Time varying catchability coefficients for CDUE</td><td>0.2</td><td>0.2</td></t<>	0 <sub>1</sub>	Time varying catchability coefficients for CDUE	0.2	0.2
$ \begin{array}{cccc} & & & & & & & & & & & & & & & & & $	$q_t$	Standard deviation for the random walk (rw) for a	-	-
$ \begin{array}{c c c c c } \hline \begin{tabular}{l c c c c } \hline \begin{tabular}{l c c c c } \hline \begin{tabular}{l c c c c c } \hline \begin{tabular}{l c c c c } \hline \begin{tabular}{l c c c c c } \hline \begin{tabular}{l c c c c c } \hline \begin{tabular}{l c c c c c c } \hline \begin{tabular}{l c c c c c c c c c c c c c c c c c c c$	$O_q$	Correlation coefficient for the rw for a	- 0.9	-
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$p_q$	Coefficients for the age-at-50% and age-at-95% (logistic selectivity)	10 - 14	- Estimated
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	$O_2 O_4 O_5 O_6$	Inflection 1 inflection 2 slope 1 and slope 2 (double logistic selectivity)	10 - 8 - 0 65 - 0 09	Estimated $(O_2 \text{ and } O_5)$
$a_{n1}$ Standard deviation for the rw for the time-varying logistic selectivity7 $a_{n1}$ $a_{n1}$ Correlation coefficient for the rw in the time-varying logistic selectivity0.9 $a_{n1}$ $a_{n1} = a_{n1}$ Correlation coefficient for the rw in the time-varying logistic selectivity $5 \cdot 10$ $a_{n1}$ $a_{n1} = a_{n1}$ Time-varying parameter vectors, inflection 1 and inflecton 2 (double logistic selectivity) $b_{n1} = a_{n1}$ $a_{n1} = a_{n1}$ Correlation coefficient for the rw (double logistic selectivity) $0.9$ $ a_{n2} - a_{n3}$ Correlation coefficient for the rw (double logistic selectivity) $0.9$ $ a_{n2} - a_{n3}$ Correlation coefficient for the rw (double logistic selectivity) $0.9$ $ a_{n2} - a_{n3}$ Correlation coefficient for the rw (double logistic selectivity) $0.9$ $ a_{n3} - a_{n4}$ Correlation coefficient for the rw (double logistic selectivity) $0.9$ $ a_{n3} - a_{n4}$ Correlation accolinitient of the rw (double logistic selectivity) $0.9$ $ a_{n4} - a_{n2}$ Number at age $a$ in year $t$ $  a_{n4} - a_{n2}$ Inducatible biomass (donnes) $  P_{n4}$ Age proportion in year $t$ $  a_{n4}$ Age proportion in year $t$ $  a_{n4}$ Age proportion in year $t$ $  P_{n4}$ Age proportion in year $t$ $  P_{n4}$ Exploitable biomass (tonnes) $  P_{n4}$ Ex	Q <sub>14</sub>	Time-varying parameter vector for the age-at-50% (logistic selectivity)	10 0 0.05 0.09	Estimated
$D_{Cn1}$ Correlation coefficient for the rw in the time-varying logistic selectivity $0.9$ $ L_{Cn1} - U_{Cn1}$ Lower and upper bounds for the age al-50% selectivity $5 \cdot 10$ $ L_{n1} - O_{Ln}$ Time-varying parameter vectors, inflection 1 and inflection 2 (double logistic selectivity) $1$ $ G_{n2} - P_{an}$ Correlation coefficient for the rw (double logistic selectivity) $1$ $ G_{n2} - P_{an}$ Correlation coefficient for the rw (double logistic selectivity) $1$ $ L_{0n} - U_{n}$ Lower and upper bounds for $\Omega_{n}$ and $\Omega_{n}$ $4 \cdot 11$ $ L_{0n} - U_{n}$ Lower and upper bounds for $\Omega_{n}$ and $\Omega_{n}$ $4 \cdot 11$ $ L_{0n} - U_{n}$ Lower and upper bounds for $\Omega_{n}$ and $\Omega_{n}$ $4 \cdot 11$ $ L_{0n} - U_{n}$ Lower and upper bounds for $\Omega_{n}$ and $\Omega_{n}$ $4 \cdot 11$ $ L_{0n} - V_{n}$ Lower and upper tourds for $\Omega_{n}$ and $\Omega_{n}$ $4 \cdot 11$ $ L_{0n} - V_{n}$ Number at age $a$ in year $t$ $  S_{n} < Age proportion in year tLower and upper tourds for \Omega_{n} S_{n} < Age proportion in year tLower and upper t (tonnes)  C_{n} < Catch at age in numbers$	π <i>σ</i> οι	Standard deviation for the rw for the time-varying logistic selectivity	7	Lotinuted
	<i>P</i> <sub>01</sub>	Correlation coefficient for the rw in the time-varying logistic selectivity	0.9	-
$Ω_n$ · $Ω_n$ · $ω_i$ Time-varying parameter vectors, inflection 1 and inflection 2 (double logistic selectivity)IEstimated $(Ω_n)$ $a_{\omega} \cdot o_{\Theta_1}$ Correlation coefficient for the rw (double logistic selectivity)1 $L_{O_0} \cdot U_0$ Lower and upper bounds for $\Omega_1$ and $\Omega_1$ 4 - 11 $L_{O_0} \cdot U_0$ Lower and upper bounds for $\Omega_2$ and $\Omega_1$ 4 - 11 $A_n$ Time-varying parameter vector of slope 1 (double logistic selectivity)4 - 11 $A_n$ Number at age a in year tEstimated $X_i(M+F)$ Instantaneous total mortality $B_n$ Vulnerable biomass (nones) $P_{an}$ Age proportion in year t $C_A$ Catch-at-age in numbers $SSBtSolitable biomass (nones)C_ACatch in year t (tonnes)C_BExpliciable biomass (tonnes)$	$Lo_{01} - U_{01}$	Lower and upper bounds for the age-at-50% selectivity	5 - 10	-
$\sigma_{23}$ $\sigma_{24}$ Standard deviation for the rw (double logistic selectivity)1- $\rho_{03}$ $-\rho_{04}$ Correlation coefficient for the rw (double logistic selectivity)0.9- $\rho_{03}$ $-\rho_{04}$ Lower and upper bounds for $\Omega_3$ and $\Omega_4$ 4 - 11- $\Omega_8$ Time-varying parameter vector of slope 1 (double logistic selectivity)4 - 11- $X_{a1}$ Number at age $a$ in year $t$ Estimated $X_{a1}$ Number at age $a$ in year $t$ $Z_i(M+F_i)$ Instantaneous total mortality $B_r$ Age proportion in year $t$ $Z_{a1}$ Catch-at-age in numbersSSBtSpawning biomass (tonnes) $P_{a1}$ Catch-per-unit-effort in year $t$ Derived variables $W_a$ Body mass-in alege (nones) $Q_{a1}$ Unfished spawning biomass (tonnes) $S_a$ Selectivity-alege $w_a$ Body mass-in alege (nones) $w_a$ Body mass-in alege (nones) $w_a$ Lognormal random recruitment deviates $\phi_a$ Lognormal random recruitment deviates $f_i$ Lognormal random free for rw $\phi_i(\Omega_a), \Omega_a)Double logistic selectivity deviates for rw\phi_i(\Omega_a), \Omega_a)Double logistic selectivity deviates for rw\phi_i(\Omega_a), \Omega_a)D$	$\Omega_{3t} - \Omega_{4t}$	Time-varying parameter vectors, inflection 1 and inflection 2 (double logistic selectivity)		Estimated ( $\Omega_{3t}$ )
$\rho_{DA}$ $Lo_R - \rho_{DA}$ $Lo_R - U_D$ Correlation coefficient for the rw (double logistic selectivity) $0.9$ $ Lo_R - U_D$ $\Omega_S$ and upper bounds for $\Omega_2$ and $\Omega_4$ $4 \cdot 11$ Estimated $\Omega_S$ $\Omega_S$ Time-varying parameter vector of slope 1 (double logistic selectivity) $4 \cdot 11$ EstimatedState variables $V_{a_1}$ Instantaneous total mortality $V = V_{a_1}$ Estimated $N_{a_1}$ Que proportion in year t $V = V_{a_1}$ $V = V_{a_1}$ $V = V_{a_1}$ $Z_1(M+F)$ Instantaneous total mortality $V = V_{a_1}$ $V = V_{a_1}$ $V = V_{a_1}$ $B_r$ Vulnerable biomass (tonnes) $V = V_{a_1}$ $V = V_{a_1}$ $V = V_{a_1}$ $CatA$ Catch-at-age in numbers $V = V_{a_1}$ $V = V_{a_1}$ $V = V_{a_1}$ $SSBt$ Spawning biomass in year t (tonnes) $V = V_{a_1}$ $V = V_{a_1}$ $V = V_{a_1}$ $V_P$ ,Exploitable biomass (tonnes) $V = V_{a_1}$ $V = V_{a_1}$ $V = V_{a_1}$ $V_P$ ,Exploitable biomass (tonnes) $V = V_{a_1}$ $V = V_{a_1}$ $V = V_{a_1}$ $V_P$ ,Exploitable biomass (tonnes) $V = V_{a_1}$ $V = V_{a_1}$ $V = V_{a_1}$ $V_P$ ,Exploitable dequilibrium spawning biomass per recruit (tonnes) $V = V_{a_1}$ $V = V_{a_1}$ $V_a$ Lognormal random ceruitment deviates $V = V_{a_1}$ $V = V_{a_1}$ $V_a$ Lognormal random recruitment deviates $V = V_{a_1}$ $V = V_{a_1}$ $V_a$ Lognormal random recruitment deviates $V = V_{a_1}$ $V = V_{a$	$\sigma_{Q3} - \sigma_{\Omega4}$	Standard deviation for the rw (double logistic selectivity)	1	-
$ \begin{array}{cccc} L_0 & Lower and upper bounds for \Omega_5 and \Omega_4 A A A A A A A A A A A A A A A A A A A$	$\rho_{\Omega 3} - \rho_{\Omega 4}$	Correlation coefficient for the rw (double logistic selectivity)	0.9	-
$\Omega_n$ State variablesEstimatedState variablesNumber at age a in year t aState variables $V_{n,a}$ Number at age a in year t AState variables $Z_n(M+F_r)$ Instantaneous total mortality obmass (tonnes)State variables $P_{a,c}$ Age proportion in year t C acta-t-age in numbersState variables $SSBt$ Spawning biomass in year t (tonnes)State variables $C_n$ Catch-at-age in numbersState variables $SSBt$ Spawning biomass in year t (tonnes)State variables $VB_n$ Catch-per-unit-effort in year tState variables $C_n$ Catch-per-unit-affort in year tState variables $S_n$ Selectivity-at-ageSelectivity-at-age $m_n$ Mature proportion-at-age (connes)State variables $V_n$ Body mass-at-age (tonnes)State variables $\phi$ Catoper-unit-affort in year tipotic state ge (connes)State variables $V_n$ Body mass-at-age (tonnes)State variable $V_n$ Body mass-at-age (tonnes)State variable $\phi_n$ Lognormal random crutiment deviatesState variable $f_i$ Lognormal random fishing mortality deviatesState variable $\phi_i$ Catify a subities selectivity deviates for rwState variable $\phi_i$ Catify a subities selectivity deviates for rwState variable $\phi_i$ Double logistic selectivity deviates for rwState variable $\phi_i$ Double logistic selectivity deviates for rwState variable $\phi_i$	$Lo_{\Omega}$ - $U_{\Omega}$	Lower and upper bounds for $\Omega_3$ and $\Omega_4$	4 - 11	-
State variables $N_{a,r}$ Number at age $a$ in year $t$ $N_{a,r}$ Number at age $a$ in year $t$ $B_r$ Vulnerable biomass (tonnes) $P_{a,r}$ Age proportion in year $t$ $Ca.t$ Catch-at-age in numbersSSBtSpawning biomass in year $t$ (tonnes) $SSBt$ Spawning biomass in year $t$ (tonnes) $C_r$ Catch in year $t$ (tonnes) $C_r$ Catch in year $t$ (tonnes) $VB_r$ Exploitable biomass (tonnes) $CPUE_r$ Catch-per-unit-effort in year $t$ Derived variablesSafed spawning biomass (tonnes) $S_a^r$ Selectivity-at-age $m_a$ Mature proportion-at-age $l_a$ Length-at-age (cnn) $w_a$ Body mass-at-age (cnnes) $\phi$ Unfrished equilibrium spawning biomass per recruit (tonnes)Stochastic deviation- $w_i$ Lognormal random ceruitment deviates $c_i$ Lognormal random recruitment deviates $c_i$ Lognormal random recruitment deviates $\phi_i$ Random $q$ deviates for rw $\delta_i$ ( $\Omega_h$ )Logistic selectivity deviates for rw $\delta_i$ ( $\Omega_h$ )Double logistic selectivity deviates for rw $\delta_i$ ( $\Omega_h$ )Double logistic selectivity deviates for rw $\delta_i$ ( $\Omega_h = \Omega_h$ )Double logistic selectivity deviates for rw $\delta_i$ ( $\Omega_h = \Omega_h$ )Double logistic selectivity deviates for rw $\delta_i$ ( $\Omega_h = \Omega_h$ )Double logistic selectivity deviates for rw $\delta_i$ ( $\Omega_h = \Omega_h$ )Double logistic selectivity deviates for rw $\delta_i$	$\Omega_{5t}$	Time-varying parameter vector of slope 1 (double logistic selectivity)		Estimated
$N_{at}$ Number at age $a$ in year $t$ $Z_t(M+F_t)$ Instantaneous stotal mortality $B_t$ Vulnerable biomass (tonnes) $P_{at}$ Age proportion in year $t$ $C_{at,t}$ Catch-at-age in numbersSSBtSpawning biomass in year $t$ (tonnes) $C_t$ Catch-at-age in numbers $VU_t$ Exploitable biomass (tonnes) $C_t$ Catch-at-age (numbers) $CPUE_t$ Catch-at-age (tonnes) $CPUE_t$ Catch-at-age (tonnes) $B_a$ Selectivity-at-age (tonnes) $B_a$ Selectivity-at-age (tonnes) $M_a$ Mature proportion-at-age $l_a$ Length-at-age (tonnes) $\phi$ Unfished spawning biomass per recruit (tonnes) $\phi$ Lognormal random recruitment deviates $\phi$ Lognormal random recruitment deviates $\phi_t$ Random $q$ deviates for rw $\phi_t$ Random $q$ deviates for rw $\phi_t$ Double logistic selectivity deviates for rw $\phi_t$ Statimated $\phi_t$ Double logistic selectivity deviates for rw $\phi_t$ Supple size for catch-at-age $M_{attrier}$ Supple size for catch-at-age $\phi_t$ Supple size for catch-at-age $M_a$	State variables			
$\begin{array}{ccc} Z_{t}(M+F_{t}) & \mbox{Instaneous total mortality} & \mbox{Instaneous total mortality} \\ B_{t} & \mbox{Vulnerable biomass (tonnes)} \\ P_{at} & \mbox{Age proportion in year t} \\ C a,t & \mbox{Catch-at-age in numbers} \\ SSBt & \mbox{Spawning biomass in year t (tonnes)} \\ C_{t} & \mbox{Catch in year t (tonnes)} \\ VB_{t} & \mbox{Exploitable biomass (tonnes)} \\ VB_{t} & \mbox{Exploitable biomass (tonnes)} \\ VB_{t} & \mbox{Exploitable biomass (tonnes)} \\ CPUE_{t} & \mbox{Exploitable biomass (tonnes)} \\ CPUE_{t} & \mbox{Exploitable biomass (tonnes)} \\ S_{t} & \mbox{Exploitable poportion-at-age} \\ I_{a} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ Stochastic deviation \\ W_{t} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ Stochastic deviation \\ W_{t} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ Stochastic deviation \\ S_{t} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ Stochastic deviation \\ S_{t} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ S_{t} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ S_{t} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ S_{t} & \mbox{Exploitable equilibrium apawning biomass per recruit (tonnes)} \\ S_{t} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ S_{t} & \mbox{Exploitable equilibrium spawning biomass per recruit (tonnes)} \\ S_{t} & Exploitable equilibrium apawning bioma$	$N_{a,t}$	Number at age <i>a</i> in year <i>t</i>		
$B_r$ Vulnerable biomass (tonnes) $P_{at}$ Age proportion in year t $P_{at}$ Catch-at-age in numbersSSBtSpawning biomass in year t (tonnes) $C_t$ Catch in year t (tonnes) $C_t$ Catch in year t (tonnes) $CPUE_r$ Catch-per-unit-effort in year tDerived variablesUnfished spawning biomass (tonnes) $B_q$ Selectivity-at-age $M_a$ Selectivity-at-age $M_a$ Body mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviationEstimated $\phi$ Cognormal random recruitment deviates $e_t$ Lognormal random recruitment deviates $\phi_i$ Lognormal random recruitment deviates $\phi_i$ Lognormal random recruitment deviates $\phi_i$ Lognormal random is for rw $\phi_i$ Lognormal random is for rw $\phi_i$ Sandom is deviativity deviates for rw $\phi_i$ Random $q$ deviates $\phi_i$ Sample isze for catch-at-age $\delta_i$ Sample isze for catch-at-age $M_i$ Sample isze for catch-at-age	$Z_t(M+F_t)$	Instantaneous total mortality		
$P_{a,t}$ Age proportion in year t $C a,t$ Catch-at-age in numbers $SSBt$ Spawning biomass in year t (tonnes) $C_t$ Catch in year t (tonnes) $C_t$ Catch in year t (tonnes) $VB_t$ Exploitable biomass (tonnes) $VB_t$ Catch-per-unit-effort in year tDerived variables $V$ $B_0$ Unfished spawning biomass (tonnes) $S_a$ Selectivity-at-age $m_a$ Mature proportion-at-age $l_a$ Length-at-age (connes) $\psi_a$ Body mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes) $Stochastic deviationVw_aBody mass-at-age (tonnes)\phiUnfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviationStochastic deviationw_iLognormal random recruitment deviatesf_iLognormal random GPUE deviates\phi_i (\Omega_{1i})Logistic selectivity deviates for rw\phi_i (\Omega_{1i})Logistic selectivity deviates for rw\delta_i (\Omega_{2i}, \Omega_{aj})Double logistic selectivity deviates for rw\delta_i (\Omega_{2i}, \Omega_{aj})Double logistic selectivity deviates for rw\delta_i (\Omega_{2i}, \Omega_{2aj})Double logistic selectivity deviates for rwT_iSample size for catch-at-ageM_iMultinomialM_iSample size for catch-at-ageM_iSampling variabilityM_iSampling variability$	$B_t$	Vulnerable biomass (tonnes)		
C a,tCatch-at-age in numbersSSBtSpawning biomass in year t (tonnes)CtCatch in year t (tonnes)VBt,Exploitable biomass (tonnes)CPUEt,Catch-per-unit-effort in year tDerived variablesB0Unfished spawning biomass (tonnes)SaSelectivity-at-agemaMature proportion-at-agelaLength-at-age (cm)waBody mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviatioEstimated $\phi$ Lognormal random recruitment deviates $e_r$ Lognormal random recruitment deviates $e_r$ Lognormal random fishing mortality deviates $\phi$ Random q deviates $\phi$ Cogistic selectivity deviates for rw $\phi_i(\Omega_{a_1} \cdot \Omega_{a_1})$ Double logistic selectivity deviates for rw $\phi_i(\Omega_{a_1} \cdot \Omega_{a_1})$ Double logistic selectivity deviates for rw $\phi_i(\Omega_{a_2} \cdot \Omega_{a_1})$ Double logistic selectivity deviates for rw $\gamma$ Sample size for catch-at-age $N_i$ Sample size for catch-at-age $N_i$ Sampling variability $a_i$ Sampling variabilitySampling variabilitySampling variabil	$P_{a,t}$	Age proportion in year t		
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$L_i$ Catch in year t (tonnes) $VB_i$ Exploitable biomass (tonnes) $CPUE_t$ Catch-per-unit-effort in year t $B_0$ Unfished spawning biomass (tonnes) $S_a$ Selectivity-at-age $m_a$ Mature proportion-at-age $I_a$ Length-at-age (cnn) $w_a$ Body mass-at-age (cnnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviationEstimated $w_i$ Lognormal random recruitment deviatesEstimated $\varepsilon_t$ Lognormal random recruitment deviatesEstimated $\phi_i$ Lognormal random fishing mortality deviatesEstimated $\phi_i$ Lognormal random fishing mortality deviatesEstimated $\phi_i$ Logistic selectivity deviates for rwEstimated $\phi_i$ Double logistic selectivity deviates for rwEstimated $\phi_i$ Sandow $\eta$ Source selectivity deviates for rwEstimated $\phi_i$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ $Others$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ $M_i$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ $M_i$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ $\phi_i$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ $\phi_i$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ $\phi_i$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ $\phi_i$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ Sandow $\eta$ <td>SSBt</td> <td>Spawning biomass in year t (tonnes)</td> <td></td> <td></td>	SSBt	Spawning biomass in year t (tonnes)		
Vb,Exploitable biomass (ionnes)CPUE,Catch-per-unit-effort in year tDerived variables $B_0$ Unfished spawning biomass (tonnes) $S_a$ Selectivity-at-age $m_a$ Mature proportion-at-age $l_a$ Length-at-age (cm) $w_a$ Body mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviationEstimated $w_i$ Lognormal random recruitment deviatesEstimated $c_i$ Lognormal random cPUE deviates- $q_i$ Random $q$ deviates for rwEstimated $\phi_i$ Logistic selectivity deviates for rwEstimated $\phi_i$ Random $q$ deviates for rwEstimated $\phi_i$ Sample size for catch-at-age800200 $W_i$ Sampling variabilityMultinomial	$C_t$	Catch in year t (tonnes)		
CrocerCatch-per-unit-entrit in year tDerived variables $B_0$ Unfished spawning biomass (tonnes) $S_a$ Selectivity-at-age $m_a$ Mature proportion-at-age $l_a$ Length-at-age (cm) $w_a$ Body mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviationEstimated $w_i$ Lognormal random recruitment deviates $e_i$ Lognormal random recruitment deviates $e_i$ Lognormal random recruitment deviates $\phi_i$ Lognormal random fishing mortality deviates $\phi_i$ Lognormal random fishing mortality deviates $\phi_i$ Random $q$ deviates for rw $\phi_i$ Logistic selectivity deviates for rw $\delta_i$ ( $\Omega_{3i} - \Omega_{4i}$ )Double logistic selectivity deviates for rwOthers-N fisherySample size for catch-at-age $SV$ Sample size for catch-at-age $a$ 800200Multinomial $a$	VB <sub>t</sub> CDUE	Exploitable biomass (tonnes)		
Bit Net Variables         Bit Net Variables       Unfished spawning biomass (tonnes)         Sa       Selectivity-at-age         ma       Mature proportion-at-age       Item State         Ia       Length-at-age (cm)       Item State       Item State         wa       Body mass-at-age (cm)       Item State       Item State       Item State $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)       Item State       Item State       Item State         Stochastic deviation       Lognormal random recruitment deviates       Estimated       -       - $t_t$ Lognormal random recruitment deviates       Estimated       -       -       - $f_t$ Lognormal random GPUE deviates       Estimated       -       -       -       - $\phi_t$ Random q deviates for rw       Estimated       -	$CPUE_t$	Calch-per-unit-enort in year t		
$D_0$ Contrastic spawning bornass (connes) $S_a$ Selectivity-at-age $m_a$ Mature proportion-at-age $l_a$ Length-at-age (cm) $w_a$ Body mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviation $w_t$ Lognormal random recruitment deviates $\varepsilon_t$ Lognormal random CPUE deviates $f_t$ Lognormal random fishing mortality deviates $\phi_t$ Random q deviates $\phi_t$ Random q deviates for rw $\delta_t(\Omega_{31} - \Omega_{41})$ Double logistic selectivity deviates for rw $\delta_t(\Omega_{31} - \Omega_{51})$ Double logistic selectivity deviates for rw $\delta_t(\Omega_{31} - \Omega_{51})$ Sample size for catch-at-age $N$ fisherySample size for catch-at-age $\delta_{2V}$ Sampling variability $a^2$ Ziegler (2013)		Unfiched snawning biomass (tonnes)		
$a_a$ Sector type arage $m_a$ Mattre proportion-at-age $l_a$ Length-at-age (cm) $w_a$ Body mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviation $w_t$ Lognormal random ceruitment deviates $\epsilon_t$ Lognormal random CPUE deviates $\epsilon_t$ Lognormal random fishing mortality deviates $\phi_t$ Random $q$ deviates $\phi_t$ Random $q$ deviates for rw $\delta_t(\Omega_{1t})$ Logistic selectivity deviates for rw $\delta_t(\Omega_{3t} - \Omega_{4t})$ Double logistic selectivity deviates for rw $\delta_t(\Omega_{3t} - \Omega_{4t})$ Double logistic selectivity deviates for rwN fisherySample size for catch-at-age800 $SV$ Sampling variability $a$ Ziegler (2013)	$\mathbf{D}_0$	Selectivity-at-age		
$u_a$ Instance proposition at age $l_a$ Length-at-age (cm) $w_a$ Body mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviation $w_t$ Lognormal random recruitment deviates $v_t$ Lognormal random CPUE deviates $\epsilon_t$ Lognormal random fishing mortality deviates $f_t$ Lognormal random fishing mortality deviates $\varphi_t$ Random $q$ deviates for rw $\delta_t(\Omega_{3t} - \Omega_{4t})$ Double logistic selectivity deviates for rw $\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rw $\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rw $\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rw $\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rw $\delta_t(\Omega_{2t} - \Omega_{5t})$ Sample size for catch-at-age $\delta_t(\Omega_{2t} - \Omega_{5t})$ Sample size for catch-at-age $\delta_t(\Omega_{2t} - \Omega_{5t})$ Sampling variability $a$ Ziegler (2013)	о <sub>а</sub> т_	Mature proportion-at-age		
$u_a$ Body mass-at-age (tonnes) $\phi$ Unfished equilibrium spawning biomass per recruit (tonnes)Stochastic deviation $w_t$ Lognormal random recruitment deviatesEstimated $\varepsilon_t$ Lognormal random CPUE deviates- $f_t$ Lognormal random fishing mortality deviates- $g_t$ Random q deviates- $\delta_t(\Omega_{3t} - \Omega_{4t})$ Double logistic selectivity deviates for rwEstimated $\delta_t(\Omega_{3t} - \Omega_{4t})$ Double logistic selectivity deviates for rw- $\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rw-N fisherySample size for catch-at-age800200 $SV$ Sampling variabilityMultinomialMultinomial	la la	Length-at-age (cm)		
	W <sub>a</sub>	Body mass-at-age (tonnes)		
Stochastic deviation $w_t$ Lognormal random recruitment deviatesEstimated $\varepsilon_t$ Lognormal random CPUE deviates- $f_t$ Lognormal random fishing mortality deviatesEstimated $\varphi_t$ Random q deviates- $\phi_t$ Random q deviates for rwEstimated $\delta_t(\Omega_{3t} - \Omega_{4t})$ Double logistic selectivity deviates for rwEstimated $\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rwEstimatedOthersN fisherySample size for catch-at-age800200SVSample size for catch-at-age800200SVSampling variabilityMultinomialMultinomial	ф.	Unfished equilibrium spawning biomass per recruit (tonnes)		
Both and on a constrained deviation $w_t$ Lognormal random recruitment deviatesEstimated $\varepsilon_t$ Lognormal random GPUE deviates- $f_t$ Lognormal random fishing mortality deviatesEstimated $\varphi_t$ Random $q$ deviates- $\delta_t(\Omega_{1t})$ Logistic selectivity deviates for rwEstimated $\delta_t(\Omega_{3t} - \Omega_{4t})$ Double logistic selectivity deviates for rwEstimated $\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rwEstimatedOthersN fisherySample size for catch-at-age800200SVSampling variabilityMultinomialMultinomial	y Stochastic deviation			
$w_t$ Dognormal random recruitment deviatesDescription $\varepsilon_t$ Lognormal random CPUE deviates- $f_t$ Lognormal random fishing mortality deviatesEstimated $\varphi_t$ Random q deviates- $\delta_t(\Omega_{1t})$ Logistic selectivity deviates for rwEstimated $\delta_t(\Omega_{3t} - \Omega_{4t})$ Double logistic selectivity deviates for rw- $\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rwEstimatedOthersN fisherySample size for catch-at-age800200SVSampling variabilityMultinomialMultinomial		Lognormal random recruitment deviates		Estimated
$ \begin{array}{cccc} f_t & \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ $	E.	Lognormal random CPLIE deviates		-
$\varphi_t$ Random q deviates- $\varphi_t$ Random q deviates- $\delta_t(\Omega_{1t})$ Logistic selectivity deviates for rwEstimated $\delta_t(\Omega_{3t}, \Omega_{4t})$ Double logistic selectivity deviates for rw- $\delta_t(\Omega_{3t}, \Omega_{5t})$ Double logistic selectivity deviates for rwEstimated $Others$ Visition of the selectivity deviates for rw-N fisherySample size for catch-at-age800200SVSampling variabilityMultinomial $a$ Ziegler (2013)-	f.	Lognormal random fishing mortality deviates		Estimated
$\begin{array}{cccc} & & & & & & & & & & & & & & & & & $	Ø,	Random <i>a</i> deviates		-
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$\delta_t(\Omega_{3t} - \Omega_{5t})$ Double logistic selectivity deviates for rwEstimatedOthers $N$ fisherySample size for catch-at-age $800$ $200$ $SV$ Sampling variabilityMultinomialMultinomial	$\delta_t(\Omega_{3t} - \Omega_{4t})$	Double logistic selectivity deviates for rw		-
Others <i>N fishery</i> Sample size for catch-at-age 800 200 <i>SV</i> Sampling variability Multinomial Multinomial	$\delta_t(\Omega_{3t} - \Omega_{5t})$	Double logistic selectivity deviates for rw		Estimated
N fishery SV     Sample size for catch-at-age Sampling variability     800     200       Multinomial     Multinomial	Others			
SV Sampling variability Multinomial Multinomial	N fishery	Sample size for catch-at-age	800	200
<sup>a</sup> Ziegler (2013)	SV	Sampling variability	Multinomial	Multinomial
	<sup>a</sup> Ziegler (2)	)13)		

<sup>b</sup>Arana (2009).

Table 2. Operating model characteristics for each case used in the estimation model and the median absolute relative error (MARE)

values of $D_{final}$ , $R_0$ , and $F_{terminal}$ obtained	d for the four cases.
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Case	Scenario	Selectivity (OM - EM)	Catchability (OM) <sup>b</sup>	Ageing Error	Ageing Error	1	MARE (%)	
		• ~ /		in OM	correction in EM	$D_{final}$	$R_0$	F terminal
TI-L	NAE - 1 <sup>a</sup>	Time-invariant Logistic	Time-invariant	NO	-	10.090	15.642	24.229
	AE - 1	Time-invariant Logistic	Time-invariant	YES	NO	25.182	101.317	48.156
	AEC - 1	Time-invariant Logistic	Time-invariant	YES	YES	11.477	18.270	14.939
	NAE - 2	Time-invariant Logistic	Time-varying	NO	-	11.319	19.970	16.765
	AE - 2	Time-invariant Logistic	Time-varying	YES	NO	26.814	103.882	38.843
	AEC - 2	Time-invariant Logistic	Time-varying	YES	YES	10.989	20.197	12.237
TI-DL	NAE - 1	Time-invariant double logistic	Time-invariant	NO	-	10.291	14.778	19.181
	AE - 1	Time-invariant double logistic	Time-in <mark>variant</mark>	YES X	NO	35.633	103.446	39.280
	AEC - 1	Time-invariant double logistic	Time-in <mark>variant</mark>	YES	YES	14.659	15.681	14.297
	NAE - 2	Time-invariant double logistic	Time-va <mark>rying</mark>	NO	-	12.950	18.818	14.508
	AE - 2	Time-invariant double logistic	Time-va <mark>rying</mark>	YES	NO	41.480	115.482	34.414
	AEC - 2	Time-invariant double logistic	Time-varying	YES	YES	14.238	18.785	15.192
TV-L	NAE - 1	Time-varying logistic	Time-invariant	NO	-	14.612	17.290	18.406
	AE - 1	Time-varying logistic	Time-invariant	YES	NO	27.305	83.878	59.282
	AEC - 1	Time-varying logistic	Time-invariant	YES	YES	13.773	21.339	18.373
	NAE - 2	Time-varying logistic	Time-varying	NO	-	16.411	23.499	17.123
	AE - 2	Time-varying logistic	Time-varying	YES	NO	35.796	104.037	47.554
	AEC - 2	Time-varying logistic	Time-varying	YES	YES	14.462	25.578	18.574
TV-DL	NAE - 1	Time-varying double logistic	Time-invariant	NO	-	18.937	13.903	14.860
	AE - 1	Time-varying double logistic	Time-invariant	YES	NO	53.060	86.932	41.639
	AEC - 1	Time-varying double logistic	Time-invariant	YES	YES	13.784	13.701	15.626
	NAE - 2	Time-varying double logistic	Time-varying	NO	-	23.581	19.589	13.904
	AE - 2	Time-varying double logistic	Time-varying	YES	NO	58.320	103.402	31.200
	AEC - 2	Time-varying double logistic	Time-varying	YES	YES	15.432	16.322	16.292

<sup>*a*</sup> NE-1 represent the base case. <sup>*b*</sup> Catchability was always estimated as a constant parameter in the EM.

**Table 3.** Operating model characteristics for each case used in the estimation model with selectivity misspecification in the absence of ageing error, and the median absolute relative error (MARE) values of  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$  obtained for the four cases for each selectivity configuration (for comparison, the scenarios where the selectivity was correctly specified, that is, the selectivity function used in the OM was maintained in the SCA, are presented in brackets in italic (see Table 2 for scenario names). Number 1 in scenarios indicates a time-invariant catchability in the OM, and number 2 in scenarios indicates a time-varying catchability in the OM.

Selectivity incorrectly specified in the SCA (without ageing error)							
Case	Scenario	Selec	ctivity		MARE (%)		
		OM	SCA	$D_{final}$	$R_0$	F terminal	
TI-LTI-DL	NAE - 1	Time-invariant logistic	Time-invariant double logistic	8.560 ( 10.090 )	14.099 ( 15.642 )	16.158 ( 24.229 )	
	NAE - 2	Time-invariant logistic	Time-invariant double logistic	10.437 ( 11.319 )	14.913 ( 19.970 )	14.888 ( 16.765 )	
TI-DLTI-L	NAE - 1	Time-invariant double logistic	Time-invariant logistic	12.477 ( 10.291 )	29.340 ( 14.778 )	25.717 ( 19.181 )	
	NAE - 2	Time-invariant double logistic	Time-invariant logistic	13.753 ( 12.950 )	42.912 ( 18.818 )	18.869 ( 14.508 )	
TV-LTI-L	NAE - 1	Time-varying logistic	Time-invariant logistic	25.175 ( 14.612 )	21.880 ( 17.290 )	38.681 ( 18.406 )	
	NAE - 2	Time-varying logistic	Time-invariant logistic	29.038 ( 16.411 )	21.907 ( 23.499 )	41.462 ( 17.123 )	
TV-DL_TI-DL	NAE - 1	Time-varying double logistic	Time-invariant double logistic	22.050 ( 18.937 )	13.149 ( 13.903 )	22.460 ( 14.860 )	
	NAE - 2	Time-varying double logistic	Time-invariant double logistic	19.609 ( 23.581 )	15.949 ( 19.589 )	22.834 ( 13.904 )	

**Table 4.** Operating model characteristics for each case used in the estimation model with selectivity misspecification in the presence of ageing error, and the median absolute relative error (MARE) values of  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$  obtained for the four cases for each selectivity configuration (for comparison, the scenarios where the selectivity was correctly specified, that is, the selectivity function used in the OM was maintained in the SCA, are presented in brackets in italic (see Table 2 for scenario names). Number 1 in scenarios indicates a time-invariant catchability in the OM, and number 2 in scenarios indicates a time-varying catchability in the OM.

Selectivity incorrectly specified in the SCA (with ageing error)							
Case Scenario Selectivity		MARE (%)					
		OM	SCA	D final	$R_0$	F terminal	
TI-LTI-DL	AE - 1	Time-invariant logistic	Time-invariant double logistic	29.842 ( 25.182 )	42.749 ( 101.317 )	38.131 ( 48.156 )	
	AE - 2	Time-invariant logistic	Time-invariant double logistic	34.041 ( 26.814 )	55.605 (103.882)	31.404 ( 38.843 )	
TI-DLTI-L	AE - 1	Time-invariant double logistic	Time-invariant logistic	33.627 ( 35.633 )	219.383 ( 103.446 )	52.021 ( 39.28 )	
	AE - 2	Time-invariant double logistic	Time-invariant logistic	36.240 ( 41.480 )	203.112 ( 115.482 )	43.297 ( 34.414 )	
TV-LTI-L	AE - 1	Time-varying logistic	Time-invariant logistic	33.376 ( 27.305 )	60.789 ( 83.878 )	39.954 ( 59.282 )	
	AE - 2	Time-varying logistic	Time-invariant logistic	37.779 ( 35.796 )	70.223 ( 104.037 )	38.499 ( 47.554 )	
TV-DLTI-DL	AE - 1	Time-varying double logistic	Time-invariant double logistic	36.160 ( 53.060 )	70.213 ( 86.932 )	29.285 ( 41.639 )	
	AE - 2	Time-varying double logistic	Time-invariant double logistic	33.399 ( 58.320 )	100.147 ( 103.402 )	24.247 ( 31.200 )	

Capítulo II

Rebuilding Patagonian toothfish off Southern Chile: evaluating trade-offs via closed-loop harvest



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# Rebuilding Patagonian toothfish off Southern Chile: evaluating trade-offs via closed-loop harvest strategy simulations

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Manuscript in preparation



#### Abstract

Management strategy simulation is a useful tool for evaluating expected performance of management procedures (MPs) against economic and conservation objectives. Successful MPs are necessary not only for conservation of exploited stocks, but also for strengthening economic resilience of fisheries. We used management strategy simulations to explore MP candidates aimed at rebuilding the Patagonian toothfish stock from Southern Chile and to examine trade-offs between fishery viability and fish conservation. The Patagonian toothfish fishery supports one of the most lucrative fisheries in Antarctic and Sub - Antarctic waters off the southern cone of South America. The harvest control rules (HCR) components of simulated management procedures consisted of (1) a rebuilding target (TSSB) corresponding to  $B_{MSY}$  or a  $0.45B_0$  or  $0.4B_0$  proxy; (2) limits (LSSB) corresponding to multiples of  $B_{MSY}$  or  $B_0$  (e.g.  $0.5B_{MSY}$ ); and (3) target fishing mortality rates corresponding to multiples of  $F_{MSY}$  or  $F_{SPR45\%}$ . We used a surplus production model in simulated stock assessments to estimate annual exploitable biomass along with the harvest control rule components given above. Twenty MPs were tested against an age-structured operating model that mimicked the Patagonian toothfish population and fishery over the period 1989 to 2012. The best MPs included HCRs with (i) LSSB =  $0.5B_{MSY}$ , TSSB =  $B_{MSY}$ , and  $F_{MSY}$ , (ii) LSSB =  $0.2B_0$ , TSSB =  $0.45B_0$ , and  $0.5F_{spr45\%}$ , and (iii) constant F<sub>MSY</sub>. The best MPs demonstrate that Patagonian toothfish could recover from its current over-fished state to levels greater than  $0.25B_0$  within the years 2022 to 2038; however, such recovery would cost at least 36-40% reduction in annual catch (~ 400 tons).

Keywords: Management strategy simulation, Management procedures, Harvest control rules, Operating model, Rebuilding strategies, Patagonian toothfish.

# Introduction

The fishery management of an exploited population has diverse goals, but generally includes avoiding overfishing, achieving high long-term catches and minimizing socio-economic risks (Punt, 2006). To these aims certain Biological Reference Points (BRPs), measured generally in terms of biomass or fishing mortality rate (F) are established, which try to balance resource conservation and exploitation. A BRP in general terms, is a metric of stock status from a biological perspective (Gabriel and Mace, 1999) and these can vary from one species to another,

but have the same end objective, i.e. to maintain the population within sustainable biomass levels. There are two types of BRPs, target and limit. A Target Reference Point (TRP) indicates the desirable status of the fishery while Limit Reference Points (LRP) are defined as levels that should not be exceeded (i.e., that if they are crossed, the fishery will be in an overfishing status, that could lead to collapse).

An overfishing status, means that the current F exceeds the F associated with an LRP and "being in an overfished state" means that the current spawning biomass (SSB) is less than a minimum target stock size (Punt and Ralston, 2007). When this happens, it produces a breakdown in the proficiency of fishery management, because one of the main specified goals is not met.

This paper explores candidates management procedures (MPs) aimed at rebuilding the overfished Patagonian toothfish (*Dissostichus eleginoides*) stock from Southern Chile (47°S to 57°S) and to examine trade-offs between fishery viability and fish conservation throughout a Management Strategy Evaluation (MSE) approach (de la Mare, 1998; Smith, 1993; Cooke, 1999; Punt and Smith, 1999; Butterworth, 2007).

A useful tool to evaluate management strategies, considering both conservation and economic objectives is the so called Management strategy evaluation or MSE also referred to as the management procedure approach or closed loop simulation. The MSE has been designed to identify fishery rebuilding strategies and established harvest strategies that are robust to uncertainty and natural variation, and that also balance biological and socioeconomic objectives (Holland, 2010).

MSE is a robust approach to designing fishery management systems through extensive computer simulation (e.g., Punt and Smith, 1999; Sainsbury *et al.*, 2000; Butterworth, 2007; Kronlund *et al.*, 2012). MSE involves assessing the consequences of a range of candidates management strategies and presenting the tradeoffs in performance across a range of management objectives (Smith, 1994). This approach employs the use of simulation testing to determine how robust the management strategies are to measurement and process error, and model uncertainty (A'mar *et al.*, 2008).

In short, MSE involves building (1) an operating model (OM) to represent all the information and assumptions about the stock and the fishery. This operating model is used to simulate data of population dynamics and the data gathering of the fishery; (2) these data are used by an estimation model (EM) to assess the stock status; (3) then, a decision rule or harvest control rule (HCR) is applied to determine catch limits in terms of TAC or allowable fishing

effort (A'mar *et al.*, 2008); and (4) different management procedures (MP) are compared to determine which one meets the desired (sometimes conflicting) objectives.

This work is the first attempt to apply the MSE approach and rebuilding strategies in a Chilean fishery. At present, Chile faces the biggest crisis in its fishing history, with almost 48% of fisheries declared in overfished or collapsed state (SUBPESCA, 2015). In an attempt to improve the fishery management, the Chilean fisheries and aquaculture law changed, making explicit the use of Maximum Sustainable Yield (MSY) or some proxy (Clark, 1991, 1993; Dorn, 2002), as a target reference point for the management of domestic fisheries. Unfortunately, in most of Chilean fisheries *F* has exceeded those related with obtaining the MSY, thus the management goal of the new fishery law is to rebuild the stocks to  $B_{MSY}$  (stock size that can produce the maximum sustainable yield) (L.G.P.A. N° 18.892). We are aware that MSY and the reference points associated to this quantity, are not a TRP but a LRP, however, it is necessary to explore rebuilding plans for the Chilean fisheries and the work that we are presenting in this paper is a starting point that can be used as example for other fisheries.

The Patagonian toothfish stock is currently in an overfished state, with critical levels of biomass and *F* that have exceeded the LRP value (Tascheri and Canales, 2015). This is a deepwater species distributed in the Southern Hemisphere, mainly between 40°S to 60°S and in the circumpolar Antarctic region (Laptikhovsky and Brickle, 2005). It presents slow growth, late maturity, and high longevity (greater than 50 years old) (Horn, 2002; Belchier, 2004). The Patagonian toothfish supports one of the most lucrative fisheries taking place in Antarctic and Sub - Antarctic waters in southern cone of South America, with catches that are profitable even at low yields, due to its high commercial value in foreign markets (US\$25/kg), mainly USA, Hong Kong, Japan and China, with exports exceeding 50 million dollars per year (Inteligencia Comercial de ProChile [Estados Unidos, Hong Kong, Japon, Chile], 2013).

The historical time series of catches of the Patagonian toothfish fishery, has been rebuilt from 1989 to 2013 by Fisheries National Service (SERNAPESCA, 2013). The highest peak in catches occurred in 1992, with catches that exceeded 30,000 tons, which led in following years to a quick decline in catches, which have remained around 2000 - 3000 tons per year in the last five years. (SERNAPESCA, 2013). The fishery is regulated by a system of total allowable catch (TAC) assigned individually to the industrial fleet through annual auctions. The TAC decreased from 3090 tons in 2014 to 1098 tons in 2015. However, despite this important decline in the TAC, the depletion of SSB is close to 15%.

The main aim of this paper is to use an MSE to investigate, compare and present the consequences of adopting alternatives management procedure to the recovery of the Patagonian toothfish fishery in the short, median and long term. Specifically, we aim to explore what MPs could be more effective to fulfill both conservation and economic objectives. To fulfill this aim we try to meet some management specific objectives, such as: 1) to identify which MPs avoid that the spawning stock falling within the critical zone, defined by a limit stock size (LSSB), and maintaining the SSB above the LSSB in 95% of projected years in the short, mediumn, and long term (i.e., P (SSB>LSSB)  $\geq$  95%); 2) to explore different MPs that could maintain SSB above a rebuilding target stock size (TSSB) in 50% of the projection years in the medium and long term (i.e., P (SSB  $\geq$  TSSB)  $\geq$  50%); 3) to evaluate MPs that could generate an average annual variability in catch (AVV) lower than 15% in the medium and long term.

# Methods

Management strategy evaluation framework

The general framework to identify fishery rebuilding strategies and sustainable harvesting in the short (2013 - 2021), medium (2022 - 2030) and long term (2031 - 2038), was realized through an MSE approach. The MSE is implemented in Management Strategy Evaluation in R, or *mseR* (computer software package) created by Kronlund *et al.*, 2012. *mseR* implements a simple closed-loop feedback simulation of a fisheries management system. The software is based in the statistical computing language R (R Development Core Team, 2006). Full details about the *mseR* program (equations, tables, description and supplementary information) can be found in the User's guide of *mseR* in\_Kronlund *et al.*, 2012.

As outlined in the introduction, the MSE requires four main steps: i) defining an OM conditioned to current fishery and population dynamics of the species, ii) applying an EM to data generated from the OM, iii) applying a harvest control rule (HCR), and iv) evaluating management procedures (MP) using different performance statistics (Figure 1).

# The operating model (mseR OM)

The *mseR* OM was conditioned and parameterized using the biological and fishery characteristics of the current Patagonian toothfish fishery developed in Chile. Parameter definitions and equations used in the description of the *mseR* OM are presented in Table 1 and Appendix A [Table A.1, equations (T1.1 - T1.21)].

The parameters used to condition the *mseR* OM (Table 1), were obtained by fitting an statistical catch at age analysis (SCA) implemented in AD Model Builder (Fournier *et al.*, 2012) to catch (1989–2012), catch-per-unit effort (CPUE; 1991–2012) and fishery catch-at-age (1991–1992; 1995-2012) of Patagonian toothfish fishery.

In particular, the *mseR* OM was a single-sex age-structured population dynamics model that mimicked the main characteristics of the Patagonian toothfish population. The population of Patagonian toothfish at year t = 1 was initialized in a deterministic, unfished equilibrium state using equations T1.10 - T1.11. The population dynamic is driven by recruitment and *F* [equations (T1.13 - T1.20)]. Simulated annual recruitment of age-1 fish [equation (T1.14)] followed a Beverton–Holt stock-recruitment relationship. Multiplicative lognormal random deviates ( $\sigma_R$ ) were included to the recruitment time-series [equation (T1.13)].

The selectivity was modeled using a time-varying logistic function in order to create more realistic models of fishery-dependent data [equation (T1.5)]. For the time-varying selectivity, the parameter that represents the age-at-50% of selectivity ( $a_{550}$ %) varied year-to-year following a random walk with autocorrelation (See Appendix A - Chapter I [equations (A.5.5 - A.5.6)].

The OM in the *mseR* program incorporated a module (called "observation model") that simulated the data gathering process (i.e., CPUE, catches, and age composition). This module incorporated process and observation errors in the simulation procedure.

The catch-at-age was simulated using the Baranov equation. In calculating the catch equation (T1.18), the parameters F and natural mortality rate, M, are assumed to operate continuously and simultaneously throughout the year.

The *mseR* OM simulated an yearly index of relative abundance (CPUE) to the existing Patagonian toothfish fishery. The index of relative abundance [equation (T1.21)] is proportional to the vulnerable biomass to the fishery and included stochastic errors as log-normal random deviates and a correction for bias by subtracting  $0.5 \sigma_I^2$  from each observation.

The simulation scheme in *mseR* program was divided into two periods, an initialization ( $t \le T_1$ -1) from 1989 to 2012 and a projection ( $T_1 \le t \le T_2$ ) period from 2013 to 2038. Stock status at ( $t = T_1$ -1), the year preceding to the beginning of the projection period, is initialized at a predetermined level of depletion of spawning biomass by solving for the  $T_1$ -1 *F*'s that maximize the cumulative catch over  $1 \le t \le T_1$ -1 subject to the constraint that realized depletion ( $d = SSB_T$ - $1/B_0$  - means the ratio between the spawning biomass in *T*-1 and the unfished spawning biomass) is approximately equal to a pre-specified level  $d^*(d^*)$  is an input depletion value that is set by user
when the *mseR* OM is conditioned.). This optimization step involves maximizing the objective function:

$$G(F') = \sum_{t=1}^{t=T_1-1} C_t - 1000 * (d - d^*)^2$$
 Eq. (1)

where  $C_t$  is the fishery catch biomass, and the other terms were described previously.

The time needed to solve this optimization was limited by: (*i*) specifying a reduced set of n fishing mortality parameters  $F' = (F'_1, F'_2, ..., F'_n)$  corresponding to a uniformly spaced grid of n points in time between t = 1 and t = T<sub>1</sub>-1; (*ii*) using a cubic spline interpolation of these n points to generate the complete fishing mortality history at all t, namely  $F' = (F_1, F_2, ..., F_{T-1})$ , and (*iii*) performing the optimization with respect to F'.

During the projection period, an HCR determines the TAC. Both  $C_t$  and  $F_t$  are computed by solving the catch equation (T1.18) for the given exploitable biomass and M. Simulated abundance relative index, [equation (T1.21)], generate the estimates of the absolute spawning and exploitable biomass at the beginning of the year.

The equilibrium functions of a fishing mortality rate F presented in Appendix A, [Table A.2, equations (T2.1 - T2.7)] are used by *mseR* OM to compute the following reference fishing mortality rates ( $F_{ref}$ ) via optimization or root-finding algorithms:

 $F_{0.1}$ : fishing mortality rate where the slope of yield-per-recruit [equation (T2.3)] is 10% of the slope at the origin.

 $F_{max}$ : fishing mortality that maximizes yield-per-recruit [equation (T2.3)].

 $F_{X\%}$ : fishing mortality that reduces spawning stock biomass-per-recruit [equation (T2.4)] to X% of the unfished level.

 $F_{\text{crash}}$ : fishing mortality that reduces equilibrium spawning biomass [equation (T2.6)] to zero.

 $F_{MSY}$ : fishing mortality that maximizes equilibrium total yield [equation (T2.7)].

Recruitment, spawning biomass, and yield reference points were obtained by substituting the corresponding reference fishing mortality rates for in T2.1 and computing the equations T2.5 - T2.7 (A complete details that include the equations, tables, description and supplementary information of *mseR* OM is given in Kronlund *et al.*, 2012)

#### Estimation Model (mseR EM)

The MSE requires an EM to assess the status of population each year. The EM was a Schaefer Surplus Production Model (SPM) implemented in AD Model Builder. Model notation and equations are given in Appendix A [Table A.3 and Table A.4, equations (T4.1 - T4.11)]. This estimator requires a time-series of CPUE and catches which were simulated for the OM.

The SPM include the effects of recruitment, growth, and M into a single production function to predict biomass in each year  $B_{t+l}$  (Biomass in the beginning of year t+1) based on four components (Cox *et al.*, 2011): (i) the predicted biomass present in the previous year  $B_t$  (Biomass in the beginning of year t), (ii) an average production function  $f(B_t)$  that depends on biomass (Surplus production as a function of biomass in the start of the year t), (iii) total landed catch during year t,  $\hat{C_t}$ , and (iv) a random deviation  $w_t$ , that incorporates process error in the population dynamics, from the average production relationship (Punt, 2003). The production model is described in equation T4.6. The catch is assumed to be taken instantaneously and after production.

The SPM produces estimates of K (which corresponds to the unfished equilibrium stock size) and intrinsic population growth rate (r) which are used to produce estimates of management derived quantities as MSY (Maximum sustainable yield),  $B_{MSY}$  (stock size that can produce the maximum sustainable yield) and  $U_{MSY}$  (Exploitation rate that can produce the maximum sustainable yield). These quantities can be used by passive adaptive management strategies that attempt to lead fisheries exploitation toward theoretically optimal levels (Walters, 1986).

The index of relative abundance (CPUE) is used in estimating production model parameters via a linear observation model of the form:

$$CPUE_t = qB_t \exp^{\zeta_t}$$
 Eq. (2)

where *q* is a constant catchability coefficient and  $\zeta_t$  is a normally distributed random observation error in year *t* [equation (T4.7)].

The deductions about the stock dynamic can be affected by the uncertainty in observations and by the process error associated to the intrinsic dynamic population, both observation and process error leads to bias in estimating. In this model a proportion  $\rho$  of the total error variance is assigned to the observations and the remainder 1 -  $\rho$  is assigned to the process error, this mechanism is called "errors-invariables estimators". Formally, errors-invariables estimators define the total error variance,  $k^2$ , as: If the observation errors proportion  $\rho = \tau^2 / (\tau^2 + \sigma^2)$  is assumed known, the individual variance components can then be expressed as  $\tau^2 = \rho k^2$ ,  $\sigma^2 = (1 - \rho)k^2$  for observation and process error, respectively. In the SPM of *mseR*,  $\rho$  act as a control parameter. According to Cox *et al.*, (2011), as  $\rho$  approaches 0, the emphasis on process error will tend to allow for relatively large random changes in the estimated stock biomass from year to year. Conversely, values of  $\rho$  near 1 will cause the model biomass to change deterministically in response to changes in fishery impacts; that is, the stock will only increase if catches are less than the deterministic surplus production. Cox *et al.*, 2009, point that according to the experience gained through simulation of production model assessments, suggest that high values of  $\rho$  performed adequately for longer-lived species, so we set  $\rho = 0.75$  in this analysis.

Conditional maximum likelihood estimates and negative log-likelihood and objective functions of the SPM are presented in Appendix A [Table A.4, equations (T4.8 - T4.11)].

The SPM outputs are used together with a proposed HCR, in the called "management procedure" (MP) module (see below), to determine catch limits as TACs. Then, catch limits are input into the *mseR* OM to update the population dynamics and the procedure is repeated several times (e.g., a hundred) The final step involves evaluating the performance of the proposed management strategies against the fishery and management objectives. All the details (i.e., equations, tables, description and supplementary information) about the SPM used by *mseR* are given in Cox *et al.* (2011).

#### Management procedure (MP)

The MP comprised the combination of an HCR and an SPM as an EM. An HCR translates the outputs of a stock assessment method into a management regulation, often as a TAC or effort control (Kronlund *et al.*, 2012)

Two harvest strategies were examined in the MPs; a constant and variable HCR. The constant HCR uses a fixed target fishing mortality rate regardless of stock abundance (Quinn and Deriso, 1999) (Figure 2a). On the contrary, in a variable HCR, the target fishing mortality is adjusted in response to changes in estimated stock abundance (Figure 2b, 2c and 2d). The variable HCR has two break points or bounded to determine annual catch limits. These bounded

represent the limit of spawning biomass stock size and the target (rebuilding target ) of the spawning biomass stock size, LSSB and TSSB, respectively (Figure 2b, 2c, and 2d). For example, the LSSB and TSSB bounded of the HCR could be set by  $0.2B_0$  and  $0.45B_0$ , respectively or  $0.5B_{MSY}$  and  $B_{MSY}$ , respectively (Figure 2c and 2d). Therefore, the LSSB and TSSB going to define if the stock is in critical, cautious or healthy state. If the spawning stock biomass (SSB) falls below or in the LSSB bounded (SSB $\leq$ LSSB) the stock would be in a critical state with risk of collapse. If the spawning stock size is maintained above the LSSB and below the TSSB (LSSB<TSSB), we can consider that the stock is in a cautious state. If the spawning stock size exceeds or it is in the TSSB (SSB $\geq$ TSSB) we can say that the stock is in a healthy state, in terms of recovery, because it is above the rebuilding target that we have established.

The HCRs (variable) use a target fishing mortality rate as a function of estimated spawning biomass stock size. The calculation of target fishing mortality rate ( $F_t$ ) (Table 2) is determined by the SPM assessment estimate of harvestable biomass  $B_t$  and the harvest strategy used (T2.1). Below the LSSB the fishing mortality is set to zero, while above the TSSB the fishing mortality is set to a reference fishing mortality ( $F_{ref}$ ) (e.g.,  $F_{SPR45\%}$ ,  $F_{MSY}$ ). Between TSSB and LSSB, the fishing mortality is linearly reduced (Figure 2b, 2c, and 2d). The calculation of the quota,  $C_t$  (catch in year t), includes a dampener ( $\lambda_1$ ) on the magnitude of the average annual variation (T2.3). The  $\lambda_1$  can take values  $0 \le \lambda 1 < 1$  and this parameter represents the fraction of previous year's quota to apply in the quota calculation for year *t*. For this case  $\lambda_1$  was equal to 0.5. This is a way to control inter-annual variability in yield.

The reference fishing mortality rates were specified in terms of  $F_{MSY}$  and  $F_{spr45\%}$ . But, a fishing moratorium ( $F_0$ ) and *status quo* ( $F_{sq}$ ) fishing morality were also tested. The MPs were defined as showed in Table 3. One hundred simulations were conducted for each MP. Each simulation involved projecting the simulated population forward for 25 years (2013-2038). In total twenty MPs were tested and they are described in Table 3. Only those MPs that were able to fulfill with at least one of the specific management objectives (Table 4) are described with more details along this paper for the sake of simplicity.

## Performance measures for management strategy simulations

Six performance measures were used to evaluate management procedures performance against conservation and economic objectives. Conservation performance was measured in terms of arithmetic mean of annual depletion of spawning biomass as follows:

$$\overline{D} = \frac{1}{t_2 - t_1 + 1} \sum_{t=t_1}^{t_2} (\frac{B_t}{B_0})$$
 Eq. (4)

Conservation performance also was measured throughout of the proportion of years across simulation where the stock status falls into the critical (SSB  $\leq$  LSSB), cautious (LSSB  $\leq$ SSB  $\leq$  TSSB), and healthy (SSB  $\geq$  TSSB) state. The proportion of years that true spawning biomass is at or below the Critical - Cautious Zone boundary (*Pcritical*) was determined as:

$$Pcritical = P(SSB \le LSSB)$$
 Eq. (5)

The proportion of years that true spawning biomass is in the Cautious state (*Pcautious*) and the proportion of years that true spawning biomass in at or above the healthy state (*Phealthy*) are given in the equations 6 and 7, respectively:

$$Pcautious = P(LSSB < SSB < TSSB)$$
Eq. (6)

 $Phealthy = P(SSB \ge TSSB)$  Eq. (7)

Economic performance was summarized in terms of the average annual catch and average annual absolute change in the catch over the time interval (AAV). This was later measured as the average absolute variation (AAV):

$$AAV = \sum_{t=t_1}^{t_2} \frac{|\hat{C}_t - \hat{C}_{t-1}|}{\sum_{t=t_1}^{t_2} \hat{C}_t}$$
Eq. (8)

Results General analysis of management procedures The results of the 20 MPs tested (Table5) showed that in the short term (2013-2021) none of these MPs meet the management objectives outlined in terms of fishery viability and fish conservation.

The simulated stock trajectories of all the MPs declined over the first 9 years of the projection (2013 - 2021). The short-term results showed that the stock of Patagonian toothfish will remain in critical condition, with zero and near-zero probability of attaining a healthy status within the first nine projected years of MPs tested (Table 5). The spawning stock showed no signs of recovery in the short term, and the median of average depletion values did not exceeded 21% in any MP. It is noteworthy that even the MPs that simulated fishery moratorium, did not produce encouraging results (Table 5, MP = C-F0). This MP maintained the stock in a critical status (SSB< LSSB), showing a low probability (0.44) that in the projected years the spawning stock biomass would recover to a cautious level between the years 2013 to 2021 (short term). However, in the medium and long term the fishery moratorium generated a recovery of spawning stock, leading the stock to a cautious status (LSSB < TSSB) in 100% of the projected years. The spawning biomass was maintained in the medium and long term within a healthy status (SSB>TSSB), in 77% and 100% of projected years, respectively (Table 5).

We will refer, from now on, exclusively to the MPs' outcomes in the medium and long term.

The MPs involving a constant HCR and reference fishing mortalities based on  $F_{SPR45\%}$ , showed poor performance in terms of conservation. Only the MP C-05F45 avoided falling into a critical status and maintained the spawning biomass within a cautious status (LSSB<SSB < TSSB) in 100% of the projected years within the medium (2022 - 2030) and long term (2031 - 2038). However, this MPs were not allow to achieve a healthy stock status (SSB $\geq$ TSSB) neither in the medium or long term. The economic objectives were met in the medium and long term by all of the MPs that used a constant HCR and reference fishing mortalities based on  $F_{SPR45\%}$ , with AAV values that ranged from 8% - 11. 3% (medium term) and 7% - 9.2% (long term) and catches between 500 - 1041 tons (medium term) and 377 - 671 tons (long term). Nonetheless, these MPs show a highly depleted spawning stock (except C-05F45) in the median and long term.

The constant HCRs that used reference fishing mortalities based in  $F_{MSY}$  showed that use a reference fishing mortality equal to  $0.5F_{MSY}$  or  $F_{MSY}$  (Table 5, MPs = C-0.5FMSY and C-FMSY), facilitated the achievement of both conservation and economic objectives (median and long term). The economic objective in terms of AAV was met for both MPs, however the median average catch does not exceed 700 tons (Table5). Under a constant HCR, a reference fishing mortality close or above  $F_{SPR45\%}$  or  $2F_{MSY}$  was risky for the stock, because did not allow it to fulfill any conservation objective. In fact, the MP that maintained the status quo in the fishing mortality level, led to a fishery's collapse after the first 9 years of the management strategy. This MP could support high catches during the first 9 years, but quickly led the stock to unsustainable levels and collapse.

The MPs involving variable HCRs showed differences depending on the HCR target and limit (bounded), based on the spawning stock biomass (LSSB and TSSB) and on the reference fishing mortality associated to each HCR.

Those MPs that used an HCR with LSSB =  $0.2B_0$  and TSSB =  $0.40B_0$  (V-0.4B0-05F45, V-0.4B0-F45, V-0.4B0-2F45, V-0.4B0-Fsq), produced a poor ability to achieve the established objectives. Only the MPs V-0.4B0-05F45 and V-0.4B0-F45, which used a reference fishing mortality  $0.5_{FSPR45\%}$  and  $F_{SPR45\%}$ , respectively, kept the stock from falling to the critical zone defined by LSSB, maintaining the spawning biomass above the LSSB in 95% of projected years in the medium and long term. These MPs (V-0.4B0-05F45 and V-0.4B0-F45) were not able to lead the stock spawning biomass to healthy levels, and they maintained spawning biomass below TSSB in all of the projected years in the median and long term, but above the LSSB. In economic terms, only the MP V-0.4B0-05F45 in the long term was able to reach an AAV lower than 15%, maintaining the median of average catch above 700 tons in the long term (Table 5).

When MPs used an HCR with LSSB =  $0.2B_0$  and TSSB =  $0.45B_0$  (V-045B0-05F45, V-045B0-2F45, V-045B0-2F45, V-045B0-Fsq) (Table 5), the performance was similar to HCR that used  $0.2B_0 - 0.4B_0$ . The use of an HCR =  $0.2B_0 - 0.45B_0$  and a reference fishing mortality  $0.5F_{SPR45\%}$  (V-045B0-05F45) maintained the spawning biomass above the LSSB in 95% of projected years (median and long term) and in the long term in a healthy status, above TSSB in the 65.2% of the projected years. This MP also enabled in the long term to get an AAV around 13% with a median average catch close to 700 tons. These catches generated a median average depletion of over 0.3 in the medium and long term.

Only the MPs based on the  $B_{MSY}$  stock status, HCR with LSSB =  $0.5B_{MSY}$  and TSSB =  $B_{MSY}$ , that used a reference fishing mortality of  $0.5F_{MSY}$  and  $F_{MSY}$ , were able to meet the conservation objectives. In 100% of the projected years, the spawning biomass was maintained above  $0.5B_{MSY}$  and  $B_{MSY}$ , in the medium and long term. The median average depletion was above 0.35 for both procedures. However, only the MP that used  $F_{MSY}$  as reference fishing mortality (V-BMSY-FMSY) could fulfill the economic objectives, reaching catches close to 650 tons.

In general, constant HCRs produce lower AAV in catches, which implies a higher stability. Constant HCRs generate higher catches than variable HCRs in the medium term, but in the long term the situation is reversed and it is possible to obtain higher yields with variable HCRs, which are associated with high values of AAV. In terms of conservation, constant HCRs presented more depleted spawning stock status in the medium and long term.

# Trade-offs among MPs that fulfill the management objectives to stock rebuilding and sustainable harvesting

Over the twenty MPs examined, only 10 were able to fulfill some or all the established management objectives (excluding the MP of fishery moratorium). These MPs were marked with an asterisk (\*) in Table 5. We analyzed how these MPs worked during the simulation trial (2013 - 2038) under different HCRs (constant and variable), defined by the limit (LSSB) and target spawning (TSSB) stock size and reference fishing mortalities (Table 5).

Both constant and variable HCRs, meet the requirement to avoid that the stock falls below the LSSB, maintaining spawning biomass above the LSSB in 95% of projected years (objective 1) in the median and long term all the MPs tested (Table 5, MPs \*).

When constant HCRs were used, only the use of a reference fishing mortality equal to  $0.5F_{MSY}$  (C-05FMSY) or  $F_{MSY}$  (C-FMSY) could maintain the spawning biomass above the TSSB (healthy status) in the medium and long term (SSB  $\geq$  TSSB) in the 50% and more of projected years. Despite the fact that those MPs meet the requirement of the management objective 2, these showed a higher depletion (lower value) of the spawning biomass in the medium and long term, with values lower than or scarcely above 30% in the long term (C-FMSY) (Table 5, Figure 3).

When variable HCRs were used, not all of these MPs (Table 5, MPs \*) were able to meet the requirement to fulfill the management objective 2. The MPs that used an HCR with LSSB =  $0.2B_0$  and TSSB =  $0.4B_0$  (V-0.4B0-05F45 and V-0.4B0-F45) with reference fishing mortalities of  $0.5F_{SPR45\%}$  and  $F_{SPR45\%}$ , failed to meet the necessary and sufficient condition to maintain the spawning stock above the TSSB in the 50% of projected years (Figure 3).

In the MPs that used an HCR with 0.2B0 - 0.45B0, only when the reference fishing mortality was reduced to the half of  $F_{SPR45\%}$  (V-045B0-05F45), the procedure was able to meet the requirement to fulfill the objective 2, and maintain the spawning stock biomass above TSS in the 62.5% of the projected years in the long term.

The MPs based on the stock status of  $B_{MSY}$  were the most efficient in reaching the objective 2, using a  $0.5F_{MSY}$  and  $F_{MSY}$  as a reference fishing mortality (V-BMSY-05FMSY, V-BMSY-FMSY). These MPs achieve in the medium and long term that the spawning stock was maintained in a healthy status in the 100% of projected years.

Despite the fact that several MPs were able to meet the requirement to achieve the management objectives (objective 1 and 2), not all the MPs that fulfilled the objectives 1 and 2 were able to balance conservation and economic objectives.

MPs that used a constant HCR were more efficient in economics term (C-05FMSY and C-FMSY), showing a higher catch stability in the median and long term (AAV <15%) with catches around 450 -550 tons in the median term and above 600 tons in the long term. Only these two MPs, which used a constant HCR were able to meet both conservation (objective 1 and 2) and economic objectives (objective 3), however the C-05FMSY showed a more depleted population status at the end of projection period (Table 5; Figure 2).

MPs based on variable HCRs, showed lower performance in balancing both conservation and economic objectives. One of the MPs that used an HCR with  $0.2B_0 - 0.4B_0$  was able to meet the objective 3 (V-0.4B0-05F45), but only in the long term. This procedure that used a reference fishing mortality equal to 0.5 *F*<sub>SPR45%</sub>, showed an AAV around 12% in the last period of the projection with catches for that period around 700 tons. Despite that this MP generated a higher yield than the other MPs that fulfilled conservation and economic objectives, it is important to point that this MP maintained a healthy spawning stock status in only 37.5% of the projected years, therefore did not met the requirement to fulfill the objective 2.

The MP V-045B0-05F45, defined by an HCR with 0.2B0 - 0.45 B0 and a reference fishing mortality of  $0.5F_{SPR 45\%}$  was able to balance both conservation and economic objective in the long term. This procedure showed an annual catch variability of ~ 13%, presenting catches in the long term near to 700 tons. This procedure also maintained the stock status with the median of average depletion above 30% in the median and long term, and above 20% in the short term.

Of the MPs based in the stock status of  $B_{MSY}$  (LSS=  $0.5B_{MSY}$  - TSS= $B_{MSY}$ ), the MP that used  $F_{MSY}$  as a reference fishing mortality was able to met the requirement of the economic objective (objective 3) and meet both conservation objectives in the medium and long term, reaching a catch of about 600 tons at the end of projection period.

Over the MPs examined, only 3 (C-FMSY, V-045B0-05F45, V-BMSY-FMSY) balanced conservation and economic objectives at the end period of the projection (25 years) and produced an average catch ranged 617 - 697 tons (Table 5, Figure 3, Figure 4). These MPs showed a low

risk of having years with catches equal to zero in the medium and long term. This average catch is, however, lower than the current TAC of the fishery (~1100 tons). It is important to consider that the current stock status is below 15% of SSB. Thus, it is difficult to expect higher catches in the medium or long term without producing further depletion of the stock. The AAV over the simulation period was between 6% - 14% (Figure 3), indicating that these control rules, (C-FMSY, V-045B0-05F45, V-BMSY-FMSY), produce a relatively stable catch from one year to the next (e.g., inter-annual variability in catch limits greater than 16% would not be acceptable) (Table 5, Figure 3, Figure 4).

The outlook was discouraging in the short and medium term for these MPs, mainly in economic terms, producing catches that ranged between 160 to 450 tons the first eighteen years of management procedures, with a high instability (high AAV) in the cases where variable HCRs were used.

It is important to point that MPs that used the reference fishing mortality  $F_{sq}$  produced the lowest depletion values under constant and variable HCRs (C-Fsq (Collapse), V-0.4B0-Fsq, V-045B0-Fsq, V-MSY-Fsq) (Figure 5). Even the constant HCR using a  $F_{sq}$ , caused the collapse of the fishery after the first 9 years of the implementation of the management procedure, therefore with this MP the stock could be overfished severely (Table 5, Figure 5). These MPs had high inter-annual variability associated in the short, medium, and long term (Figure 5).

In terms of catches, MPs with  $F_{sq}$  and variable HCRs showed an important risk of having years with catches equal to zero and a high probability that the stock would not recover and remained in a cautious and critical size in the long-term (Table 5, Figure 5).

### Discussion

The MSE has been designed to identify fishery rebuilding strategies and established harvest strategies that are robust to uncertainty and natural variation, and that balance biological and socioeconomic objectives (Holland, 2010). The design and implementation of effective management strategies to rebuilding and maintaining the balance between conservation and economic objectives in a fishery is an important but difficult task. One of the first objectives of the MSE approach is to balance multiple objectives, such as maintain in a low risk of overfishing and stock collapse, and, a stability in TACs over time and maximum yields. However, in cases such as the Patagonian toothfish presented in this paper, balancing this objectives is difficult when the current stock status is in a critical condition.

The results of MSE can be sensitive to several factors associated with the fishery, the population dynamic, and assumptions regarding the resource or environmental characteristic. For example, assuming that CPUE reflects population abundance, a certain type of stock recruitment relationship, or the existence of random error in recruitment, among others (Cox *et al.*, 2013). These assumptions are used in the assessment based on the fact that they are realistic, although they may be incorrect.

In spite of problems and challenges faced when an implementation of a management strategy is made, MSEs are our best means of evaluating long-term performance of various management procedures. The benefits obtained when it is properly implemented are big, mainly because i) MSE can help identify and facilitate effective implementation of management strategies that balance a variety of objectives including limiting biological risk but also increasing profitability and stability of harvest over time; ii) It implies the use of simulation testing to determine the robust feedback-control management strategies, involving process error and model uncertainty; ii) MSE has been specifically designed to realistically account for error and uncertainty in data and model structures and to provide explicit quantitative management advice that can be directly applied by fishery managers to set catch or effort limits; iv) MSEs also generally assess performance based on multiple objectives rather than focusing solely on optimal economic performance and v) because several hypotheses can be tested more efficiently and with more robustness and their effects in the short medium and long term can be analyzed (Holland, 2010).

The analysis of management strategies is key when establishing a resource's rebuilding and management plans. MSE has been successfully used in fisheries' rebuilding plans: such as the South African Hake fishery (Butterworth and Rademeyer, 2005), the Rock lobster fishery in New Zealand (Starr *et al.*, 1997) and in the West coast rockfish fishery in US (Punt and Ralston, 2007), among others.

In this paper we used management strategy simulations to explore MP candidates aimed at rebuilding the Patagonian toothfish stock from Southern Chile and to examine the trade-offs between fishery viability and fish conservation. These MPs demonstrate that the current stock status of Patagonian toothfish does not allow the fishery recovery in the short term (i.e. the first 9 years of management strategy). Generally, rebuilding timelines are typically limited to 10 years, unless the biology of the stock makes this infeasible in which case the rebuilding schedule can be lengthened by one mean generation time (Holland, 2010).

The Patagonian toothfish lives for more than 50 years, therefore it is unlikely to recover the fishery in a short term, considering that, currently, the depletion of spawning biomass is lower than 15%. In fact, even when we simulated total moratorium, the spawning biomass took more than 9 year to exceed LSSB in the 95% of the projected years and took the same time to exceed the TSSB in more than 50% of projected years. If the fishing mortality is maintained in the "status quo", the stock will be in big risk of collapse in the short term.

The results obtained from the MPs evaluated showed that only ten over twenty MPs evaluated (without including  $F_0$ ), fulfilled at least one of the conservation and economics objectives established.

Only the MP that used a reference fishing mortality equal to  $F_{MSY}$  (C-FMSY), met both economic and conservation objectives when constant HCRs were used. Variable HCRs that used LSS=0.2*B*<sub>0</sub> - TSS=0.40*B*<sub>0</sub> were not able to balancing the management objectives. However the variable HCR that used LSSB=0.2*B*<sub>0</sub> - TSSB=0.45*B*<sub>0</sub> fulfilled both economic and conservation objectives when a reference fishing mortality equal to 0.5*F*<sub>SPR45%</sub> was used (V-045B0-05F45). The same situation happened with the HCR that used LSSB=0.5*B*<sub>MSY</sub> - TSSB=*B*<sub>MSY</sub> and a reference fishing mortality equal to *F*<sub>MSY</sub> (V-BMSY-FMSY).

Despite that these MPs were able to balance proposed conservation and economic objectives, in economic terms the outlook was discouraging, because the current TAC should be reduced almost a half to maintain the stock in a cautious - healthy condition and to get stable catch (AAV<15%) in the medium and long term. Under these MPs, the catch and AAV in the short term are too low and too high, respectively, which can lead to years with zero catches. This is a typical situation when MSEs are implemented because the initial years of MPs represent the most critical period in any fisheries management strategy evaluation process. The initial period is the time when yields may need to be reduced significantly, from historical levels (Cox *et al.*, 2013).

None of these MPs improved catch average, and the main differences among them are given in the short term, mainly in the AAV. We believe that a minimum catch plan in the next ten years could improve the yields in the medium and long term. While it is true that some MPs presented high catches in the short and medium term under constant HCRs, this was not sustainable for the fishery in the medium and long term, leading to catches below 100 tons in the long time.

It is important to begin to develop recovery plans for the fishery, because each day foreign markets are more demanding and the fishery sustainability certification is very valuable. In fact, the Argentine stock of Patagonian toothfish is in process of certification by Marine Stewardship Council (MSC) and this is a big possibility to open the fishery to other markets and it could increase its commercial added value.

The most fisheries are in a depleted status with discouraging prospects in the short, medium and long term. For this reason, it is very important to develop joint efforts between scientists, fisheries managers, and stakeholders and to work together to achieve a balance between conservation and economic objectives.

#### Acknowledgements

This work was funded by a CONICYT scholarship (Master program of Fisheries Science), supported by the Ministry of Education in Chile, a Canada-Chile Leadership Exchange Scholarship, supported by Government of Canada, and a Program COPAS Sur-Austral PFB-31, supported by Universidad de Concepción, Chile. We thank the Instituto de Fomento Pesquero de Chile (IFOP) and Subsecretaría de Pesca de Chile (SUBPESCA) for providing the data.

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## Figures



Figure 1. Schematic representation of the feedback control simulation in the management

strategy evaluation.





**Figure 2.** An example of harvest strategies tested. (a) Constant HCR, (b) - (d) Variable HCR's. In (b), LSSB and TSSB values are set at multipliers of 0.2 and 0.40 (0.2  $B_0$  - 0.4 $B_0$ ) of Unfished spawning biomass ( $B_0$ ), respectively. In (c), LSSB and TSSB values are set at multipliers of 0.2 and 0.45 (0.2  $B_0$  - 0.5 $B_0$ ) of the Unfished spawning biomass ( $B_0$ ), respectively. In (d), LSSB and TSSB values are set at multipliers of 0.5 and 1 (0.5 $B_{MSY}$  -  $B_{MSY}$ ) of the biomass at maximum sustained yield ( $B_{MSY}$ ), respectively. The reference fishing mortality over the range of stock status is indicated by the solid line (2Fmsy, 2Fspr45%, Fmsy, Fspr45%, 0.5Fmsy and 0.5 Fspr45%).



**Figure 3.** Trade-offs among median of average catch over replicates, median of average depletion over replicates and median of annual average variation (AAV) in catch over replicates. The dotted line to the left panel indicates a spawning biomass depletion value equal to 30% and the dotted line to the right panel indicates an AAV equal to 15%.



Figure 4. Comparison among the MPs that fulfill all the established operational objectives.



Figure 5. Comparison among the MPs that maintained the reference fishing mortality in the status quo.

## Tables

**Table 1.** Description and values (if applicable) for abundance index, structural parameters, state variables, derived variables and stochastic deviation used in the Patagonian toothfish population dynamics operating model in *mseR* program. (Modified from Kronlund *et al.*, 2012).

Symbol	Value	Description
$T_1$	25 (2013)	Year when the management procedure begins
$T_2$	50 (2038)	Total number of years to simulate
Α	30	Number of age - classes
t	1,2,,T	Time step
а	1,2,,A	Age - class in years
$B_0$	24.513	Unfished spawning biomass (1000s tonnes)
h	0.6	Recruitment function steepness
М	0.15	Instantaneous natural mortality rate (yr <sup>-1</sup> )
$L_{\infty}$	287.1	Asymptotic length (cm)
$L_{l}$	29.58	Length-at-age 1 (cm)
k	0.021	von Bertalanffy growth constant
$c_1$	2.59e-12	Scaling constant for weight at length (mm to tonnes)
<i>C</i> <sub>2</sub>	3.2064	Allometric factor
$a_{50}$	14	Age-at-50% maturity
<i>a</i> <sub>95</sub>	17	Age-at-95% maturity
sa50	10	Age-at-50% selectivity
<i>sa</i> <sub>95</sub>	14	Age-at-95% selectivity
q	0.017	Surv <mark>ey catch<mark>ability coefficient</mark></mark>
$\sigma_R$	0.6	Standard erro <mark>r of log-recruitme</mark> nt
$\sigma_I$	0.2	Standard deviation for the CPUE
$\sigma_L$	0.15	Standard erro <mark>r of length-at-ag</mark> e
$R_0$	1210070	Unfished recruitment
$m_a$		Proportion mature-at-age
$S_a$		Proportion selectivity-at-age
Wa		Weight-at-age (kg)
$\phi$		Unfished equilibrium spawning biomass per recruit
$N_{a,t}$		Number of age a fish in year t
$B_{a,t}$		Biomass of age a fish in year t
$SSB_t$		Spawning biomass in year t
$N_t$		Spawning numbers in year t
$I_t$		Survey biomass estimate
$\omega_{R,t}$	0	log-normal recruitment residual
$\delta_t$	N(0,1)	Uncorrelated log-recruitment residual
$\mathcal{E}_t$	N(0,1)	Uncorrelated log-survey residual
$C_{a,t}$		Fishery catch numbers
$C_t$		Fishery catch biomass
$d^*$	0.13	input depletion value t= 2012 (before to starting the projection)

**Table 2.** Harvest control rule component of the simulated management procedure. Calculation of the target removal rate  $F_t^{'}$  implements for the recovery of Patagonian toothfish fishery. The calculation of the quota ( $C_t$ ) includes a dampener ( $\lambda$ 1) on the magnitude of yearly variability (Modified from Kronlund *et al.*, 2012)

T2.1	$\psi = (SSB_t, F_{ref}, LSSB, TSSB, \lambda_1$	$(C_{t-1})$	Rule parameters
T2.2	$ \begin{array}{ll} 0 \\ F_{t}^{'} = & F_{ref} \left( \frac{\hat{SSB}_{t} - LSSB}{TSSB - LSSB} \right) \\ F_{ref} \\ \end{array} $	$\hat{SSB}_{t} < LSSB$ $LSSB \leq \hat{SSB}_{t} < TSSB$ $\hat{SSB}_{t} \geq TSS$	LSSB limit biomass reference points TSSB target biomass reference points $F_{ref}$ removal rate reference $F'_t$ target removal rate $\hat{SSB}_t$ Spawning biomass estimate
T2.3	$C_{t} = \lambda_{1}C_{t-1} + (1 - \lambda_{1})\frac{F_{t}}{M + F_{t}} (1 - \lambda$	$-\exp^{-M-F_t})SSB_t$	$C_t$ catch in year t $\lambda_1$ dampener parameter
		* 🦉	$\star$



 Table 3. Summary of operating model characteristics that define the scenarios for the

management procedure simulations

MPs	HCRs	LSSB - TSSB	Reference		
			Fishing Mortality		
C-F0	Constant	-	$F_0$		
C-05F45	Constant	-	0.5 F <sub>SPR45%</sub>		
C-F45	Constant	-	F <sub>SPR45%</sub>		
C-2F45	Constant	-	2 F <sub>SPR45%</sub>		
C-05FMSY	Constant	-	$05 F_{MSY}$		
C-FMSY	Constant	-	$F_{MSY}$		
C-2FMSY	Constant	-	$2 F_{MSY}$		
C-Fsq	Constant	-	$F_{sq}$		
V-0.4B0-05F45	Variable	0.2B <sub>0</sub> - 0.4B <sub>0</sub>	0.5 F <sub>SPR45%</sub>		
V-0.4B0-F45	Variable	$0.2B_0 - 0.4B_0$	F <sub>SPR45%</sub>		
V-0.4B0-2F45	<b>V</b> ariable	$0.2B_0 - 0.4B_0$	2 F <sub>SPR45%</sub>		
V-0.4B0-Fsq	Variable	$0.2B_0 - 0.4B_0$	$F_{sq}$		
V-045B0-05F45	Variable	$0.2B_0 - 0.45B_0$	0.5 F <sub>SPR45%</sub>		
V-045B0-F45	Variable	0.2B <sub>0</sub> - 0.45B <sub>0</sub>	F <sub>SPR45%</sub>		
V-045B0-2F45	Variable	0.2B <sub>0</sub> - 0.45B <sub>0</sub>	2 F <sub>SPR45%</sub>		
V-045B0-Fsq	Variable	0.2B <sub>0</sub> - 0.45B <sub>0</sub>	$F_{sq}$		
V-BMSY-05FMSY	Variable	0.5B <sub>MSY</sub> - B <sub>MSY</sub>	$05 F_{MSY}$		
V-BMSY-FMSY	Variable	0.5B <sub>MSY</sub> - B <sub>MSY</sub>	$F_{MSY}$		
V-BMSY-2FMSY	Variable	0.5B <sub>MSY</sub> - B <sub>MSY</sub>	$2 F_{MSY}$		
V-MSY-Fsq	Variable	0.5B <sub>MSY</sub> - B <sub>MSY</sub>	$F_{sq}$		

**Table 4.** Management Objective definitions for evaluating the Patagonian toothfish fishery

 management procedures.

Management Objectives	Description
Objective 1	To identify what MPs avoid that the spawning stock falling within the
	critical zone, defined by a limit stock size (LSSB), and maintaining the SSB
	above the LSSB in 95% of projected years in the short, median, and long
	term (i.e. $P$ (LSSB < SSB) $\ge$ 95%).
Objective 2	To explore different MPs that could maintain SSB above a rebuilding target
	stock size (TSSB) in 50% of the projection years in the median and long
	term (i.e. $P$ (SSB $\ge$ TSSB) $\ge$ 50%).
Objective 3	To evaluate MPs that could generate an average annual variability in catch
	(AVV) lower than 15% in the median and long term.



 Table 5. Summary of the different MPs in short, medium and long term to evaluate the fulfillment of conservation objectives and economic objectives.

MPs	Objective 1 P(SSB>1 SSB) >0.95			Objective 2 P(SSB>TSSB) >0 5			Objective 3	<b>Dbjective 3</b> Median of		Average Depletion		Median of Average Catch		Catch	
	short	Medium	Long	short	Medium	Long	Short	Medium	Long	short	medium	long	short	medium	long
C-F0	0.444	1	1	0	0.778	1	0	0	0	0.208	0.392	0.531	0	0	0
C-05F45*	0.333	1	1	0	0	0	28.204	8.052	7.639	0.182	0.264	0.289	0.44	0.527	0.671
C-F45	0	0.111	0	0	0	0	16.426	8.912	8.831	0.158	0.18	0.163	0.695	0.817	0.92
C-2F45	0	0	0	0	0	0	11.803	11.301	9.27	0.128	0.092	0.082	1.044	1.041	0.377
C-05FMSY*	0.889	1	1	0	0.556	0.875	27.209	8.226	7.704	0.181	0.259	0.28	0.453	0.547	0.697
C-FMSY*	0.889	1	1	0	0.77 <mark>8</mark>	1	27.443	5.705	6.578	0.184	0.271	0.318	0.431	0.452	0.617
C-2FMSY*	0.444	0	0.125	0	0	0	11.64	12.273	7.874	0.125	0.087	0.092	1.073	1.015	0.107
C-Fsq (Collapse)	0.111	0.333	0.75	0	0	0. <mark>25</mark>	25.778	0	0	0.078	0.116	0.243	1.382	0	0
V-0.4B0-05F45*	0.444	1	1	0	0	0.375	71.796	18.594	12.278	0.204	0.321	0.344	0.21	0.421	0.717
V-0.4B0-F45*	0.444	1	1	0	0	0	62.187	<b>22</b> .024	18.284	0.197	0.28	0.268	0.276	0.636	0.962
V-0.4B0-2F45	0.444	1	0.5	0	0	0	54. <mark>90</mark> 9	<b>27</b> .298	26.609	0.192	0.234	0.204	0.372	0.775	1.01
V-0.4B0-Fsq	0.389	0.333	0.125	0	0	0	51.182	<mark>3</mark> 7.677	39.648	0.183	0.185	0.155	0.533	0.868	0.979
V-045B0-05F45*	0.444	1	1	0	0.222	0.625	74.863	18.892	13.716	0.204	0.331	0.359	0.198	0.374	0.697
V-045B0-F45*	0.444	1	1	0	0	0	65.429	20.542	18.69	0.199	0.294	0.288	0.248	0.569	0.939
V-045B0-2F45	0.444	1	0.75	0	0	0	56.753	25.674	24.818	0.195	0.251	0.223	0.332	0.743	1.009
V-045B0-Fsq	0.444	0.444	0.125	0	0	0	51.335	34.549	36.269	0.186	0.195	0.167	0.496	0.847	1.025
V-BMSY-05FMSY*	0.889	1	1	0.222	1	1	93.54	23.236	16.246	0.207	0.348	0.381	0.163	0.303	0.686
V-BMSY-FMSY*	0.889	1	1	0.222	1	1	93.342	20.574	14.384	0.207	0.358	0.399	0.161	0.249	0.649
V-BMSY-2FMSY	0.889	1	1	0.111	1	0.5	85.129	30.547	27.698	0.2	0.291	0.257	0.222	0.648	1.006
V-MSY-Fsq	0.889	0.833	0.875	0.111	0.389	0	77.956	40.575	39.104	0.198	0.248	0.207	0.279	0.812	1.062

## **DISCUSIÓN GENERAL**

La composición de edades, la selectividad y capturabilidad son componentes claves en los modelos edad estructurados, sin embargo, es escasa la literatura que examina cómo los errores en la determinación de la edad y los supuestos sobre la selectividad y la capturabilidad interactúan para afectar la calidad del asesoramiento derivado de los modelos de evaluación de stock.

En este estudio se aplicó un enfoque de simulación-estimación para evaluar cómo el error en la composición de edades puede afectar las estimaciones de parámetros de importancia tanto para la evaluación de stock y el manejo. Antes de evaluar el desempeño del SCA frente a cada uno de los escenarios, se testearon todas las posibles fuentes de error por separado. Primero se evaluó el funcionamiento y comportamiento del OM en equilibrio y con patrones de mortalidad por pesca más y menos informativos que los provenientes del SCA con los datos de la pesquería. Posteriormente, se testearon los escenarios y el desempeño del SCA incorporando de manera gradual cada fuente de incertidumbre (error de proceso y de observación) en el OM, para evaluar el efecto real de la especificación incorrecta de la edad.

# Efecto de la incorrecta determinación de la edad en los parámetros de importancia para la evaluación de stock y el manejo.

El análisis de simulación-estimación sugiere que la determinación incorrecta de la edad del bacalao de profundidad afecta el desempeño del modelo de evaluación SCA, generando sesgo positivo e imprecisión en los parámetros  $D_{final}$ ,  $R_0$  y  $F_{terminal}$ . Los resultados revelan que una incorrecta determinación de la edad muestra un estado de la población más optimista (sobreestimación de  $D_{final}$ ). El error en la composición de edades generó que el SCA subestimara la trayectoria de la biomasa desovante (Figura S2), lo que coincide con lo reportado por Reeves (2003) para Gadus morhua. Este efecto podría ser caso específico y podría incrementarse en especies longevas, de crecimiento lento y madurez tardía, como el bacalao de profundidad. De todos los parámetros analizados,  $R_0$  fue el parámetro que presentó el mayor sesgo positivo e imprecisión, con una alta variabilidad intercuartil. Este parámetro escala la población, por lo tanto compromete todas las estimaciones de la evaluación de stock y las estrategias de manejo derivadas de ésta. La incorrecta determinación de la edad también generó un sesgo positivo y una baja precisión en F<sub>terminal</sub>. Esto coincide con lo reportado por Liao et al. (2013), quienes encontraron que en presencia de error de edad,  $F_{terminal}$  fue sobrestimado en aproximadamente un 19%. F<sub>terminal</sub> es un parámetro clave, debido a que representa el punto de partida de la proyección cuando se calcula la cuota o se evalúan las estrategias de explotación. Horbowy (2008), señaló que posibles errores en las capturas predichas y en la estimación del tamaño del stock, son atribuibles a la especificación errónea de la mortalidad por pesca del ultimo año.

### Efecto del tipo de selectividad y selectividades tiempo-variantes en ausencia de error de edad

En ausencia de error de edad, SCA generó estimaciones cercanas a los valores verdaderos. Aunque, en algunos escenarios existió sesgo e impresión, pero la magnitud de este sesgo e imprecisión fue menor en comparación a los escenarios con error de edad. En general D<sub>final</sub> fue más insesgado y preciso en escenarios que utilizaron selectividad logística (invariante y tiempoinvariante). Escenarios con selectividad doble logística (invariante y tiempo-variante) tendieron a generar un sesgo positivo en D<sub>final</sub> generando resultados más optimistas, principalmente con la función tiempo-variante. La selectividad doble logística genera resultados menos conservativos y puede conducir a estimaciones más inciertas de la biomasa y a biomasas crípticas, donde la proporción de peces viejos estimada puede no reflejar las observaciones de la pesquería (Maunder & Piner, 2015). Las estimaciones de  $R_0$  fueron similares entre selectividades tiempo invariantes (logística y doble logística) con estimaciones centradas en sus valores verdaderos o cercanas a éstos. Pero entre selectividades tiempo-variantes un mayor sesgo positivo fue encontrado con la función logística, aunque este sesgo no superó el 15%.  $F_{terminal}$  fue positivamente sesgado entre selectividades tiempo-invariantes principalmente con la función logística. El sesgo y la imprecisión disminuyeron cuando se utilizaron selectividades tiempovariantes. Probablemente funciones tiempo-variantes al ser más flexibles, permiten un mejor ajuste de la composición de edades.

#### Interacción entre el error de edad y la selectividad tiempo-invariante y tiempo-variante

El SCA disminuyó su desempeño en la estimación de  $D_{final}$  (mayor sobreestimación) cuando la incorrecta determinación de edad interactuó con una selectividad doble logística tiempo-invariante en comparación a cuando se utilizó una selectividad logística tiempo-invariante. Por el contrario, las estimaciones de  $F_{terminal}$  fueron levemente más precisas y menos sesgadas con la selectividad doble logística tiempo-invariante. Estas diferencias fueron menos pronunciadas en la estimación de  $R_0$ . En la selectividad doble logística, la disponibilidad de peces viejos al arte de pesca disminuye después de una edad máxima. Esta situación acentúa el problema de una incorrecta determinación en la edad. Las edades más viejas (15 años o más) no se pueden leer correctamente utilizando escamas. Además, la selectividad doble logística asigna

una menor probabilidad de observar esos peces viejos en la pesquería. Como resultado, el stock se percibe menos agotado.

La selectividad tiempo-variante fue incluida en el OM para evaluar cómo el error de edad interactúa con modelos realistas de pesquerías que cuentan sólo con datos dependientes de la pesquería. Debido a que la selectividad tiempo-variante se espera que ocurra en la mayoría de las pesquerías donde la CPUE es el único índice de abundancia. La selectividad tiempo-variante (logística y doble logística) generó un mayor sesgo positivo y una menor precisión en  $D_{final}$  en comparación a las selectividades tiempo-invariantes. Esto fue más pronunciado con la función doble logística. A pesar de que las diferencias en sesgo y precisión pueden no ser demasiado grandes, los valores absolutos de D<sub>final</sub> pueden generar una falsa percepción de un stock menos agotado. Por ejemplo, el valor absoluto de  $D_{final}$  fue entre 10% a 20% cuando selectividades tiempo-variantes interactuaron con el error en la composición de edades. Este rango de valores es suficiente para cambiar el estado de la pesquería (Material suplementario - Figura S3), desde un estado de sobrepesca a un estado de colapso. Esto demuestra la importancia de incluir selectividades tiempo-variantes en la evaluación de estrategias de manejo para establecer tasas de exportación sustentables. Las selectividades tiempo-variantes generaron un efecto similar a D<sub>final</sub> en la estimación de  $F_{terminal}$ . Por el contrario  $R_0$ , presentó un menor sesgo y una mayor precisión cuando selectividades tiempo-variantes interactuaron con el error de edad. Probablemente la selectividad tiempo-variante compensa algún tipo de ruido proveniente del error de edad, a diferencia de la selectividad tiempo-invariante.

Usar selectividades tiempo-variantes tiene ventajas y desventajas. Provee una mayor flexibilidad para acomodar la incertidumbre, pero aumenta considerablemente el número de parámetros a estimar. Esto pudo incrementar el error relativo y la imprecisión en las estimaciones de  $D_{final}$  y  $F_{terminal}$ . Martell & Stewart (2014) sugieren que en ausencia de conocimiento acerca de la selectividad, se debería asumir una selectividad tiempo-variante.

#### Interacción entre el error de edad y la capturabilidad tiempo-variante

Cuando los datos se generaron con una capturabilidad tiempo-variante y ésta interactuó con una composición de edades incorrectamente determinada, el desempeño del SCA disminuyó aún mas en la estimación de  $R_0$  y  $D_{final}$ . Estos parámetros mostraron un incremento marginal en el sesgo positivo y en la falta de precisión en comparación a cuando la capturabilidad fue tiempoinvariante. Lo opuesto sucedió en las estimaciones de  $F_{terminal}$ , donde las estimaciones fueron menos sesgadas y más precisas. Esto implica que en presencia de una capturabilidad tiempovariante, el efecto de una incorrecta determinación de la edad sobre  $D_{final}$  y  $R_0$  puede ser incluso más severo. La capturabilidad tiempo-variante es común y debería esperarse en la mayoría de las pesquerías de datos dependientes (Winters & Wheeler, 1985; Wilberg *et al.*, 2010). Cada punto de datos para el índice relativo es una muestra de la abundancia, no un censo, por lo tanto contiene error de observación (Maunder & Piner, 2015). Factores tales como cambios en la abundancia, el área habitada por el stock, el ambiente, el comportamiento de los peces o arte de pesca, regulaciones de manejo, entre otras, pueden inducir a una capturabilidad tiempo-variante (Wilberg *et al.*, 2010). La variabilidad de la capturabilidad fue generada a través de una caminata aleatoria, debido a que es difícil determinar el momento exacto en que varía la capturabilidad en una pesquería. En este caso, sólo una pequeña variación fue permitida en el OM. Probablemente si la variabilidad hubiese sido más alta, el desempeño del SCA con capturabilidad tiempo variante y error de edad podría haber sido incluso más bajo.

## Corrección del error de edad dentro del modelo de estimación SCA

Los resultados sugieren que cuando no hay suficiente información para cuantificar el error en la determinación de la edad y corregir la composición de edades (i.e., datos empíricos de lecturas de escamas y otolitos), es posible efectuar una corrección en el modelo de estimación. En general la determinación incorrecta de la edad derivada de lecturas de escamas y otolitos puede ser corregida (e.g., Liao *et al.*, 2013) cuando información suficiente de ambas estructuras (escamas y otolitos) del mismo pez pueden ser comparadas. Sin embargo, esto no siempre es posible.

El método aplicado para cuantificar y predecir el error en las lecturas de edades fue efectivo para corregir el problema de la incorrecta determinación de la edad. La matriz a partir de la cual el error de edad fue simulado y corregido, representa los errores reales presentes en la determinación de la edad del bacalao de profundidad. La corrección de la incorrecta determinación de la edad redujo el sesgo e incrementó la precisión de todos los parámetros. Esta corrección fue aplicada a una variedad de escenarios para testear el desempeño del modelo y la robustez de la corrección frente a cada escenario. Esta matriz de error de lectura de edades puede ser utilizada para corregir el problema de error en las lecturas de edades de la pesquería.

Efecto de una incorrecta especificación de la selectividad en ausencia de error de edad.

Los resultados demuestran que el efecto de una incorrecta especificación de la selectividad afectó el desempeño del SCA en escenarios sin error de edad. Por ejemplo, cuando una selectividad logística tiempo-invariante fue utilizada en el OM y en el SCA se asumió una selectividad doble logística,  $D_{final}$  incrementó levemente su sesgo positivo, pero  $R_0$  y  $F_{terminal}$  fueron levemente menos sesgados positivamente en comparación al escenario donde la selectividad se especifico correctamente (i.e., logística tiempo-invariante en el OM y en el SCA).  $D_{final}$  fue relativamente robusto a esta incorrecta especificación de la selectividad, lo que coincide con lo reportado por He *et al.* (2011). El efecto positivo sobre  $R_0$  y  $F_{terminal}$ , puede deberse a que la selectividad doble logística puede absorber algo del error de observación de la composición de edades de los peces más viejos. Además, como no puede compensar la presencia de peces más viejos en la captura, la mortalidad por pesca disminuye ( $F_{terminal}$ - con menor sesgo positivo).

Por el contrario, cuando una selectividad tiempo-invariante doble logística fue utilizada en el OM y una selectividad logística tiempo-invariante en el SCA, se encontró un mayor sesgo positivo e imprecisión en todos los parámetros estimados, en comparación a cuando el OM utilizó una selectividad logística tiempo-invariante y el SCA asumió una doble logística tiempoinvariante. Esta incorrecta especificación de la selectividad (doble logística tiempo-invariante en el OM y logística tiempo-invariante en el SCA) por si sola podría generar un mal entendimiento del estado del stock.  $R_0$  fue altamente sobreestimado con una media del *RE* cercana al 30%. Del mismo modo, Wang *et al.* (2014) encontró un mayor gradiente en los perfiles de verosimilitud de  $R_0$  y una mayor imprecisión cuando utilizó esta combinación de selectividades para *Thunnus obesus*. El incremento del sesgo positivo en  $F_{terminal}$ , sugiere que el SCA compensa la falta de peces viejos con un incremento en la mortalidad por pesca.

Cuando los datos provinieron de una selectividad tiempo-variante (logística o doble logística), pero el SCA asumió que la selectividad era tiempo-invariante (logística o doble logística), la precisión en todas las estimaciones disminuyó y la variabilidad intercuartil se incrementó.  $D_{final}$  y  $R_0$  fueron los parámetros más afectados.  $D_{final}$  exhibió un mayor sesgo positivo en comparación al que presentó en los otros escenarios con selectividad incorrectamente especificada.  $R_0$  fue sesgado negativamente en el escenario con selectividad logística (tiempo-variante en el OM y tiempo-invariante en el SCA) y fue casi insesgado con la selectividad doble logística (tiempo-variante en el OM y tiempo-invariante en el SCA).  $F_{terminal}$  presentó el mayor rango intercuartil cuando se usó una selectividad logística (tiempo-variante en el OM y tiempo-invariante en el SCA).

La incorrecta especificación de la selectividad afectó la percepción de estado del stock. El uso de una selectividad tiempo-invariante cuando la selectividad es tiempo-variante puede afectar fuertemente la toma de decisiones para el manejo pesquero. Por esta razón, Martell & Stewart (2014) sugieren que en ausencia de conocimiento acerca de la selectividad, una selectividad tiempo-variante debería ser asumida.

#### Interacción entre la incorrecta especificación de la selectividad y el error de edad

El efecto de la incorrecta determinación de la edad sobre los parámetros de interés puede ser exacerbado o enmascarado por un supuesto incorrecto sobre la selectividad.

Cuando los datos provinieron de una selectividad logística tiempo-invariante y el SCA asumió una selectividad doble logística tiempo-invariante,  $D_{final}$  exhibió un sesgo positivo marcadamente superior, debido a la interacción entre el error de edad y la selectividad incorrectamente especificada. Punt *et al.* (2002), Yin & Sampson (2004) y Martell & Stewart (2014) indican que una incorrecta asunción de la selectividad puede conducir a estimaciones sesgadas de la biomasa desovante y de la depleción. La interacción del error de edad con la selectividad incorrectamente especificada, condujo en este caso a estimaciones incluso más sesgadas. En contraste, el efecto del error de edad fue enmascarado en las estimaciones de  $R_0$  y  $F_{terminal}$  (menos sesgadas positivamente), probablemente debido a que el error de edad presente en el OM con una selectividad logística tiempo-invariante, es compensado por la selectividad tiempo-invariante doble logística del SCA, ya que el SCA asume que no hay peces de mayor edad en la captura.

Cuando la selectividad fue doble logística tiempo-invariante en el OM y logística tiempovariante en el SCA, un efecto contrario al escenario previo fue observado. Aquí el efecto del error de edad fue suavemente enmascarado en  $D_{final}$ , pero acentuado en  $R_0$  y  $F_{terminal}$ , con un alto sesgo positivo en  $R_0$  (mediana del RE > 200%).

Asumir que la selectividad (logística y doble logística) es tiempo invariante (SCA) cuando en realidad es tiempo-variante (OM), enmascara los efecto del error de edad en todos los parámetros.  $D_{final}$ ,  $R_0$  and  $F_{terminal}$  exhibieron un menor sesgo positivo y mayor precisión en comparación a cuando la selectividad fue tiempo variante en el OM y en el SCA. Estos cambios en la edad de selectividad que no son tomados en cuenta por el SCA amortiguan y enmascaran el efecto del error de edad. Los cambios en la edad máxima de selectividad impactan las estimaciones de los puntos de referencia para el manejo (Goodyear, 1996). La incorrecta especificación de la selectividad, con datos provenientes de una capturabilidad tiempo-variante, cuando la composición de edad ha sido incorrectamente determinada, conduce a un incremento en el sesgo positivo y en la imprecisión de los parámetros  $D_{final}$  y  $R_0$ , exacerbando el efecto del error de edad, pero enmascarando el efecto del error de la edad en las estimaciones de  $F_{terminal}$ .

## Implicancias para el manejo

El sesgo y la imprecisión en los parámetros estimados generados por el error de edad puede claramente afectar el proceso de la toma de decisiones para el manejo pesquero. Los resultados muestran que la evaluación de stock de bacalao de profundidad no es robusta al problema de la subestimación de la edad. El actual estado de depleción de la biomasa desovante del bacalao de profundidad es bajo un 15%, por lo que incluso un pequeño cambio en el valor de la depleción (~5% - 10%) podría significar un cambio en el estado de la pesquería.

Los parámetros examinados aquí son claves para determinar las capturas límites y evaluar estrategias de manejo. Frente a la declinación de los stock pesqueros, como en el caso del bacalao de profundidad, es necesario contar con la información más fidedigna posible para la evaluación de stock (Richards & Megrey, 1994). Una mejor comprensión del comportamiento de los modelos de evaluación, podría conducir a una mejor estimación del estado de la población y por lo tanto a un mejor manejo de la pesquería.

Se aplicó la corrección de edad a los datos reales de la pesquería y se obtuvo una mejora substancial en la estimación de los parámetros  $D_{final}$ ,  $R_0$  y  $F_{terminal}$ , siendo éstos menos sesgados y más precisos. Después de aplicar la corrección a los datos de la pesquería, se llevo a cabo la evaluación de estrategias de manejo (MSE), para evaluar la recuperación de la pesquería. El análisis de estrategias de manejo es clave cuando se desean establecer planes de manejo y evaluar la recuperación de un recurso. MSE ha sido utilizado exitosamente en planes de recuperación de pesquerías, tales como la pesquería de merluza de Sud África (Butterworth & Rademeyer, 2005), la pesquería de langosta de Nueva Zelandia (Starr *et al.*, 1997) y la pesquerías de peces de rocas de Estados Unidos (Punt & Ralston, 2007), entre otras.

En Chile, aun no hay estudios que hayan aplicado esta metodología para evaluar la recuperación de pesquerías, así que este es un estudio piloto que puede ser usado como un ejemplo para otras pesquerías en estado de sobrepesca o depletadas. En este trabajo se utilizaron simulaciones de estrategias de manejo para explorar procedimientos de manejo (MP) alternativos, destinados a la recuperación del stock de bacalao de profundidad del sur de Chile. Estos

procedimientos de manejo demostraron que el actual estado del stock no permite la recuperación de la pesquería en el corto plazo (i.e. los primeros 9 años de la estrategia de manejo). En general, los plazos de recuperación se limitan normalmente a 10 años, a menos que la biología de la población no lo permita, en cuyo caso el periodo de recuperación se puede alargar dependiendo del tiempo generacional de la especie (Holland, 2010). De hecho, incluso cuando se simuló la moratoria de la pesquería, le tomó más de 9 años a la biomasa desovante exceder el tamaño limite del stock en el 95% de los años proyectados y le tomó el mismo tiempo alcanzar el tamaño objetivo del stock (TSSB) en más del 50% de los años proyectados. Si la mortalidad por pesca se mantuviera en el status quo, el stock se encontraría en un gran riesgo de colapso en el corto plazo.

Los mejores MPs incluyeron HCRs con (i) LSSB =  $0.5B_{MSY}$ , TSSB =  $B_{MSY}$ , y  $F_{MSY}$ , (ii) LSSB =  $0.2B_0$ , TSSB =  $0.45B_0$ , y  $0.5F_{spr45\%}$ , y (iii)  $F_{MSY}$  constante. Los mejores MPs demostraron el stock podría recuperarse de su estado actual a niveles mayores que  $0.25 B_0$  dentro de los años 2022 -2038, sin embargo, tal recuperación implica un costo de una reducción de la captura anual de al menos un 40% (> 400 ton). Esta es una situación típica cuando se implementa un MSE, debido a que los años iniciales de los MPs son el periodo mas critico de un proceso de evaluación de estrategias de manejo y es aquí donde los rendimiento pueden necesitar ser reducidos a niveles extremos (Cox *et al.*, 2013). Un plan de capturas mínimas en los próximos 10 años podría mejorar los rendimientos en el mediano y largo plazo de esta pesquería.

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# APÉNDICES CAPITULO I



### Appendix A. Age structured operating model (OM)

This appendix presents the equations for the age-structured operating model implemented in R. The model notation and parameters are given in Table 1 (see paper). The equations are presented in Table A1.

## A.1. Life history schedules:

The length-at-age ( $l_a$ ) was modeled following a von Bertalanffy growth model (A.1.1) and the weight-at-age ( $w_a$ ) was obtained from the weight–length relationship (A.1.2).

The maturity-at-age (A.1.3) was used to define the proportion of the mature population at each age. A logistic maturity-at-age ( $m_a$ ) function was applied.

#### A.2. Stock-recruitment relationship

The unfished equilibrium spawning biomass per recruit ( $\phi$ ) was modeled as shown in equation A.2.1. The unfished recruitment ( $R_0$ ) was defined as shown in equation A.2.2.

The parameters a (A.2.3) and b (A.2.4) are the Beverton-Holt stock-recruitment relationship parameters.

#### A.4. Basic abundance dynamics

The operating model creates the population dynamics with a continuous fishing mortality, where the number of fish in age group a, at the start of each year t, was calculated as shown in equation A.3.1. The abundance at age 1 ( $N_{a,t}$ ) corresponds to annual recruitment of age-1 (A.3.2), which is log-normally distributed about a Beverton–Holt stock-recruitment relationship, parameterized as a function of steepness (h). The SSB<sub>t</sub> of fish in age group a, at the start of each year t, was calculated as shown in equation A.4.3.

### A.3. Initial condition

The initial conditions were modeled with equations A.4.1 - A.4.3. The equation A.4.1 represents the number of fish in age group a in the initial year (year 1). In this equation (A.4.1) random recruitment deviations were included. The equation A.4.2 gives the number of fish in the plus group in year 1. The spawning biomass of fish in age group a in year 1 was calculated in equation A.4.3.

## A.5. Fishery selectivity

Logistic (A.5.1) and double logistic (A.5.3) selectivity functions were assumed for the fishery. Each form of selectivity was a time-invariant or a time-varying function.

For time-varying logistic selectivity (A.5.2),  $\Omega_1$  (age 50% of selectivity) varied year to year, following a random walk with autocorrelation. The initial value (year 1) was drawn randomly from a standard normal distribution  $\delta_t \sim N(0, \sigma_{\Omega_1}^2)$ . For years 2 to 24, the autocorrelation random walk was applied as follows:

$$rs_{t}\begin{cases}\delta_{1} & t=1\\ \rho_{\Omega_{1}} * rs_{t-1} + (1-\rho_{\Omega_{1}}) * \delta_{t} & t=2,...,T\end{cases}$$
A.5.5

A logit transformation was applied to the  $rs_t$  values to get values between 0 to 1. Then,  $\Omega_1$  values were allowed to vary between the lower ( $Lo_{\Omega_1}$ ) and upper bounds ( $U_{\Omega_1}$ ) of  $\Omega_1$  as:

$$\Omega_{1t} = Lo_{\Omega_1} + rs_t * (U_{\Omega_1} - Lo_{\Omega_1})$$
A.5.6

The time-varying logistic selectivity was defined as presented in equation A.5.2.

For time-varying double logistic selectivity, the  $\Omega_3$  (Inflection 1) and  $\Omega_4$  (Inflection 2) parameters varied year to year following a random walk with autocorrelation. The same procedure was applied for the time-varying logistic and double logistic selectivity, but here the random walk was applied to both  $\Omega_3$  and  $\Omega_4$ . The time-varying double logistic selectivity is defined in equation A.5.4.

#### A.6. Fishery catch

The catch of fish of age a during year t (in numbers) was determined using the Baranov catch equation (A.6.1). Catch-at-age matrices were obtained for the first eighteen years of the fishery using age compositions derived from scale-based age readings and, for the final six years, using age compositions was derived from otolith-based age readings. Age compositions were then transformed to proportions-at-age using equations A.6.3-A.6.6.

The biomass caught by the fishery was calculated as shown in equation A.6.3.

#### A.7. Fishery-dependent information

A fishery-dependent index (CPUE) was generated (A.7.1). The coefficient of catchability was generated in the OM as either a constant parameter (q) or as a random walk process ( $q_t$ ), depending on the cases and scenarios.

When a time-varying catchability was used in the data generation process, the parameter varied year to year following a random walk with autocorrelation. The initial value (year 1), in log-space to avoid negative values, was drawn randomly from a standard normal distribution  $(\varphi_t \sim N(0, \sigma_q^2))$ . For years 2 to 24, it was modeled using the autocorrelation random walk function:

$$rq_{t}\begin{cases} \varphi_{1} & t=1\\ \rho_{q} * rq_{t-1} + (1-\rho_{q}) * \varphi_{t} & t=2,...,T \end{cases}$$
 A.7.3

Finally, a linear regression was applied and the residuals (r) were taken to obtain  $q_t$ :



# Table A.1. Patagonian toothfish fishery-operating model for generating age-structured population

dynamics, indices of relative abundance, and age-proportion data.

A.1 Life history schedules A.1.1 - A.1.2	$l = l * (1 - \exp^{(-k(a-a_0))})$ $w = cl^{d}$	
A.1.3	$m_a = 1/1 + \exp[-g(a - m_a)]$ where $g = \log(19)/(m_a - m_a)$	$m_{\rm c}$ )
A.2 Stock-recruitment relationship		<i>m</i> <sub>1</sub> )
A.2.1	$exp^{-M(A-1)}m_{*}w_{*}$	
	$\phi = \sum_{a=1}^{n} \exp^{-M(a-1)} m_a w_a + \frac{m_F - m_A m_A}{1 - \exp^{-M}}$	
A.2.2	$R_0 = B_0 / \phi$	
A.2.3 - A.2.4	$a = \frac{4hR_0}{B_0(1-h)}$ $b = \frac{5h-1}{B_0(1-h)}$	
A.3 Basic abundance dynamics		
A.3.1	$(N_{a,t})$	a = 1
	$N_{a,t} \int N_{A-1,t-1} \exp^{-M + F_{t-1}S_{a-1}}$	a = 2,, A - 1
	$\int N_{A-1,t-1} \exp^{-M+F_{t-1}S_A} + N_{A,t-1} \exp^{-M+F_{t-1}}S_A$	a = A
A.3.2	$4hR_0SSB_{t-1}$ (w0.5 $\sigma_p^2$ )	$\mathbf{N}(0, 2)$
	$N_{1,t} = \frac{1}{B_0(1-h) + (5h-1)SSB_{t-1}} \exp(1 - 4k)$	$v_t \sim N(0, \sigma_R)$
A.3.3	$SSB = \sum_{n=1}^{A} m w N$	
	$SSD_t = \sum_{a=1}^{m_a w_a v_{a,t}}$	
A.4 Initial condition		
A.4.1	$N_{a,1} = R_0 \exp^{-M(a-1)} \exp^{(w_t - 0.5\sigma_R^2)} $	$w_t \sim N(0, \sigma_R^2)  1 \le a \le A - 1$
A.4.2	$N_{A,1} = N_{A-1,1} / (1 - \exp^{-M})$	
A.4.3	$SSB_{a,1} = N_{a,1}W_a$	
A.5 Fishery selectivity		
A.5.1	$S_a = \frac{1}{1 + (-g^*(a - \Omega_a))}$ , where $g = \log(19)/(\Omega_2 - \Omega_1)$	
A.5.2	$1+e^{-1}$	
	$S_{a,t} = \frac{1}{1 + e^{(-g(a - \Omega_{tt}))}}, \text{ where } g = \log(19) / (\Omega_2 - \Omega_1)$	
A.5.3	$1/(1+e^{[-1*\Omega_5^{*(a-\Omega_3)}]})*[1-(1/(1+e^{[-1*\Omega_6^{*(a-(\Omega_3+\Omega_4))}]}))]$	]
	$S_a = \frac{MAX_a(num_a)}{MAX_a(num_a)}$	_
A.5.4	$1/(1+e^{[-1*\Omega_5*(a-\Omega_{3t})]})*[1-(1/(1+e^{[-1*\Omega_6*(a-(\Omega_3+\Omega_{4t}))]})$	))]
	$S_{a,t} = \frac{MAX_a(num_a)}{MAX_a(num_a)}$	
A.6 Fishery catch		
A.6.1	$C_{a,t} = N_{a,t} S_a F_{a,t} \frac{(1 - e^{(-Z_{a,t})})}{Z_{a,t}}$	
A.6.2	$Cw = \sum_{a=1}^{A} C_{a,t} w_a$	
A.6.3 - 6.4	$C_{a,t(1989-2006)} = C_{a,t} * P(a   a')$ $C_{a,t(2007-2012)} = C_{a,t}$	$*E(a \mid a')$
A.6.5	$\tilde{C}_t = \sum_{r=1}^{A} C_{a, t_{(1989-2012)}}$	
A.6.6	$P_{a,t} = \frac{\frac{C_{a,t_{1989-2012}}}{\tilde{C}_t}}{\tilde{C}_t}$	
A.7 Fishery dependent information		
A.7.1 - A.7.2	$CPUE = q * VB_t * e^{(c_t - 0.5\sigma_t^2)} \qquad CPUE = q_t * VB_t * e^{(c_t - 0.5\sigma_t^2)}$	$\mathcal{E}_t \sim N(0, \sigma_I^2)$

#### Appendix B. Statistical catch-at-age model (SCA)

The life history schedules, stock-recruitment relationship, initial condition, basic abundance dynamics, fishery selectivity, and fishery catch as in the operating model (see equations A.1.1-A.5.6 and A.6.2), except for the catchability parameter (q), which was a time-invariant parameter in the EM. The model notation and parameters are given in Table 1 (see paper). The maximum likelihood and log-likelihood estimates from the EM are given in Table B.1.

## Ageing error correction procedure

The P(a/a) matrix with the maximum likelihood estimation (MLE) of  $y_{max}$  and m was used to correct the ageing error. The correction of the error involved multiplication of the estimated age proportion, for the years 1984 to 2006, by the transpose (*T*) of the P(a/a) matrix as follows:

$$C_{a,t(scales)} = N_{a,t}S_{a}F_{a,t}\frac{(1-e^{(-Z_{a,t})})}{Z_{a,t}}*T(P(a'|a))$$

$$t=1989,...,t=2006$$

$$B.2.1$$

$$C_{a,t(otoliths)} = N_{a,t}S_{a}F_{a,t}\frac{(1-e^{(-Z_{a,t})})}{Z_{a,t}}$$

$$t=2007,...,T=2012$$

After the "corrected" catch-at-age was obtained, the proportion-at-age was calculated as:

$$\hat{P}_{t,a} = \frac{C_{a,t}}{\sum_{t}^{T} C_{a,t}}$$
B.2.2

This "corrected" age composition (proportion) matrix was input into the multinomial likelihood in the objective function in the EM (Table B.1, equation B.1.4).

Table B.1. Likelihood function for fitting the statistical catch-at-age model to simulated index and catch-at-age-observations.

Estimated parameters	
B.1.1	$\Theta_1 = (R_0, \overline{R}, \{w_t\}_{t=1-A}^{t=T-1}, \overline{F}, f_t, \Omega_1, \Omega_2, \Omega_3, \Omega_5 \delta_t, q_{mle});$
Maximum likelihood estimates	
B.1.2 (Catches)	$L_{1} = n_{c} \ln(\sigma_{C}) + \frac{1}{2\sigma_{C}^{2}} \sum_{t=1}^{t=T} \ln\left(\frac{C_{t}}{\hat{C}_{t}}\right)^{2}$
B.1.3 (abundance index, CPUE)	$L_{2} = n_{I} \ln(\sigma_{I}) + \frac{1}{2\sigma_{I}^{2}} \sum_{t=1}^{t=T} d_{t}^{2}$
	$d_{t} = z_{t} - \overline{z}; \overline{z} = \frac{\sum_{t=1}^{t=T} z_{t}}{n_{t}}; z_{t} = \ln(cpue_{t}) - \ln(VB_{t}); q_{mle} = \exp(\overline{z});$
B.1.4 (Age composition)	$L_{3} = \sum_{t=1}^{t=T} n_{t} \sum_{a=1}^{a=A} \left[ \hat{P}_{t,a} \ln(P_{t,a}) \right], \ n_{t} = 200$
B.1.5 (Recruitment deviations and mean recruitment)	$L_{4} = n_{w} \ln(\sigma_{R}) + \frac{1}{2\sigma_{R}^{2}} \sum_{t=1}^{T-1} w_{t}^{2}; w_{t} = \ln(\overline{R}e^{w_{t}}) - f(R_{t}); f(R_{t}) = Beverton \& Holt$
B.1.6 (Fishing mortality estimates)	$P_{1} = \frac{1}{2\sigma_{f}^{2}} \sum_{t=1}^{t=T} f_{t}^{2}; \bar{F}e^{f_{t}}; f_{t}, \sum_{t=1}^{t=T} f_{t} = 0; \sigma_{t} = 0.01 \text{ if initial phase, 0.4 otherwise}$
B.1.7* (Deviates for fishing selectivity)	$P_{2} = \frac{1}{2\sigma_{s}^{2}} \sum_{t=1}^{t=T} \delta_{t}^{2}; \delta_{t} = \ln(\Omega_{1t}) - \ln(\Omega_{1t+1}); \Omega_{1t} = \Omega_{1t-1}e^{\delta_{t-1}}$
Objective function	
B.1.8 (Total likelihood)	$L_T = \sum_k L_k + \sum_l P_l$

\*Likelihood function for selectivity parameters that varied following a random walk:  $\Omega_1$ ,  $\Omega_3$ ,  $\Omega_5$ . The term  $\delta_t$  represents the random number with normal distribution used in the random walk process.



# Appendix A. Management strategy evaluation

Table A1. Patagonian toothfish fishery- *mseR* operating model equations for generating agestructured population dynamics, indices of relative abundance, and age-proportion data (Modified from Kronlund *et al.*, 2012)

Parameters		
T1.1	$\Theta = (B0, h, \delta, q, \sigma, \tau, L\infty, L1, k, M, a50, a)$	95, sa50, sa95)
Life history schedules		
T1.2	$l_a = L_{\infty} + (L_1 - L_{\infty}) \exp^{(-k(a-1))}$	
T1.3	$w_a = c_1 l_a^{c_2} (1 + 0.5 c_2 (c_2 - 1) \sigma_L^2)$	
T1.4	$m_a = 1/1 + \exp[-g(a - a_{50})]$	where $g = \log(19)/(a_{95} - a_{50})$
Fishery selectivity T1.5	$S_{a,t} = 1/1 + \exp[-g(a_s - a_{s50,t})]$	where $g = \log(19) / (a_{S95} - a_{S50})$
Stock-recruitment relationship		
T1.6	$\phi = \sum_{a=1}^{A=1} \exp^{-M(a-1)} m_a w_a + \frac{\exp^{-M(A-1)} m_A w_A}{1 - \exp^{-M}}$	
T1.7	$R_0 = B_0 / \phi$	
T1.8 - T2.9	$a = \frac{4hR_0}{B_0(1-h)}$ $b = \frac{5h-1}{B_0(1-h)}$	
Initial condition		
T1.10	$N_{a,1} = R_0 \exp^{-M(a-1)}$	$1 \le a \le A - 1$
T1.11	$N_{A,1} = N_{A-1,1} / (1 - \exp^{-M})$	
T1.12	$B_{a,1} = N_{a,1} w_a$	
State dynamics		
T1.13		t = 1
	$\omega_{R,I} = \begin{cases} \sigma_R \\ \sigma_{-\delta} \end{cases}$	
		<i>t</i> > 1
T1.14	$N_{1,t} = \frac{aB_{t-1}}{exp[\frac{\omega_{R,t} - 0.5\sigma_R^2 / (1-\gamma_R^2)}{2}]}$	
	$1 + bB_{t-1}$	
T1.15	$N_{a,t} = N_{a-1,t-1} \exp^{-M + S_a F_{t-1}}$	$2 \le a \le A - 1$
T1.16	$N_{A,t} = N_{A-1,t-1} e^{-M + S_{A-1}F_{t-1}} + N_{A,t-1} \exp^{-M + S_A F_t}$	-1
T1.17	$B = \sum_{n=1}^{A} m w N$	
	$\sum_{t} \sum_{a=1}^{t} a^{a} a^{a} a^{a} a^{a}$	
T1.18	$C_{a,t} = \frac{s_a F_t}{M + s_a F_t} (1 - \exp^{-S_a F_t}) N_{a,t}$	
T1.19	$C_{i} = \sum_{i=1}^{A} C_{i} W_{i}$	
T1 20		
11.20	$ = \int (M/2T_1)[2h_1(T_1 -  2t - T_1 ) + h_2( 2t - T_1 )] $	$-T_1  +2t - T_1 $ $t \le T_1 - 1$
	$C_t - \sum C_t w = 0$	$t \ge T_1$
	$\int \frac{1}{a} $	1

Fishery dependent information T1.21

 $CPUE = qB_t \exp^{(\varepsilon_t - 0.5\sigma_t^2)}$ 

T2.1	$\Omega = (\tilde{F}, \Theta)$			Parameters
T2.2	$\int 1$		<i>a</i> = 1	Survivorship to age <i>a</i>
	$\ell_a = \left\{ \ell_{a-1} \exp^{(-M-S_{a-1}\tilde{F})} \right\}$		$2 \le a < A$	
	$\int_{\ell_{A-1}} \exp^{(-M-S_{A-1}\tilde{F})}/$	$(1 - \exp^{(-M - S_A \tilde{F})})$	a = A	
T2.3	$\phi_{y} = \sum_{a=1}^{A} \ell_{a} S_{a} w_{a} \tilde{F} (1 - \exp^{(-L)})$	$(M-S_a\tilde{F})/(M+S_a\tilde{F})$	7)	Yield per recruit
T2.4	$\phi_{ssb} = \sum_{a=1}^{A} \ell_a m_a w_a$			Spawning stock biomass per recruit
T2.5	$\tilde{R} = (a\phi_{ab} - 1)/b\phi_{ab}$			Equilibrium recruitment
T2.6	$\tilde{B} = \tilde{R} \phi_{ssb}$			Equilibrium spawning Stock biomass
T2.7	$\tilde{C} = \tilde{B} \frac{\tilde{F}}{M + \tilde{F}} (1 - \exp^{-\tilde{F}})$			Equilibrium total yield
		* *	6 🖈	

Table A2. Equilibrium functions of a fishing mortality rate  $\tilde{F}$  (Modified from Kronlund *et al.*, 2012)

Table A3. Notation for the surplus production stock assessment model (Modified from Cox et al.,

2011)

Symbol	Description									
	Indices and index ranges									
Т	Year in which stock assessment is performed									
t	Year, where $t = 1,, T$									
n	Number of non-missing observations for the index									
i	Index for non-missing survey observations									
	Data									
$\hat{C}_t$	Catch biomass removed during year t									
$I_t$	Stock relative abundance observation for year t									
	Leading model parameters									
MSY	Maximum sustainable yield									
$U_{MSY}$	Optimal exploitation rate									
	Nuisance parameters									
q	Catchability coeffici <mark>ent for abundanc</mark> e index (CPUE)									
<i>k</i> <sup>2</sup>	Total error variance									
ρ	Observation error proportion of total variance (assumed known)									
	State variables									
$B_t$	Biomass at the beggining of year t									
	Derived reference points									
$B_{MSY}$	maximum sustainable yield biomass level									
	Priors distribution									
$N(\mu^{MSY}, \sigma^{MSY})$	Normal prior YMSY									
$N(\mu^U, \sigma^U)$	Normal prior UMSY									
	Statistical error distributions									
$\zeta_t \sim N(0, \rho k^2)$	Observation error in year t for index									
$\omega_t \sim N(0, (1 \text{-} \rho) \ k^2)$	Process error in year t									

Table A4. Surplus production model used for annual stock assessments within management procedure simulations (Modified from Cox *et al.*, 2011)

Model parameters	
T4.1	$\Theta = (U', MSY', \{\omega_t\}_{t=1}^{t=T-1})$
Parameter transformations	
T4.2	$U_{MSV} = \exp(U')$
T4.3	$MSY = \exp(MSY')$
Biomass dynamics model	
T4.4	$B_1 = 2MSY / U_{MSY}$
T4.5	$B_{MSY} = MSY / U_{MSY}$
T4.6	$\int [B_t + 2U_{MSY}B_t(1 - \frac{B_t}{B_{MSY}}) - \hat{C}_t] \exp^{\omega_t} \qquad 1 \le t \le T - 1$
	$B_{t+1} = \begin{cases} B_t + 2U_{MSY}(1 - \frac{B_t}{2B_{MSY}}) - \hat{C}_t & t = T \end{cases}$
Residuals	
T4.7	$\xi_t = \log_e(I_t / B_t)$
Conditional maximum likelihood estimates	
T4.8	$\log q = \frac{1}{n} \sum_{i=1}^{n} \xi_{i}$
T4.9	$n_{j=1}^{n}$
	$K = \frac{1}{n_{i} + T - 1} \left[ \frac{1}{\rho} \sum_{i=1}^{r} (\zeta_{i} - \log q) + \frac{1}{1 - \rho} \sum_{i=1}^{r} \omega_{i} \right]$
Negative log-likelihood and objective function	
T4.10	$\ell(\mathbf{I}   \Theta) = \frac{n.T - 1}{2} \log_e \left[\frac{1}{\rho} \sum_{i=1}^n (\xi_i - \log q)^2 + \frac{1}{1 - \rho} \sum_{i=1}^{T-1} \omega_y^2\right]$
T4.11	$G(\Theta   \mathbf{I}) \propto \ell(\mathbf{I}   \Theta) + \frac{1}{2(-MSY)} (MSY - \mu^{MSY})^2 + \frac{1}{2(-U')^2} (U_{MSY} - \mu^{U'})^2$
	$2(\sigma^{-1})$ $2(\sigma^{-1})^{2}$



# MATERIAL SUP<mark>LEMENTARI</mark>O - CA</mark>PITULO I



Supplementary Materials

Supplementary material is available at the ICESJMS online version of the manuscript.

# Supplementary Tables

Table S.1. Age-reading error matrix P(a'|a) for of one simulation. Rows and columns of the matrix P(a'|a) correspond to scales age a'

and otoliths age *a*, ,respectively.

	Age-reading error matrix																													
	True Ages (Otoliths)																													
		1	2 3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
	1	1	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	2	0	1 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	3	0	0 0.519	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	4	0	0 0.481	0.006	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5	0	0 0	0.994	0.027	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	6	0	0 0	0	0.973	0.180	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	7	0	0 0	0	0	0.820	0.548	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	8	0	0 0	0	0	0	0.452	0.813	0.001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	9	0	0 0	0	0	0	0	0.187	0.915	0.025	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	10	0	0 0	0	0	0	0	0	0.084	0.931	0.155	0.005	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	11	0	0 0	0	0	0	0	0	0	0.044	0.820	0.426	0.049	0.004	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	12	0	0 0	0	0	0	0	0	0	0	0.025	0.557	0.639	0.190	0.033	0.005	0.001	0	0	0	0	0	0	0	0	0	0	0	0	0
•	13	0	0 0	0	0	0	0	0	0	0	0	0.012	0.306	0.654	0.396	0.132	0.035	0.009	0.003	0.001	0	0	0	0	0	0	0	0	0	0
l S	14	0	0 0	0	0	0	0	0	0	0	0	0	0.005	0.150	0.503	0.523	0.294	0.124	0.047	0.018	0.007	0.003	0.002	0.001	0.001	0	0	0	0	0
Sca	15	0	0 0	0	0	0	0	0	0	0	0	0	0	0.002	0.067	0.312	0.493	0.422	0.259	0.136	0.067	0.034	0.018	0.010	0.006	0.004	0.002	0.002	0.001	0.001
	16	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0.001	0.028	0.166	0.363	0.435	0.366	0.253	0.158	0.096	0.058	0.036	0.023	0.016	0.011	0.008	0.006
	17	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.011	0.078	0.221	0.348	0.381	0.333	0.256	0.184	0.129	0.090	0.064	0.046	0.034	0.026
	18	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.004	0.034	0.117	0.230	0.313	0.336	0.309	0.260	0.207	0.161	0.125	0.097	0.076
	19	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.002	0.014	0.056	0.132	0.215	0.274	0.295	0.285	0.257	0.221	0.187	0.156
	20	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.001	0.005	0.025	0.067	0.128	0.190	0.235	0.257	0.258	0.245	0.224
	21	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.002	0.010	0.032	0.069	0.115	0.161	0.197	0.219	0.228
	22	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.001	0.004	0.014	0.034	0.064	0.099	0.134	0.163
	23	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.002	0.006	0.016	0.033	0.055	0.082
	24	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.001	0.002	0.007	0.016	0.029
	25	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.001	0.003	0.007
	26	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.001
	27	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	28	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	29	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	30	0	0 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Sum	1	1 1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Supplementary Figures

Figure S.1. Pair-wise and marginal (diagonal) distributions based on a sample of 1000000 points from the joint posterior for logistic model. Parameters are: maximum predicted age ( $y_{max}$ ) and slope (*m*). Sigma represent the standard deviation. Posterior means and maximum likelihood estimates are indicated by the blue circles and red squares, respectively.



Figure S.2. Proportion of the spawning biomass (SSB) estimates that are within of the 95% confidence interval (95% CI) for the true SSB generated from the OM (24 year-period). Circle (•) and square (•) symbols represent that all and none of the SSB estimates are within of 95% CI, respectively. Upper ( $\blacktriangle$ ) and lower ( $\blacktriangledown$ ) triangles indicate that SSB estimates were overestimated and underestimated, respectively (i.e., the estimates were outside of 95% CI) and the diamond (•) indicates than the estimates are partially within of 95% CI. See Table 2 for tag names (cases and scenarios)



Figure S.3. Estimated median values of  $D_{final}$ ,  $R_0$ , and  $F_{terminal}$ , for the 4 cases and the six scenarios combining ageing error with catchability. The black dot line represents the median (med) of each value for each scenario. The dark gray dashed line correspond to the first quartile (Q1 - 25th percentile) and light gray dashed line correspond to the third quartile (Q3 - 75th percentile). See Table 2 for tag names (cases and scenarios).

