Development of a Bayesian framework for data limited stock assessment methods and management scenarios proposal. Case studies of cuttlefish (Sepia officinalis) and pollack (Pollachius pollachius)

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THESE

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Développement d'un cadre Bayésien pour l'évaluation de stocks à données limitées et élaboration de scénarios de gestion, cas particuliers de la seiche (*Sepia officinalis*) et du lieu jaune (*Pollachius pollachius*)

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Table des matières

Avant-propos

J'ai grandi sur un bout de terre entouré d'eau, l'île de la Réunion. Je voyais les hommes partir en mer sur un canot de bois, et revenir avec du poisson frais. De la nourriture, sortie tout droit des entrailles de la mer. Et puis j'ai commencé à pratiquer la plongée sous-marine, je me suis émerveillée devant ces animaux colorés qui habitaient les fonds. Il ne m'a pas fallu longtemps pour être certaine de ce que je voulais faire : un métier qui permette de concilier la préservation des poissons tout en aidant les pêcheurs à continuer ce métier que j'admirais tant. Je crois bien que j'ai trouvé.

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Abstract

The assessment and the management of fish stocks aim at achieving a sustainable exploitation of the resources provided by the oceans. While progress have been made in this field for some stocks of great commercial importance, the situation is different for the so-called "data limited" stocks. Often historically less exploited, these stocks do not benefit from the same economical resources nor workforce to conduct the stock assessments required to set management measures. This work is based on two case studies, pollack (*Pollachius pollachius*) and cuttlefish (*Sepia officinalis*). The aim is to investigate the stock assessment methods adapted to data-limited situations. A first introductive part presents the background of fish stock assessment as well as the two case studies. This first chapter is followed by a review of data-limited stock assessment methods. The third part compares the results of a two-stage biomass model with the results of a multi-annual generalized depletion model applied to the English Channel stock of cuttlefish. An improved version of the Bayesian two-stage biomass model is also presented. In the fourth part, a Stock Synthesis model based on integrated analysis methods is applied to the stock of pollack in the Celtic Seas Ecoregion. The results are compared to the results of simpler models which require less data. The Stock Synthesis model results are sensitive to the assumptions on the natural mortality value, which relies on the growth parameters of the stock. The fifth part presents the collection and analysis of new data which will allow a better estimate of pollack stock status. A Bayesian hierarchical model is constructed, allowing information transfer between three stocks and the update of pollack biological parameters. The last chapter concludes this work by summarizing the main results. The discussion is extended to the research perspectives.

Keywords: data-limited stock, stock assessment, management advice, Bayesian model, *Pollachius pollachius*, pollack, *Sepia officinalis*, cuttlefish

Résumé

L'évaluation et la gestion des stocks de poissons ont pour objectif d'atteindre une exploitation durable des ressources fournies par les océans. Si les progrès dans ce domaine sont bien réels pour certains stocks de grande importance commerciale, la situation est différente pour les stocks dits à données limitées. Souvent historiquement moins exploités, ces stocks ne bénéficient pas des mêmes ressources, tant économiques qu'humaines, pour réaliser une évaluation de stock permettant par la suite la mise en place de mesures de gestion. Ce travail s'appuie sur deux cas d'étude, le lieu jaune (*Pollachius pollachius*) et la seiche (*Sepia officinalis*), afin d'explorer des méthodologies d'évaluation de stocks adaptées aux situations de données limitées. Après une première partie introductive reprenant le contexte de l'évaluation des stocks et présentant les deux cas d'étude, une revue des méthodes d'évaluation de stocks à données limitées est proposée. Une troisième partie compare les résultats d'un modèle de biomasse à deux stades et d'un modèle multi-annuel de déplétion généralisé appliqués au stock de seiche de Manche. Une version améliorée du modèle de biomasse à deux stades codé en Bayésien est également présentée. Le travail se poursuit avec l'application d'un modèle d'analyse intégrée Stock Synthesis au stock de lieu jaune de mer Celtique. Les résultats sont comparés aux résultats de modèles plus simples nécessitant moins de données. Les résultats du modèle Stock Synthesis s'avèrent sensibles aux hypothèses sur la valeur de mortalité naturelle, dont le calcul dépend des paramètres de croissance du stock. La cinquième partie présente l'acquisition et le traitement de nouvelles données qui pourront permettre une meilleure estimation de l'état du stock de lieu jaune. Un modèle hiérarchique Bayésien est construit, permettant un transfert d'information entre trois stocks et la mise à jour des paramètres biologiques du lieu jaune. Le dernier chapitre conclut ce travail en reprenant les principaux résultats obtenus et en élargissant la discussion sur des perspectives de recherche.

Mots clés : stock à données limitées, évaluation de stock, avis de gestion, modèle Bayésien, *Pollachius pollachius*, lieu jaune, *Sepia officinalis*, seiche

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Abréviations et définitions

Abréviations françaises

CICTA : Commission Internationale pour la Conservation des Thonidés de l'Atlantique.

CIEM : Conseil International pour l'Exploration de la Mer. Définit les unités fonctionnelles et fournit les recommandations de capture.

CPANE : Commission des Pêches de l'Atlantique du Nord-Est.

CPUE : Capture par Unité d'Effort.

CSTEP : Comité Scientifique, Technique et Économique de la Pêche qui fournit les avis scientifiques sur lesquels reposent les décisions de la Commission européenne, afin de mettre en œuvre la politique commune de la pêche de l'Union Européenne.

DOM : Département d'Outre-Mer.

EVHOE : Évaluation des ressources Halieutiques de l'Ouest de l'Europe. Campagne scientifique.

Halieutique : Science de l'exploitation des ressources vivantes aquatiques (Nom commun). Qui concerne la pêche, notamment la pêche en mer (Adjectif).

INN : Pêche illicite, non déclarée et non réglementée

IFREMER : Institut Français de Recherche pour l'Exploitation de la Mer.

k : Biomasse vierge.

K : Coefficient instantané de croissance de l'équation de Von Bertalanffy.

L_∞ : Longueur maximale ou asymptotique.

M : Coefficient de mortalité naturelle.

ObsMer : Programme d'Observateurs embarqués en Mer.

OCSAN : Organisation de Conservation du Saumon de l'Atlantique Nord.

ORGP : Organisation Régionale de Gestion de la Pêche.

ORP : Organisation Régionale de Pêche.

PCP : Politique Commune de la Pêche.

SIH : Système d'Information Halieutique.

TAC : Total Admissible de Capture.

TOM : Territoire d'Outre-Mer.

t_0 : Age initial où la longueur du poisson est théoriquement égale à zéro.

UE : Union Européenne.

ZEE : Zone Économique Exclusive.

Abréviations anglaises

AIC : Akaike Information Criterion. Le critère d'information d'Akaike est une mesure de qualité d'un modèle statistique qui pénalise les modèles en fonction du nombre de paramètres inclus.

BIC : Bayesian Information Criterion. Le critère d'information bayésien dérive de l'AIC. La pénalité appliquée tient compte non seulement du nombre de paramètres, mais aussi de la taille de l'échantillon.

Cefas : Centre for Environment, Fisheries and Aquaculture Science.

CGFS : Channel Ground Fish Survey. Campagne scientifique.

DB-SRA : Depletion Based Stock Reduction Analysis.

DCAC : Depletion Corrected Average Catch.

DCF : Data Collection Framework.

DLM : Data-Limited Methods. Méthodes d'évaluation de stock employées dans un contexte de données limitées.

DLS : Data-Limited Stock. Stock à données limitées.

DOC : Department Of Commerce.

FAO : Food and Agriculture Organization.

IBTS : International Bottom Trawl Survey. Campagne et programme scientifique.

ICES : International Council for the Exploration of the Sea. Même définition que pour CIEM.

LB-SPR : Length Based Spawning Potential Ratio.

MSE : Management Strategy Evaluation. Démarche qui consiste à mener des simulations pour tester la robustesse à l'erreur et à l'incertitude de différentes stratégies de gestion.

MSY : Maximum Sustainable Yield. Rendement maximum durable.

NASA : National Aeronautics and Space Administration.

New MoU : New Memorandum of Understanding.

NOAA : National Oceanic and Atmospheric Administration.

OFL : Overfishing Limit.

OTB : Bottom Otter Trawl. Chaluts de fond à panneaux.

SSB : Spawning Stock Biomass. Biomasse de géniteurs au sein d'un stock.

SSS : Simple Stock Synthesis.

UK : United Kingdom.

VPA : Virtual Population Analysis.

WGCEPH : Working Group on Cephalopod Fisheries and Life History. Groupe de travail européen du CIEM sur les céphalopodes.

WGCSE : Working Group for the Celtic Seas Ecoregion. Groupe de travail européen du CIEM qui s'occupe, entre autres, de l'évaluation du stock de lieu jaune.

WGNEW : Working Group on Assessment of New MoU Species. Groupe de travail européen du CIEM sur l'évaluation des espèces du nouveau mémorandum.

Index des figures

Index des tableaux

CHAPITRE 1

CHAPITRE 1 : Introduction générale

"*When the Last Tree Is Cut Down, the Last Fish Eaten, and the Last Stream Poisoned, You Will Realize That You Cannot Eat Money.*"

Alanis Obomsawin (1972), from **"Conversations with North American Indians" by Ted Poole in "Who is the Chairman of This Meeting? A Collection of Essays" edited by Ralph Osborne.**

1.1. Contexte de l'évaluation et de la gestion des stocks de poissons

1.1.1. Retour historique sur l'émergence de la gestion des stocks

La pêche est une activité ancestrale, d'une importance cruciale tant sur le plan économique que social ou culturel. Autrefois limitée aux eaux continentales et aux zones maritimes côtières, cette activité a connu d'importants changements avec la révolution industrielle. L'aire des zones maritimes exploitées s'est étendue, la taille des bateaux a commencé à croître, et le nombre d'espèces exploitées a considérablement augmenté. Cependant, les ressources de l'océan n'étant pas inépuisables, de nombreux stocks de poissons ont été surexploités. Cette surexploitation a eu pour conséquence directe la nécessité d'évaluer et de gérer les stocks. Par stock, nous entendons partie exploitable de la population d'une espèce dans une zone donnée, constituant également une unité de gestion. L'évaluation des stocks consiste à indiquer aux gestionnaires les choix possibles en termes de gestion et leurs conséquences (Hilborn et Walters, 1992 [125]). La gestion, en revanche, consiste à définir et à mettre en place des mesures permettant une exploitation durable des ressources halieutiques en tenant compte non seulement des avis de gestion, mais aussi des considérations politiques, économiques, sociales et culturelles (Cochrane, 2002 [53]). Les notions d'évaluation des stocks et de gestion des stocks sont donc liées, mais ont des objectifs qui diffèrent.

Un exemple frappant des conséquences de la surexploitation est l'effondrement des stocks constituant la pêcherie de morue de Terre-Neuve et du Labrador, dont les captures approchaient les 1 100 000 t en 1968 avant de tomber à 300 000 t en 1977 (GNL, 2005 [106]; DFO, 2015 [67], 2016a [68], 2016b [69]). Des mesures de gestion sont alors instaurées par le gouvernement Canadien, dans le but d'enrayer cette chute brutale. Ces mesures s'avèrent hélas insuffisantes pour protéger ces stocks qui finissent par s'effondrer en 1992. La biomasse estimée tombe alors à un niveau si bas que la menace d'une incapacité des stocks à se reconstruire plane. Le 2 Juillet 1992, la bombe est lâchée : le gouvernement Canadien impose un moratoire fermant complètement la pêche de la morue. Les dégâts sont considérables, 30 000 personnes qui dépendaient de cette activité depuis de nombreuses générations se retrouvent sans emploi. Un mince espoir persiste dans les cœurs : le moratoire devrait permettre aux stocks de se reconstituer. Hélas, les mesures de gestion arrivent trop tard, et ce qui devait être une situation temporaire se transforme en une longue attente. Ce n'est que 19 ans plus tard que les premiers indices d'une remontée de biomasse sont détectés. Mais il est probable que l'écosystème a été modifié et il n'existe à ce jour aucune certitude sur la capacité des stocks à revenir aux niveaux de biomasse initiaux. Cet exemple montre bien la rapidité avec laquelle un stock peut être détruit en l'absence de mesures de gestions adéquates, et la reconstruction lente et difficile qui en découle.

L'intérêt croissant de la recherche pour le domaine de l'évaluation des stocks a été initié par des volontés politiques. Peu à peu, la coopération entre les États apparaît comme une nécessité pour une gestion optimale de la pêche. Les gouvernements de différents pays expriment alors leur volonté de mettre en place une commission permettant de réguler conjointement l'exploitation des stocks. C'est en 1902 qu'a lieu la première réunion du Conseil International pour l'Exploration de la Mer (CIEM) à Copenhague. Cet organisme scientifique international a été initialement créé pour stimuler et coordonner la recherche marine dans les pays membres fondateurs qui étaient l'Allemagne, le Danemark, la Finlande, la Norvège, les Pays-Bas, le Royaume-Uni, la Russie et la Suède. Un des principaux objectifs était de fournir un conseil scientifique sur la gestion des pêches aux gouvernements des États membres. Lors de cette première réunion, trois comités sont créés. Le comité B est chargé de se pencher sur l'épineuse question de la surexploitation, notion qu'il est nécessaire de définir pour qu'une gestion puisse être envisagée. En 1954, la Commission des pêcheries de l'Atlantique du Nord-Est (CPANE) est fondée afin de gérer les pêches dans l'Atlantique du Nord-Est. Contrairement au CIEM, la CPANE a un mandat de gestion. Elle fonde ses recommandations autant que possible sur les avis du CIEM avec qui elle peut travailler en étroite collaboration (Tambs-Lyche, 1980 [249]). Aujourd'hui, le CIEM regroupe près de 1600 chercheurs venant principalement des vingt pays membres et fournit un avis scientifique annuel pour plus de 260 stocks dans l'Atlantique nord-est.

En 1982, les Nations Unies adoptent la convention des Nations Unies sur le droit de la mer, aussi appelée convention de Montego Bay (UN, 1982 [256]) visant à promouvoir l'ordre, la stabilité, la prédictibilité et la sécurité des océans du monde. La notion de zone économique exclusive (ZEE) y est définie. Chaque Etat côtier est autorisé à fixer une limite extérieure jusqu'à 200 milles des lignes de base. Ces lignes constituent la limite géographique séparant le domaine émergé d'un État côtier du domaine maritime. Au sein de sa ZEE, un État possède des droits souverains quant à l'exploration, l'exploitation, la conservation et la gestion des ressources naturelles et des fonds marins. L'extension de la ZEE procure aux États l'autorité nécessaire à la lutte contre la pêche illicite, non déclarée et non réglementée (INN) qui constitue un véritable danger pour l'exploitation durable des stocks (Koffie-Bikpo, 2010 [162]).

En 1995, l'Accord des Nations Unies sur les stocks de poissons (Article 6, UN, 1995 [257]) et le code de conduite de la FAO pour une pêche responsable (Article 7, FAO, 1995 [82]) recommandent l'adoption de l'approche de précaution pour la gestion des stocks de poissons. Le but est de définir des points de référence plus conservateurs pour maintenir la biomasse à des niveaux permettant une exploitation durable du stock. En 2002 se tient le sommet mondial sur le développement durable à Johannesburg, durant lequel est réaffirmée la volonté de maintenir ou de restaurer tous les stocks de poissons à un niveau de biomasse permettant une exploitation durable. Cet objectif, qui devait être atteint en 2015 (UN, 2002 [256]), n'est que partiellement rempli. Bien que les mesures de gestion mises en place aient permis à certains stocks d'atteindre le niveau de biomasse visé, il reste encore des efforts considérables à fournir pour que l'ensemble des stocks sortent de la situation de surexploitation. L'Organisation des Nations Unies pour l'alimentation et l'agriculture (FAO) suit de près l'évolution historique des niveaux de captures et l'état des stocks au niveau mondial. Le pourcentage de stocks en situation de surexploitation a connu une forte hausse entre 1974 et 1989, passant de 10% à 26%. Après 1990, les efforts de réglementation ont permis de freiner cette tendance à la hausse sans pour autant parvenir à l'inverser. Parmi tous les stocks évalués en 2013, 31.4% étaient en situation de surexploitation (FAO, 2016 [83]).

Pour bien comprendre la nécessité de gérer la pêche à une échelle plus grande que celle des pays, il faut se référer à la notion de tragédie des biens communs (Lloyd, 1833 [167]; Hardin, 1968 [118]). Cette théorie stipule que lorsqu'il existe une compétition pour l'accès à une ressource limitée, la stratégie adoptée individuellement mènera à une combinaison de décisions minimisant l'intérêt de tous. Plus concrètement, selon cette théorie, un pêcheur supposera que tous les autres pêcheurs chercheront à capturer le plus grand nombre de poissons possible. Ainsi, au lieu de ne prélever qu'une petite quantité chaque année, il cherchera à maximiser cette quantité dès les premières années afin de privilégier ses intérêts personnels. Cette situation n'est pas optimale, tant pour le stock de poissons que pour les pêcheurs à titre individuel, car la ressource risque alors de s'effondrer, tout comme les captures des pêcheurs. En revanche, si un organisme de gestion impose des règles telles que des quotas de pêche, il est possible d'éviter la situation de surexploitation du stock et de chercher à atteindre une situation maximisant l'intérêt de tous. C'est dans ce but que divers organismes internationaux ont été créés par les pays exploitant les ressources marines.

Les organisations régionales de pêche se répartissent en deux catégories, celles avec mandat de gestion (ORGP) et celles dont le mandat se limite au rendu d'avis et de recommandations de gestion (ORP). Parmi les ORGP, certaines gèrent des espèces hautement migratoires, c'est le cas des commissions thonières telles que la commission internationale pour la conservation des thonidés de l'Atlantique (CICTA). D'autres, comme l'organisation des pêches de l'Atlantique Nord-Est (NEAFC) ou de la Méditerranée et Mer Noire (CGPM), gèrent des stocks de poissons par zone géographique. Pour couvrir l'ensemble des pêcheries de l'Union Européenne dans le monde, la Commission européenne est partie contractante de quinze ORGP, dont six spécifiques à la gestion de la pêche au thon (EU, 2016 [81]). Pour les espèces démersales et les petits pélagiques des eaux européennes de l'Atlantique Nord-Est, la Commission européenne et certaines ORGP comme l'organisation de conservation du saumon de l'Atlantique Nord (OCSAN) et la NEAFC s'appuient sur les avis du CIEM pour établir les mesures de gestion.

1.1.2. Émergence de modèles d'évaluation de stock et concept de rendement maximum durable

Parmi les modèles d'évaluation de stock, on distingue les modèles globaux des modèles analytiques. Les premiers évaluent l'impact de la pression de pêche sur l'abondancec du stock sans chercher à décrire les phénomènes biologiques qui interviennent. Ils nécessitent une quantité réduite de données (effort de pêche et captures totales) et devancent chronologiquement les modèles analytiques qui s'intéressent quant à eux aux processus intervenant dans la dynamique du stock (croissance, reproduction et mortalité de chaque classe d'âge). Les débuts de l'histoire des modèles de dynamique de population de poissons sont marqués par deux difficultés qui s'avèrent étroitement liées : le traitement mathématique de la mortalité, et la définition du terme de surexploitation (Ulltang, 2002 [255]). Face au premier problème, Baranov (1918) [13] définit des taux de mortalité instantanés et propose une description algébrique formelle d'un modèle de population qui sera pas la suite souvent reprise dans les modèles de dynamique de population. Cependant, ses travaux étaient en russe et émergeaient dans un contexte de guerre civile à Saint-Pétersbourg, ville où il était basé. Il a donc fallu attendre la fin des années 30 pour que ses travaux soient pris en compte.

Ce sont principalement les travaux de Hjort et al. (1933) [126] et de Graham (1935) [108] sur des modèles de croissance de population qui ont permis de définir la notion de surexploitation, qui correspond à un état du stock dans lequel toute augmentation de l'effort de pêche résulte en une diminution de la capture équilibrée. Faisant suite aux travaux de Graham (1935) [108] sur les modèles de surplus de production et les modèles de dynamique de biomasse, Schaefer (1954) [240] développe la courbe de surplus de production symétrique qui représente la relation entre l'abondance du stock et la pression de pêche exercée. Les travaux de Schaefer sont ensuite repris par ses collègues Pella et Tomlinson (1969) [200] pour aboutir à une courbe dont la forme est déterminée par un paramètre de forme dépendant du niveau de robustesse du stock étudié. Parmi les modèles de production couramment utilisés, on compte également le modèle de Fox (1970) [91] dont l'élaboration est basée sur une idée de Garrod (1969) [96]. Ces modèles globaux permettent d'estimer le rendement maximum durable (MSY en anglais pour « Maximum Sustainable Yield ») qui correspond au niveau maximal de captures moyennes ou de rendement pouvant être régulièrement prélevé d'un stock dans les conditions environnementales existantes. Le rendement maximum durable dépend également des traits d'histoire de vie du stock et du diagramme d'exploitation (structure en taille ou en âge des captures). La convention de Montego Bay de 1982 appelle à l'adoption de mesures de conservation permettant le maintien ou la restauration des stocks exploités à des niveaux d'exploitation qui résultent en des captures maximales durables. Le rendement maximum durable est ainsi posé comme objectif à atteindre.

Les travaux sur les modèles de rendement par recrue de Thompson et Bell (1934) [251], Ricker (1954) [220] et Beverton et Holt (1957) [22] ont ensuite joué un rôle majeur dans le développement des évaluations de stock analytiques. En se basant sur ces travaux, Gulland (1965) [115] développe le modèle d'analyse de cohortes (en anglais VPA pour Virtual Population Analysis). Aujourd'hui très répandue dans le domaine des évaluations de stocks, cette méthode consiste à reconstruire la série historique du nombre de poissons par classe d'âge en appliquant un taux de mortalité composé de la mortalité par pêche et de la mortalité naturelle.

L'effort de pêche est une mesure de la pression de pêche exercée sur un stock de poissons. Il peut par exemple être mesuré par le temps de pêche d'un chalutier ou le nombre de casiers posés au cours d'une unité de temps définie. La mesure de l'effort dépend de la technique de pêche utilisée. Lorsque la pression de pêche augmente, le taux de mortalité par pêche (F) suit la même tendance. L'évolution des captures moyennes en fonction de F forme une courbe qui passe par un maximum, le MSY, obtenu pour la valeur de mortalité par pêche F_{MSY} (Fig. 1.1). Lorsque la mortalité par pêche atteint le point de référence limite F_{MSY}, le rendement de la pêche en termes de captures est théoriquement optimal et le stock est en situation de pleine exploitation. Si la mortalité par pêche est inférieure à F_{MSY}, le stock est en situation de sous-exploitation. Si au contraire cette mortalité est supérieure au F_{MSY}, le stock est surexploité. Il s'agit là d'une surexploitation de croissance, qu'il convient de différencier de la surexploitation de recrutement. Cette dernière est observée lorsque la biomasse de géniteurs est si faible qu'une relation linéaire positive peut être établie entre la biomasse de géniteurs et le recrutement.

Afin de déterminer le statut d'un stock, la valeur de F est comparée à F_{MSY} et le niveau de biomasse de géniteurs B est comparé à la biomasse de géniteurs requise pour que la mortalité par pêche soit égale à F_{MSY} (B_{MSY}). Parfois, des points de référence déduits de méta-analyses sur plusieurs stocks sont employés comme approximations de B_{MSY}. Il est par exemple possible de comparer la biomasse de géniteur à la biomasse vierge ou biomasse non-exploitée (B_0). Les approximations de B_{MSY} couramment employées se situent en général entre $0.25B_0$ et $0.4B_0$ (Sainsbury, 2008 [237]; Punt et al., 2014 [215]). Outre ces points de référence permettant de détecter une surexploitation de croissance, un point de référence limite couramment utilisé pour définir le niveau de biomasse de géniteurs en dessous duquel le recrutement est affecté est $0.2B_0$ pour les stocks productifs (Myers et al., 1994 [191]) et $0.3B_0$ pour les stocks peu productifs (Musick, 1999 [190]; Mace et al., 2002 [172]).

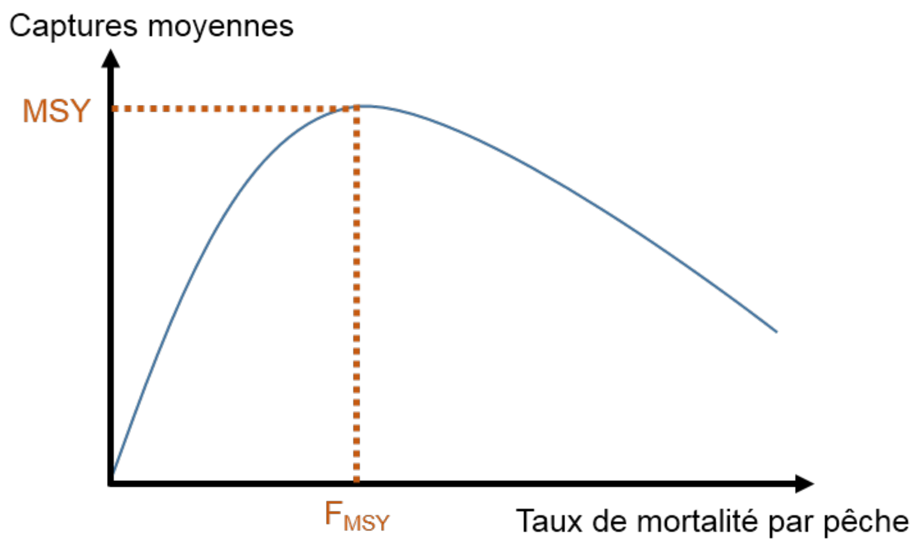

FIGURE 1.1 – Illustration du concept de MSY.

1.1.3. Les mesures de gestion

Diverses mesures de gestion existent pour gérer un stock. Les limitations peuvent porter sur les captures totales (TAC), sur les captures de certaines catégories comme les juvéniles (mise en place d'une taille minimale de capture) ou sur l'effort de pêche (fermetures spatiales ou temporelles de la pêche, contrôle du nombre de licences de pêche accordées). Les mesures techniques permettant de modifier la sélectivité en taille des engins de pêche (instauration de tailles minimales pour les mailles de filet) peuvent entraîner des bénéfices importants en termes économique et écologique (Gascuel et al., 2011 [98]).

Afin de déterminer des mesures adéquates, il est nécessaire de développer des modèles d'évaluation permettant de déterminer l'état des stocks et de prédire les niveaux de captures permettant une exploitation durable. Pour de nombreux stocks à forte valeur commerciale, la structure en âge des captures est estimée au moyen de coûteux échantillonnages, ce qui permet d'appliquer des modèles d'analyse de cohortes. Cependant, de nombreux stocks ne disposent pas d'une quantité suffisante de données pour mener une évaluation de stocks de type VPA. Il devient alors nécessaire de trouver des méthodes alternatives pour gérer ces stocks.

Aux Etats-Unis, l'amendement de 2006 de la loi Magnuson-Stevens (DOC et al., 2007 [71]) stipule qu'une limite annuelle de captures doit être attribuée à tous les stocks, à quelques rares exceptions près. Il est précisé que les mesures de gestion doivent s'appuyer sur les meilleures connaissances scientifiques disponibles. Des plans de reconstruction des stocks doivent être développés et mis en place, avec une attention particulière pour les stocks pauvres en données (Seagraves et Collins, 2012 [241]). Cet amendement, cité dans plusieurs publications et rapports sur les stocks pauvres en données (Carruthers et al., 2014 [40]; Berkson and Thorson, 2015 [19]; Geromont et Butterworth, 2015 [103]; Newman et al., 2015 [194]), semble avoir joué un rôle moteur dans la course à la production d'avis de gestion pour ces stocks.

En 2012, l'atelier WKLIFE (ICES, 2012d [140]) est créé par le CIEM pour répondre à la demande, initiée par les États et les ORGP, de fournir des avis quantitatifs pour l'ensemble des stocks concernés par la gestion communautaire des pêches. Ce groupe de travail a pour but de déterminer comment les traits d'histoire de vie peuvent être utilisés pour pallier au manque de données et ainsi fournir des avis de gestion pour les stocks dits « à données limitées ».

1.1.4. Description des stocks à données limitées

Donner une définition exacte des stocks à donnés limitées n'est pas une tâche aisée. Les puristes diront que tous les stocks de poissons méritent cette dénomination, car il est quasiment impossible de parvenir à récolter la quantité et la qualité de données nécessaires à une évaluation de stocks entièrement fiable. Il est fréquent que les données de captures et d'échantillonnage au début de l'exploitation d'un stock soient manquantes, et que les premières années de données disponibles soient de mauvaise qualité (imprécision des données déclarées, biais dans l'échantillonnage scientifique. . .). Deux autres problèmes récurrents sont la pêche illégale et la pêche récréative : il est souvent difficile d'estimer les quantités prélevées, ce qui contribue à augmenter l'incertitude associée aux niveaux totaux de captures.

En règle générale, on considère qu'un stock est « à données limitées » lorsque la quantité et/ou la qualité des données est insuffisante pour permettre une évaluation de stock standard de type VPA. Cependant, se limiter aux deux catégories « riche en données » et « à données limitées » pour classifier un stock est une vision simplifiée de la réalité. En vérité, il existe un dégradé de catégories dont la richesse en données diminue progressivement du stade « riche en données » jusqu'au stade « pauvre en données ». C'est pour mieux prendre en compte cette diversité et pour travailler dans un cadre plus structuré que l'atelier WKLIFE a mis au point une classification allant de 1 à 6 (Table 1.1) et permettant une meilleure description des stocks (ICES, 2012a [137]). La catégorie 1 correspond aux stocks les plus riches en données et la catégorie 6 aux stocks les plus pauvres en données. En parallèle, une classification des méthodes d'évaluation de stocks en fonction de la quantité et de la nature des données disponibles est mise au point par le SISAM (Strategic Initiative for Stock Assessment Methods) afin d'assister les groupes de travail et les ateliers du CIEM dans la sélection des méthodes les plus appropriées lors de l'évaluation d'un stock (ICES, 2012e [141]). L'objectif de l'atelier WKLIFE est de gagner en efficacité en proposant pour chaque catégorie des méthodes adaptées en mettant à profit toutes les données disponibles. Il s'avère que plus de 60% des stocks pour lesquels le CIEM fournit un avis annuel sont classifiés en catégorie 3-6.

TABLE 1.1 – Description des catégories définies dans la classification de ICES (2012a) [137]

Category	Description
1	Data-rich stocks with full analytical assessments and forecasts as well as stocks with quantitative assessments based on production models.
2	Stocks with quantitative assessments and forecasts which for a variety of reasons are merely indicative of trends in fishing mortality, recruitment, and biomass.
3	Stocks for which survey indices (or other indicators of stock size such as reliable fishery-dependant indices; e.g. lpue, cpue, and mean length in the catch) are available that provide reliable indications of trends in stock metrics such as mortality, recruitment, and biomass.
4	Stocks for which a reliable time-series of catch can be used to approximate MSY.
5	Data-poor stocks for which only landings data are available.
6	Stocks where landings are negligible compared with discards. It also includes stocks that are part of stock complexes and are primarily caught as bycatch species in other targeted fisheries. The development of indicators may be most appropriate to such stocks.

Deux principaux courants voire philosophies coexistent lorsqu'il s'agit d'évaluer un stock à données limitées. La première voie est de considérer que face à un manque criant de données, il est préférable d'employer des modèles peu gourmands en données. Des méthodes simples permettant de rapidement donner un avis sur l'état d'un stock sont alors privilégiées. La deuxième voie est de considérer qu'il faut utiliser les modèles habituellement employés pour l'évaluation des stocks riches en données, en les adaptant à ces cas où les données sont manquantes. Cette deuxième voie aura davantage vocation à définir un objectif de collecte de données.

Plutôt que de s'opposer, ces deux voies se complètent. Il arrive que les données disponibles soient dans un premier temps si limitées que seuls des modèles simples basés sur des hypothèses fortes puissent être appliqués. En parallèle, si davantage de moyens sont alloués à l'évaluation et à la gestion du stock, il devient possible de collecter de nouvelles données et/ou de consacrer plus de moyens humains pour adapter des modèles standards à une situation de données limitées. Par ailleurs, il est essentiel de comparer les résultats de différentes méthodes afin de détecter les problèmes pouvant émaner par exemple d'hypothèses non compatibles avec le stock étudié. La quantification la plus précise possible des incertitudes associées aux résultats est également d'une grande importance, et les statistiques Bayésiennes vont alors devenir un précieux atout.

1.2. Emploi de l'approche Bayésienne en halieutique

1.2.1. Présentation du principe d'inférence Bayésienne et exemples d'utilisation

L'approche Bayésienne découle du théorème de Bayes, dont la découverte est attribuée au révérend Thomas Bayes. Après sa mort, son article intitulé « An Essay towards solving a Problem in the Doctrine of Chance » a été publié par son ami Richard Price dans « Philosophical Transactions of the Royal Society » en 1763. Le mathématicien français Laplace a par la suite publié les mêmes conclusions 11 ans plus tard, a priori sans savoir que la découverte n'était pas une nouveauté. Les travaux de Bayes montrent comment la probabilité inverse ($P(B|A)$) peut être utilisée pour calculer la probabilité d'évènements antécédents ($P(A)$) à partir de l'occurrence d'évènements suivants ($P(B)$) (Bolstad et Curran, 2016 [24]). En d'autres termes, l'idée est de partir des effets observés pour en comprendre les causes.

Le plus simple pour appréhender les statistiques Bayésiennes est peut-être de se dire qu'on cherche à faire fonctionner un modèle comme fonctionnerait notre pensée. Si nous lisons dans un magazine, pour la première fois de notre vie, que dormir sur le côté gauche permet un meilleur sommeil, il est peu probable que nous considérions cette information comme étant la vérité absolue. Nous allons peut-être tester cela, ou faire davantage de recherches sur le sujet. Au fur et à mesure que nous accumulerons des preuves confirmant ou infirmant l'information lue dans le magazine, nous mettrons à jour notre degré de certitude. Si le magazine est une revue scientifique, alors notre esprit sera davantage influencé, nous accorderons plus de crédibilité à l'information a priori. Ce serait l'équivalent d'un prior informatif dans un modèle Bayésien. Notre degré de certitude final, après avoir fait des tests, serait l'équivalent du posterior ayant été mis à jour par les données.

Contrairement aux statistiques fréquentistes, l'approche Bayésienne permet l'emploi de distributions a priori sur les paramètres estimés par le modèle. Les sources d'informations peuvent êtres variées, allant d'estimations trouvées dans la littérature à des connaissances d'experts. Si aucune information n'est connue a priori, on pourra utiliser une distribution a priori non informative, par exemple une loi uniforme avec des bornes larges. Si au contraire des informations existent, on peut opter pour une distribution a priori informative. L'information donnée a priori au modèle sera ensuite confrontée aux données observées et la distribution de probabilité sera mise à jour. Pour la suite de ce manuscrit, nous nommerons « prior » la distribution de probabilité a priori. Si le nombre de données observées est faible et que le prior est informatif, il est probable que le posterior (distribution de probabilité a posteriori) soit grandement influencé par le prior. En revanche si de nombreuses données sont observées, l'influence du prior sera faible et le résultat final devrait alors se rapprocher de ce qui serait obtenu par les statistiques fréquentistes classiques.

Les statistiques Bayésiennes permettent également une quantification et une propagation dans le modèle des différentes sources d'incertitudes. On obtient alors une quantification exhaustive de l'incertitude totale associée aux sorties du modèle. Une idée sous-jacente de l'approche Bayésienne est qu'une probabilité est subjective et qu'il n'existe donc pas de valeur de probabilité qui puisse être considérée comme étant la « vraie » valeur. La validité d'un modèle étant décrite en termes probabilistes, il n'existe donc pas non plus de modèle « vrai » ou parfait (Dezfuli et al., 2009 [66]).

Jusqu'au milieu des années 80, les statistiques Bayésiennes étaient encore très peu utilisées car la résolution analytique de certaines équations pouvait s'avérer compliquée. Le développement de l'utilisation des méthodes basées sur des simulations a grandement simplifié ce problème (Rossi et al., 2005 [234]). Les méthodes de Monte-Carlo par chaînes de Markov (MCMC) en sont un exemple. Le principe est de générer de manière aléatoire des vecteurs suivant une distribution de probabilité donnée. Un grand nombre de tirages est effectué, ce qui permet d'après la loi des grands nombres de calculer une approximation de la probabilité recherchée (Ando, 2010 [9]).

1.2.2. Intérêt de l'inférence Bayésienne dans un contexte de données limitées

L'approche Bayésienne est aujourd'hui utilisée dans de nombreux domaines. En économie, elle permet d'évaluer les risques pris lors d'une opération financière. Dans le domaine du marketing, cette approche peut être employée afin de modéliser la réaction des consommateurs face à différents produits. Le but est alors de déterminer les caractéristiques dont doit être doté un produit afin d'optimiser le profit. Les statistiques Bayésiennes s'avèrent particulièrement utiles dans un contexte de données limitées, et lorsque les informations disponibles proviennent de différentes sources (Rossi et al., 2005 [234]). Les méthodes Bayésiennes prennent également une place de plus en plus importante en médecine grâce à leurs performances en cas de données manquantes et leur capacité à intégrer des sources de données variées. Leur utilisation a entraîné l'émergence de nouvelles méthodes d'analyse de données biomédicales, en particulier dans le domaine de l'apprentissage automatique (Lee et Abbott, 2003 [164]; Lucas, 2004 [168]).

Dans le domaine de l'halieutique, il est rare qu'un scientifique n'ait absolument aucune idée sur la distribution des paramètres au début du processus d'évaluation de stock. Certaines limites biologiques sont intuitives, et les connaissances existantes sur les autres pêcheries permettent de se forger une idée sur les bornes approximatives de certains paramètres. Un exemple simple est que la croissance ne peut pas être négative, ce qui constitue en soi une information a priori. Par conséquent, le cadre Bayésien est tout indiqué pour le domaine des sciences de la pêche (Hilborn et Walters, 1992 [125]).

Les sources d'incertitude associées aux résultats des modèles d'évaluation de stocks sont multiples et peuvent se classer en 4 catégories. Une première cause est le choix de structure du modèle : le choix d'un modèle mal adapté à la dynamique de population du stock peut entraîner un biais dans les résultats. Deux autres sources d'incertitude fréquemment évoquées sont l'erreur d'observation pouvant provenir d'erreurs lors de l'échantillonnage de données, et l'erreur de processus liée au bruit associé aux équations de processus du modèle. Une dernière catégorie d'incertitude est l'erreur d'implémentation qui reflète l'inadéquation des limites de capture et d'effort avec les réalités politiques ou économiques (Hilborn 1997 [123], Butterworth et Punt 1999 [34], Punt et Donovan 2007 [214]). Si la quantification des incertitudes est d'une grande importance en évaluation de stock, elle l'est d'autant plus pour les stocks à données limitées dont les incertitudes sont en général plus grandes. On voit alors l'intérêt d'utiliser le cadre Bayésien, qui permet de propager les différentes sources d'incertitude dans le modèle afin d'estimer avec précision les incertitudes totales associées aux estimations finales.

Une autre propriété particulièrement intéressante de l'approche Bayésienne est le cas des modèles hiérarchiques qui permettent de transférer de l'information entre différentes unités statistiques, par exemple entre différents stocks de poissons ou différentes années (Rivot, 2003 [221]; Parent et Rivot, 2013 [196]; Rivot, 2013 [222]), ce qui constitue une direction très prometteuse pour l'évaluation des stocks à données limitées (Chrysafi et Kuparinen, 2016 [51]). Les travaux de Punt et al. (2011) [217] illustrent bien l'application de ce qu'ils ont nommé l'approche « Robin Hood » pour reprendre l'histoire de Robin des bois. Le principe est de construire un modèle Bayésien incluant plusieurs stocks de poissons dont les degrés de richesse en données varient. L'information contenue dans les stocks riches en données sera « volée » et redistribuée aux stocks pauvres en données. Plus concrètement, plusieurs stocks d'une même espèce peuvent avoir des traits d'histoire de vie similaires (âge à maturité, croissance, relation taille-poids. . .) ou liés par une relation incluant la température. Des stocks d'espèces différentes pêchés par les mêmes flottilles peuvent être soumis à une même pression de pêche et peuvent avoir des variations de recrutement similaires dues à des modifications des conditions environnementales partagées par ces stocks. Le modèle hiérarchique permet de mettre à profit toutes ces informations afin d'améliorer l'évaluation des stocks.

1.3. Application de méthodes d'évaluation de stocks à données limitées sur deux cas d'étude

Au cours de cette étude, nous allons nous intéresser à deux stocks à données limitées : la seiche *Sepia officinalis* Linné, 1758 de Manche (Fig. 1.2) et le lieu jaune *Pollachius pollachius* Linné, 1758 de Mer Celtique (Fig. 1.3). Le choix de ces deux cas d'étude permet d'explorer à la fois les méthodes d'évaluation de stock adaptées à une espèce de la famille des gadidés à durée de vie relativement longue (le lieu jaune) et les méthodes plus appropriées pour une espèce à cycle de vie court (la seiche). Le stock de lieu jaune de Mer Celtique a été classifié en catégorie 4.1.2 par l'atelier du CIEM WKLIFE (ICES, 2012d [140]). En revanche, le stock de seiche de Manche n'étant pas sur la liste des stocks à gestion communautaire, il n'a pas été assimilé à une catégorie. Des données de captures et des indices d'abondance étant disponibles pour ce stock, il serait possible de l'assimiler à la catégorie 3 (Table 1.1).

1.3.1. Présentation de la seiche de Manche

Parmi les cas d'étude explorés par le premier atelier du WKLIFE (ICES, 2012d [140]), seul l'anchois *Engraulis encrasicolus* Linné, 1758 présentait un cycle de vie court d'environ trois ans (ICES, 2012c [139]). Il semblait donc intéressant de se pencher sur le cas des stocks caractérisés à la fois par des données limitées et par un cycle de vie court. La seiche *Sepia officinalis* Linné, 1758 (cuttlefish en anglais) est un céphalopode sémelpare à vie courte et croissance rapide (Guerra, 2006 [113]; Guerra et al., 2015 [114]). Dans la Manche, la durée de son cycle de vie est estimée à 2 ans. Les œufs éclosent près des côtes en été et les jeunes seiches migrent au large vers les zones d'hivernage au centre de la Manche Ouest. Le recrutement peut être très fluctuant d'une année à l'autre. Quelques mois plus tard, une migration a lieu vers les côtes au printemps, puis de nouveau une migration au large en automne pour les seiches âgées d'un an. Les individus matures entament une dernière migration vers les côtes au printemps de leur deuxième année afin de se reproduire et meurent quelques mois plus tard (Boucaud-Camou et Boismery, 1991 [25]). Des travaux récents ont montré que sa taille de maturité sexuelle aurait diminué et serait à présent de 13 cm en moyenne pour les femelles et de 12.28 cm pour les mâles (Gras et al., 2016 [111]). Cette modification des traits d'histoire de vie pourrait être due au réchauffement des eaux, et souligne la variabilité de la taille de maturité pour cette espèce. La croissance montre également une forte variabilité saisonnière et inter-annuelle. La croissance peut varier en fonction de la zone géographique, potentiellement à cause d'une dépendance aux conditions environnementales locales (Challier et al., 2005 [44]).

Toutes les seiches de Manche sont considérées comme appartenant au même stock (Denis et Robin, 2001 [65]). Le stock de seiche de Manche est une ressource partagée entre la France, le Royaume-Uni et la Hollande, et entre la pêche côtière et hauturière. La seiche est pêchée au casier et au chalut le long des côtes au printemps lorsque les adultes âgés de deux ans migrent vers les eaux peu profondes pour se reproduire, et à la fin de l'été avant que les individus immatures ne migrent vers les zones d'hivernage plus profondes. Elle est également pêchée au large par une flottille de chalutiers hauturiers en hiver.

FIGURE 1.2 – Photo de seiche (*Sepia officinalis* Linné, 1758).

Pour la seiche de Manche, les campagnes scientifiques BTS et CGFS menées respectivement par le CEFAS et l'Ifremer permettent de calculer deux indices d'abondance indépendants. Pour ce stock, la limitation dans les données provient à la fois de la difficulté de lire les statolithes et de la particularité du cycle de vie court de cette espèce. Le lecture des statolithes ne permet une détermination de l'âge qu'au cours des huit premiers mois de la vie de la seiche (Bettencourt et Guerra, 2001 [20]). En outre, bien qu'un modèle structuré en âge à pas de temps mensuel ait été développé pour une application ponctuelle, il ne peut pas être appliqué en routine (Royer et al., 2006 [236]). De nouvelles méthodes adaptées aux espèces à cycle de vie court doivent donc être privilégiées.

Le stock de seiche n'est pas soumis à des mesures de gestion s'appliquant à l'ensemble du stock. Les mesures sont locales, et consistent souvent en une délimitation des zones où les engins de pêche passifs (casiers, trémails) et actifs (chaluts) peuvent être utilisés.

La pêche artisanale de seiche est particulièrement développée en Normandie, où certaines mesures de gestion spécifiques ont été mises en place, telles que des licences de pêche pour la seiche. Dans les eaux françaises, le chalutage est en général interdit dans la zone des 3 milles. Des dérogations spécifiques sont en revanche régulièrement accordées pour la pêche de la seiche, sous réserve que la maille minimale soit de 80 mm pour le cul de chalut et que les captures accessoires ne dépassent pas 20% des captures totales.

1.3.2. Présentation du lieu jaune de Mer Celtique

Le lieu jaune *Pollachius pollachius* Linné, 1758 (pollack en anglais) est un gadidé dont la taille maximale répertoriée par la FAO et Fishbase [1] est de 130 cm (Cohen et al., 1990 [54]) et le poids maximum de 18.1 kg (IGFA, 2001 [152]). L'âge maximal répertorié par la FAO et Fishbase est de 8 ans (Cohen et al., 1990 [54]), cependant le lieu jaune peut vivre jusqu'à 15 ans d'après Pethon (1998) [202] et Suquet (2001) [248]. Les juvéniles se trouvent principalement dans des eaux peu profondes, tandis que les adultes migrent vers des zones dont la profondeur est comprise entre 40 et 100 mètres (Pawson, 1995 [198]). La reproduction a lieu entre février et mai des eaux Ibériques à la Mer Celtique, et peut s'étendre jusqu'en juin pour le stock de Norvège (Moreau, 1964 [189]). Au cours de cette période, les individus matures forment des groupes de forte densité (Suquet, 2001 [248]). La taille de première maturité sexuelle est estimée comme étant supérieure à 35 cm en Norvège par Heino et al. (2012) [121], cependant aucune valeur précise n'est indiquée car les stades de maturité n'avaient été déterminés que macroscopiquement pour cette étude. L'âge de première maturité sexuelle est estimée autour de 3 ans pour un poids de 1.5 kg (Suquet, 2001 [248]). Des études récentes basées sur des analyses microscopiques des gonades ont montré que la taille de première maturité sexuelle du lieu jaune des eaux Ibériques était significativement différente entre les femelles (47.5 cm) et les males (36.1 cm) (Alonso-Fernández et al., 2013 [8]).

Jusqu'à ce jour, même si l'identité du stock n'est pas clairement définie (ICES, 2014a [143]), le lieu jaune des zones VI et VII constitue une unité de gestion (ICES, 2016a [147]). Charrier et al. (2006) [46] ont montré qu'il existait une différentiation génétique significative entre les individus originaires de la Manche Ouest et les individus provenant du Golfe de Gascogne. Mais cette différentiation étant faible, des études complémentaires seraient nécessaires pour confirmer les résultats. Les captures proviennent principalement des chalutiers et des fileyeurs, et les plus fortes concentrations se retrouvent dans la Manche Ouest (en zone CIEM VIIe), avec environ 60% des captures provenant de cette zone (ICES, 2016a [147]). Les plus forts taux de capture se produisent pendant la période de reproduction car les agrégations rendent les individus matures plus vulnérables à la pêche (Suquet, 2001 [248]). A cause de sa préférence pour les épaves et les fonds rocheux, le lieu jaune est parfois difficile à capturer au chalut en dehors de la période de reproduction.

Les raisons de la dénomination de « stock à données limitées » diffèrent quelque peu pour les deux stocks. Contrairement au stock de seiche, le stock de lieu jaune ne dispose pas de série d'indices d'abondance issue de campagne scientifique exploitable pour son évaluation. La campagne scientifique IBTS est une campagne européenne d'évaluation des stocks de poissons pour la partie sud de la Mer du Nord et la Manche Est. Elle est réalisée tous les ans par l'Ifremer depuis 1976 vers le mois de janvier dans le but de déterminer des indices biologiques sur différentes espèces. Bien que cette campagne capture occasionnellement du lieu jaune, le nombre d'individus pêchés est insuffisant pour calculer un indice d'abondance fiable.

FIGURE 1.3 – Photo de lieu jaune (*Pollachius pollachius* Linné, 1758).

Le lieu jaune des zones VI et VII est exploité principalement par la France, le Royaume Uni et l'Irlande. La méthode d'évaluation de stock actuellement employée par le groupe de travail européen WGCSE est la méthode de capture moyenne corrigée par la déplétion (DCAC pour "Depletion Corrected Average Catch") et un TAC est en place depuis 2000. Comme souligné par le groupe de travail WGNEW (ICES, 2014a [143]), les statistiques de capture de lieu jaune pour les zones CIEM VI et VII sont considérées comme étant de bonne qualité, mais une collecte de données plus intensive serait nécessaire afin de mieux comprendre la structure du stock.

En France, les captures de lieu jaune par la pêche récréative ont été estimées à 3500 tonnes (+/- 2500) lors d'une enquête téléphonique menée en 2006-2008 (ICES, 2010 [136]). Une étude plus récente menée en 2011-2013 par (Levrel et al., 2013 [165]) a estimé ce niveau de capture annuel à 3301 tonnes, dont 2274 tonnes seraient conservées. La taille moyenne des individus capturés serait de 47.5 cm et la taille moyenne des individus conservés de 50.5 cm, ce qui est bien au-dessus de la taille minimale légale de capture. Le manque de données par zones sur les traits d'histoire de vie du lieu jaune a été souligné par le groupe de travail WGNEW (ICES, 2014a [143]). D'après leur rapport, la méthode du DCAC pourrait être améliorée en incluant les captures significatives de la pêche récréative. Ils recommandent de collecter des données sur la pêche récréative afin d'améliorer la gestion du stock.

La taille minimale de débarquement de lieu jaune est de 30 cm pour les États membres européens. Pour la zone VI, le TAC est passé de 11 000 t en 2000 à 397 t en 2011-2013. Pour la zone VII, le TAC est passé de 17 000 t en 2000-2005 à 13 495 t en 2011-2013. Les données de débarquements totaux montrent une tendance décroissante entre 1990 et 2009, mais semblent se stabiliser autour de 4 000/4 500 t pour les dernières années.

1.3.3. Problématique de la thèse et plan adopté

L'objectif initial majeur de cette thèse était de développer des modèles d'évaluation adaptés aux deux cas d'étude de stocks à données limitées : la seiche de Manche et le lieu jaune de Mer Celtique. Plusieurs questions ont émergé au cours des trois années d'étude. Comment choisir les bonnes méthodes pour évaluer un stock à données limitées ? Quel bénéfice l'utilisation d'un cadre Bayésien apporte-t-il dans un cas de données limitées ? Comment quantifier au mieux les incertitudes associées aux résultats des modèles ? Peut-on déterminer une hiérarchie dans la nature des nouvelles données à collecter ?

Afin de répondre à ces questions, une revue des méthodes d'évaluation de stocks à données limitées est proposée dans le deuxième chapitre. Le chapitre qui suit est axé sur les méthodes d'évaluation adaptées à un stock à données limitées et à cycle de vie court. Ce troisième chapitre sur le stock de seiche est articulé en deux parties. La première partie présente une version simple d'un modèle Bayésien de biomasse à deux stades, dont les résultats sont comparés à ceux d'un modèle de biomasse à deux stades construit avec les statistiques fréquentistes. Une comparaison avec les sorties d'un modèle de déplétion généralisée est également présentée. Dans la seconde partie de ce troisième chapitre, une deuxième version plus élaborée du modèle Bayésien de biomasse à deux stades est présentée.

Le quatrième chapitre s'intéresse au deuxième cas d'étude, le stock de lieu jaune, et s'articule également en deux parties. La première partie présente la construction d'un modèle Stock Synthesis pour le stock de lieu jaune, dans le but d'évaluer l'état du stock. Les résultats sont comparés aux sorties d'un modèle LB-SPR (voir le chapitre 2 pour la description de cette approche). La deuxième partie privilégie un objectif de gestion du stock. Les résultats de nombreux modèles simples sont comparés, et trois modèles Stock Synthesis déclinés en différents niveaux de richesse en données sont testés. Pour ces deux parties du quatrième chapitre, plusieurs analyses de sensibilité sont menées et permettent de déterminer l'importance relative de la précision des différents types de données. Le cinquième chapitre propose une mise à jour de certains paramètres biologiques du stock de lieu jaune à travers l'utilisation d'un cadre hiérarchique Bayésien. Enfin, le sixième chapitre consiste en une discussion générale sur les principaux résultats de cette thèse et propose une ouverture sur l'intérêt de la collaboration entre les scientifiques et les pêcheurs pour améliorer l'évaluation des stocks à données limitées.

CHAPITRE 2

CHAPITRE 2 : Revue des méthodes existantes pour l'évaluation de stocks à données limitées

"*Not everything that can be counted counts, and not everything that counts can be counted.*"

William Bruce Cameron (1963), from **Informal Sociology: A Casual Introduction to Sociological Thinking.**

Présentation de l'article "General guidelines for providing MSY advice for data-limited stocks"

Cet article propose une méthodologie générale à adopter pour mener une évaluation des stocks à données limitées et établir des règles de gestion au MSY. Plusieurs méthodes d'évaluation de stocks à données limitées ont été développées et testées au cours des dernières années. Sans être totalement exhaustif, cet article reprend les principales méthodes existantes et présente les hypothèses qui y sont associées. Les données nécessaires à l'application des modèles et les limites de ces derniers sont précisées. Des exemples d'application de ces modèles à différents stocks sont également listés.

Avant de pouvoir déterminer les modèles pouvant être utilisés, la première étape est de définir les objectifs de gestion pour le stock étudié et de rassembler l'ensemble des données disponibles. Une fois cette étape complétée, il est possible d'établir une première sélection de modèles adaptés au cycle de vie de l'espèce et aux données disponibles.

Commençons par les modèles adaptés aux espèces à cycle de vie moyen ou long. Lorsqu'il n'existe que des données de captures, le modèle DCAC (≪ Depletion Corrected Average Catch ≫) est en général utilisé. Il est cependant déconseillé d'appliquer cette méthode lorsque la mortalité naturelle est supérieure à 0.2 années^{-1}. Lorsque des informations sur les traits d'histoire de vie s'ajoutent, les modèles DB-SRA (≪ Depletion-Based Stock Reduction Analysis ≫), CMSY (≪ Catch-MSY ≫) et SSS (≪ Simple Stock Synthesis ≫) peuvent être appliqués. Tout comme le modèle DCAC, ces modèles requièrent des hypothèses sur l'état du stock a priori, sous différentes formes. Lorsque les données de captures sont inexistantes ou peu fiables, mais que des données de fréquences de tailles sont disponibles, les méthodes LRPs (≪ Length-Reference Points ≫), LB-SPR (≪ Length-Based Potential Ratio ≫) et LCA (≪ Length Cohort Analysis ≫) peuvent être un choix judicieux.

L'idée sous-jacente est que les fréquences de tailles sont un indicateur de l'état d'un stock. La composition en individus de grande taille peut par exemple indiquer si un stock est surexploité. Enfin, lorsqu'à la fois des données de captures, des informations sur les traits d'histoire de vie et des indices d'abondance sont disponibles, les modèles Fla4a (≪ Stock Assessment For All ≫), SS (≪ Stock Synthesis ≫) et SPiCT (≪ Surplus Production model in Continuous Time ≫) peuvent être utilisés.

Lorsque l'espèce du stock considéré a un cycle de vie court, les modèles habituels risquent de ne pas être adaptés. Cet article présente trois méthodes possibles dans les cas de cycle de vie court. Si des données de captures et d'effort sont disponibles, le modèle MAGD (≪ Multi-Annual Generalized Depletion Model ≫) présente l'avantage de pouvoir intégrer des données à haute fréquence : mois, semaine, voire jour. Cette caractéristique peut s'avérer très utile pour des stocks où la gestion peut être rapidement modifiée et adaptée. Une deuxième approche explorée est le modèle de biomasse à deux stades, un cas particulier des modèles de surplus de production qui nécessite des données de captures et une série d'indices d'abondance. Ce type de modèle est particulièrement intéressant à employer dans un cadre Bayésien afin de mettre à profit toutes les informations disponibles. Enfin, les modèles de type Stock Synthesis présentent une grande capacité d'adaptation et peuvent donc être utilisés pour les stocks à cycle de vie court si des données sur les traits d'histoire de vie s'ajoutent aux captures et aux indices d'abondance.

Une fois qu'une liste de modèles a été sélectionnée, il est important d'une part de comparer les résultats de plusieurs modèles, d'autre part de tester la sensibilité des résultats aux hypothèses des modèles. Des hypothèses sont souvent faites quant à des valeurs de mortalité naturelle, ou lorsqu'une estimation de l'état du stock est donnée a priori. Des hypothèses sont également formulées sur les données de capture. Ainsi, lorsqu'aucune information n'est disponible sur les niveaux de prélèvements par la pêche récréative, il arrive souvent qu'ils soient considérés comme nuls. Or ceci entraîne un risque de biais supplémentaire qui s'ajoute aux résultats.

La dernière étape est la mise en place de recommandations de gestion. Afin de prendre une décision au regard de l'ensemble des résultats, il peut être pratique d'appliquer ce qu'on appelle en anglais ≪ model averaging ≫. Le principe est de synthétiser l'ensemble des résultats des différentes analyses de sensibilité en prenant en compte la totalité des incertitudes. Lorsque c'est possible, il est également utile d'évaluer et de hiérarchiser les données additionnelles utiles à l'amélioration de l'évaluation du stock.

General guidelines for providing MSY advice for data-limited stocks

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Abstract

After the severe biomass declines experienced by many fish stocks, fishery scientists have concentrated their work on a set of large stocks that represented the bulk of both landings and fishermen's income. Financial and human resources devoted to those species enabled to carry out extensive data collection programs. Stock assessment and management were developed in a "data-rich"context. The depletion of major stocks then led to a diversification of fished resources, but not all stocks could benefit from the same data collection efforts. Thus the scientific community was urged to develop alternative stock assessment methods for "data-poor"or "data-limited"stocks. The workshop WKLIFE was created by the International Council for the Exploration of the Sea (ICES) to work specifically on this new challenge. Several methods have already been developed to assess data-limited fisheries. Simulation testing and application on case studies have helped improve knowledge on the emerging methods. Nevertheless, it has become difficult to choose the right methods among the wide range of models developed. One of the objectives of WKLIFE is to provide MSY advice for several stocks using a standardized methodology. In this work, we propose guidelines to provide MSY advice for data-limited stocks.

Keywords: data-limited method, stock assessment, MSY advice, maximum sustainable yield, fisheries management

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Ce chapitre fait l'objet d'un article scientifique qui a été soumis dans une revue scientifique à comité de lecture.

Résumé

Suite au drastique déclin de biomasse dont de nombreux stocks de poisson ont été victimes, les scientifiques spécialisés en halieutique ont concentré leurs efforts sur un ensemble de stocks importants en matière de quantités débarquées et de valeur commerciale. Les moyens humains et financiers alloués à ces espèces ont permis la mise en place de programmes de collecte de données de grande ampleur. Les évaluations de stock et la gestion ont été développées dans un contexte « riche en données ». L'effondrement de stocks majeurs a par la suite entraîné une diversification des ressources exploitées, mais tous les stocks ne pouvaient pas bénéficier des mêmes efforts de collecte de données. La communauté scientifique a donc été poussée à développer des méthodes alternatives d'évaluation de stocks pour les stocks « pauvres en données » ou « à données limitées ». L'atelier WKLIFE a été créé par le Conseil International pour l'Exploration de la Mer (CIEM) afin de se pencher sur ce nouveau défi. Plusieurs méthodes ont d'ores et déjà été développées pour évaluer les pêcheries à données limitées. Les études sur des données simulées et sur des cas d'études réels ont permis d'améliorer les connaissances sur les méthodes émergentes. Néanmoins, il est devenu difficile de choisir les méthodes appropriées parmi le large panel de modèles développés. L'un des objectifs de l'atelier WKLIFE est de fournir une approximation de MSY pour plusieurs stocks en utilisant une méthodologie standardisée. Ce travail propose des lignes directrices afin de fournir une approximation de MSY pour les stocks à données limitées.

Mots clés : méthode pour données limitées, évaluation de stock, avis au MSY, rendement maximum durable, gestion des pêches

2.1. Introduction

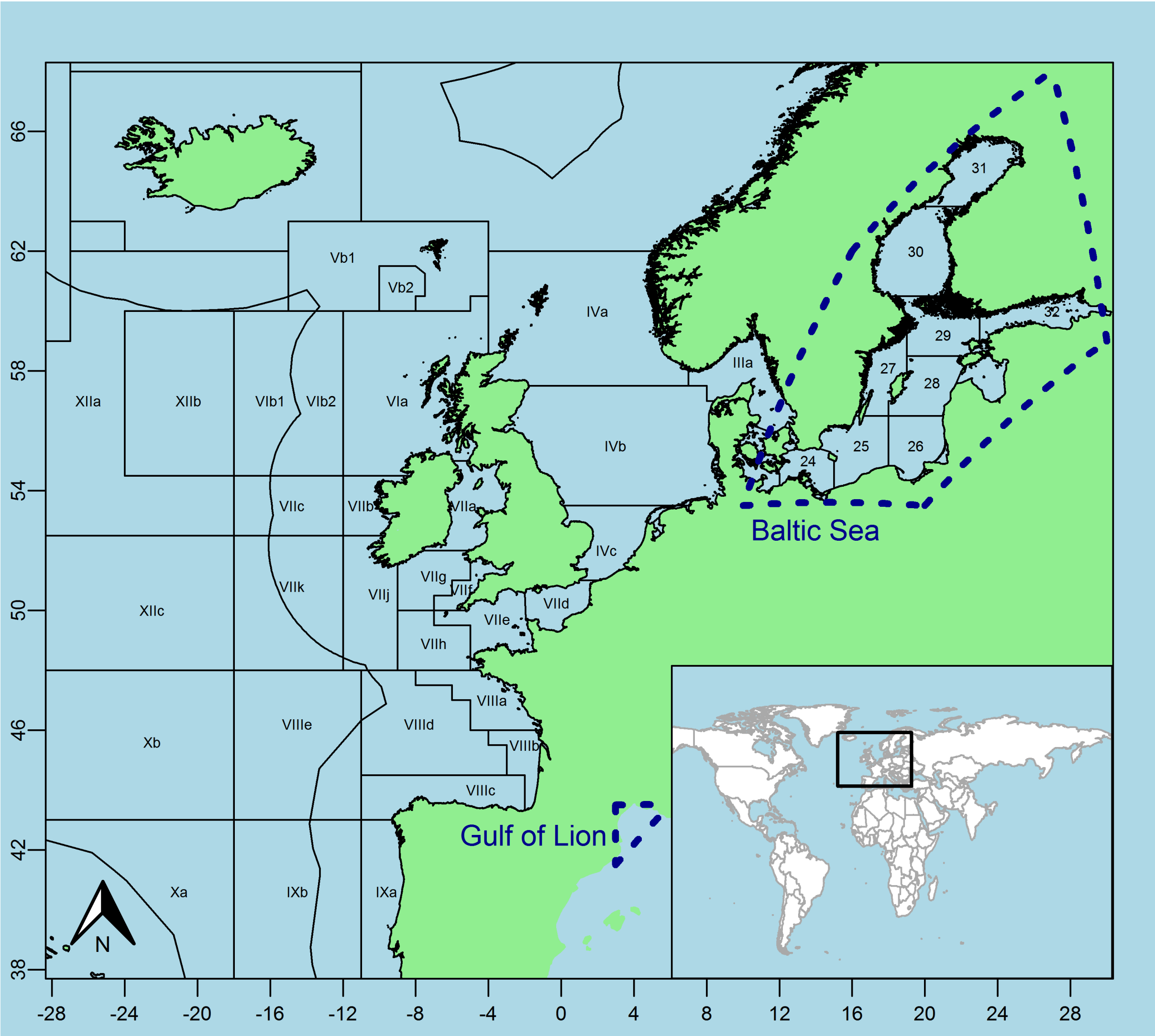

FIGURE 2.1 – Map of ICES Subareas.

The field of fisheries stock assessment science is subject to conventional economic-driven laws: low-value fisheries do not benefit from the same amount of funding nor the same working hours as their high-value counterparts (Bentley and Stokes, 2009 [18]). "Data-poor" and "data-limited" are the terms commonly used for the fish stocks where the limited amount or low quality of available data hinders the application of standard quantitative stock assessment models (Smith et al., 2009a [244]; Honey et al., 2010 [129]). Yet providing management advice is a must even for data-limited fisheries (UN, 1995 [257]). With the over-exploitation of major commercial species, resulting in a decline of their abundance, a diversification of exploited resources has occurred in some parts of the world. According to Costello et al. (2012) [61], only 20% of global catches would come from formally assessed fisheries.

Besides the small amount and low quality of the data, the particularities of a species' life history can be a limitation for conducting a standard stock assessment. Cephalopods, which experience short life span and highly variable growth and recruitment (Boyle and Boletzky, 1996 [27]; Boyle and Rodhouse, 2005 [26]; Challier, 2005 [43]; Domingues et al., 2006 [73]), are an example of such species. Despite the worldwide increase in cephalopod catches (Arkhipkin et al., 2015 [11]), there is a lack of routine stock assessment methods for these short-lived species (Rodhouse et al., 2014 [229]). The difficulty of age and growth determination is an additional obstacle to achieving this goal (Lipinski et al., 1998 [166]; Jackson et al., 2000 [153]; Bettencourt and Guerra, 2001 [20]).

There is a trade-off between time- and money-consuming data collection and use of simpler but possibly less accurate models. When increasing the time and effort allocated to data collection is considered an unrealistic objective or when some data are not available, typical data-rich stock assessment methods might not be appropriate. Alternative methods requiring less data and time are thus considered. However, commercial fisheries are not static systems and the role of stock assessment changes during the development of fisheries (Hilborn and Walters, 1992 [125]). Uncertainty in the results can be decreased by gradually incorporating additional data in the model. The available data, the relevant assessment methods and even management objectives change through the monitoring process, possibly leading to the application of a full age-based analytical model.

One of the difficulties and requirement in stock assessment science is to correctly describe the uncertainty associated with the results. The need to set assumptions is particularly strong for data-limited stocks because of the lack of information. We recommend that the sensitivity of the results to initial assumptions be tested to better estimate total uncertainty. Identifying the parameters to which results are the most sensitive also allows a better targeting of the additional data required.

A Management Strategy Evaluation (MSE) should also be applied when possible in order to gauge the performance of data-limited methods and associated harvest control rules. The MSE approach is the use of simulation to identify trade-offs relative to management objectives, and evaluate the consequences of alternative strategies or decision options (Smith, 1994 [242]; Smith et al., 1999 [243]). The recent development of new tools (e.g., Carruthers et al., 2014 [40]) has facilitated the implementation of MSE for data-limited stocks.

In this work, we propose a step by step approach to provide MSY proxies for data-limited stocks. We focus on the perspective of stocks evaluated by the International Council for the Exploration of the Sea (ICES). In Europe, the workshop WKLIFE (ICES, 2012d [140]) deals specifically with data-limited stocks and aims at improving statistical methods to assess these stocks, as well as harvest control rules allowing stocks' sustainability. Some of our conclusions are based on the work performed during the various meetings of WKLIFE. We do not intend to give an exhaustive overview of existing data-limited stock assessment methods, but rather a synthesis of selected promising methods which have already been tested through simulation process or case studies.

2.2. First step: identification of management objectives and synthesis of all available data

The choice of stock assessment model should be driven by two considerations: data availability, and management objectives. Before conducting a stock assessment, realistic short-term and long-term management objectives must indeed be defined according to the fishery specificity and the available workforce. For example, the main objective can be to minimize the probability of the stock to be over-fished, or to maximize the catch, in a limited amount of time. It is then important to identify available data and information about the biology of the studied species which are relevant to help choosing the adapted model. Reliability of the data must also be discussed.

To help experts conduct stock assessment for data-limited stocks, the workshop WKLIFE has created categories according to the type and quality of available information for the stock. Stocks in category 1 have a complete set of data (catch-at-age, including discards, and a survey index-at-age). A full analytical assessment is therefore conducted, with application of the ICES Maximum Sustainable Yield (MSY) rule. Stocks in category 2 have incomplete catch-at-age data (discards are omitted) and a complete survey index-at-age. F_{MSY} is replaced by $F_{0.1}$, and a change limit of +/- 20% is applied. Category 3 stocks have survey-based assessments which indicate trends, category 4 stocks have reliable catch data, category 5 stocks are data-poor stocks and category 6 stocks are negligible landings stocks and stocks caught in minor amounts as bycatch (ICES, 2012d [140]). Stocks in categories 3 to 6 can be considered data-limited.

While this classification is useful to better describe and classify the variety of stocks managed by ICES, there are often unused available data within each category. Each country participating in a working group delivers data according to the official data call sent by ICES, but required data usually depend on the model used for the assessment of the stock. The consequence is that not all existing data are made available for the working group. Partial length composition data can, for example, be used in an adapted stock assessment framework. In addition to the list of mandatory data described in the official data call, expert group members should be encouraged to bring and make use of all available data and associated information on uncertainty.

2.3. Second step: selection of adapted models

The next step is to select a range of models adapted to the management objectives, the available data, and the specificity of the stock's biology. Fig. 2.2 summarizes the methods presented in this work, grouped by the type of available data.

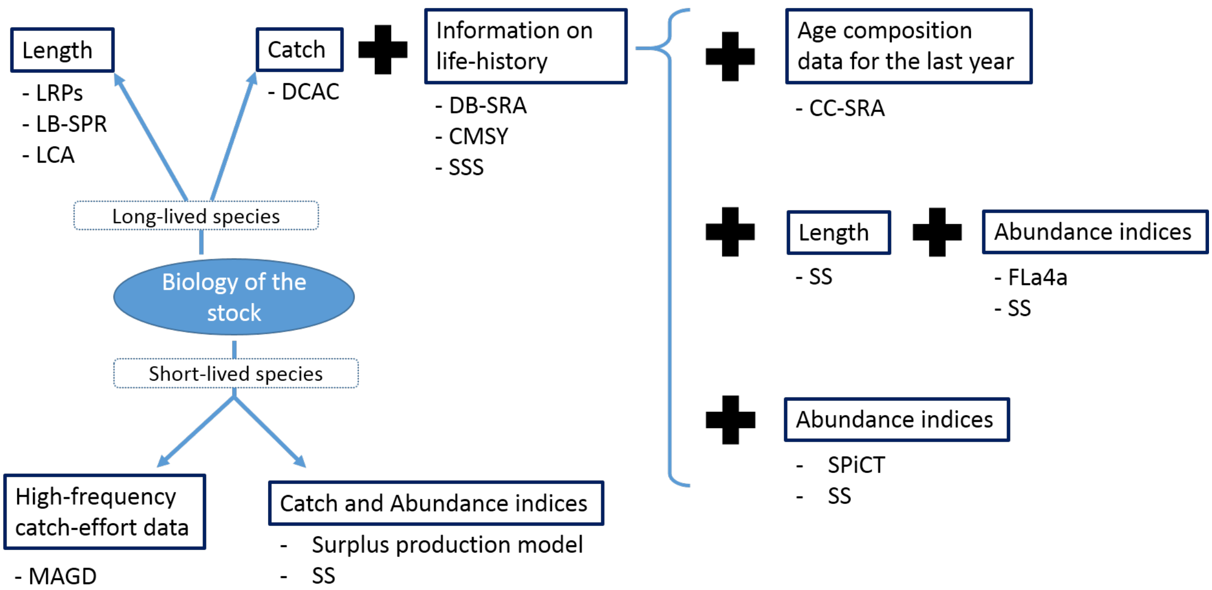

FIGURE 2.2 – Synthesis of the existing data-limited methods presented in this work and data needed to use these methods. LRPs is the Length-based Reference Points method, LB-SPR is the Length-Based Spawning Potential Ratio, LCA is the Length Cohort Analysis, DCAC is the Depletion Corrected Average Catch, DB-SRA is the Depletion-Based Stock Reduction Analysis, SSS is the Simple Stock Synthesis, CC-SRA is the Catch-Curve Stock Reduction Analysis, SS is the Stock Synthesis model, Fla4a is the Assessment for All initiative, SPiCT is the stochastic Surplus Production Model in Continuous Time and MAGD is the Multi-Annual Generalized Depletion model.

2.3.1. Catch-only methods

Catch-based methods are useful when only a historical catch series is available, although these models might not be suitable for stocks which are already depleted (Carruthers et al., 2014 [40]).

DCAC and DB-SRA

The Depletion-Corrected Average Catch (DCAC) is a simple method for estimating sustainable yields for data-limited fisheries (MacCall, 2009 [170]). The underlying assumption is that the average catch must have been sustainable in case of unchanged abundance. In case of an increase or decrease in stock abundance, estimated subjectively by expert opinion, a correction is applied to the average catch. The method is based on the hypothesis that data adequately captures the entire range of a population, and that a production function with compensation exists for the stock (Dorn et al., 2011 [75]). It requires a time series of cumulative removals (generally more than ten years, to approximate generation time), but should avoid including years of low catches due to low effort. Total catch should be used rather than just landings. Prior distributions are also required for the natural mortality rate (M), the ratio of fishing mortality at MSY on natural mortality rate (F_{MSY}/M), the ratio of biomass at MSY on pristine biomass (B_{MSY}/B_0), and the depletion (Δ). Δ is the change in biomass relative to B_0 during the period over which removals occurred (MacCall, 2009). The main weaknesses of DCAC is its sensitivity to assumptions about the depletion and the need of a long time series of catches. Furthermore, DCAC should not be used if M is above 0.2 y^{-1} because the depletion correction value becomes small and the DCAC is then simply the average of the catch value as M increases to higher values (MacCall, 2009 [170]). This method is usually adapted for category 4 stocks because only reliable catch data are available.

Stock reduction analysis (SRA) is a simple method using historical catch data and estimates of relative stock reduction caused by fishing to build possible trajectories of stock evolution (Kimura and Tagart, 1982 [161]). A Bayesian implementation of a stochastic stock reduction analysis was computed by Walters et al. (2006) [263] using large numbers of Monte Carlo simulation trials. They argue that with this implementation, few further steps could lead to full Bayesian stock assessment if more data sources were available.

The Depletion-Based Stock Reduction Analysis method (DB-SRA) merges stochastic SRA with DCAC (Dick and MacCall, 2011 [70]). Age at maturity and annual removals from a single fishery are required, as well as priors on M, F_{MSY}/M, B_{MSY}/k (where k is the unfished biomass) and relative depletion level in a recent year. It permits the connection between production and biomass through a delay-difference production model and produces probability distributions of management reference points concerning yield and biomass (MSY, B_{MSY}). The only unknown parameter is the unfished biomass which can be estimated given a relative depletion level near the end of the time series. The specific form of the production function used is a hybrid of the Pella-Tomlinson and Schaefer functions, but other functions could theoretically be used. The model assumes that recruitment and maturity are knife-edge functions of age, and that production is lagged by age at maturity. Recruitment is deterministic, growth is time-invariant, and selectivity is asymptotic and stationary. Selectivity pattern is assumed to be equal to the maturity pattern.

Dick and MacCall (2011) [70] compared outputs of DB-SRA with corresponding estimates from recent data-rich assessments. Their results suggest that the method is effective for estimating sustainable yields for data-poor stocks with historical catch data and life history parameters. Arnold and Heppell (2015) [12] compared DCAC and DB-SRA methods, by applying it to a data-rich and overfished stock. The overfishing limit (OFL) corresponds with the MSY. Both methods underestimated the OFL in case of catch error scenario, with slightly less bias for DB-SRA. In the parameter error scenario, and in the scenario of combination of catch and parameter error, estimation of OFL was less biased with DCAC than with DB-SRA. Wetzel and Punt (2011a) [267] studied the performance of DCAC and DB-SRA at estimating the catch at F_{MSY} based on simulated data. Both methods were highly sensitive to the assumed distribution for the ratio of the current to starting biomass and to the assumed distribution for the depletion. While their work shows that these methods are effective at limiting overfishing, the long-term effects of the resulting control rules was not evaluated. For this purpose, Wiedenmann et al. (2013) [270] conducted a Management Strategy Evaluation (MSE) based on three life-histories (slow, medium and fast) and tested three exploitation scenarios (under, fully, and overexploited). The probability of overfishing (P_{OF}) was calculated as the proportion of years in which the fishing mortality exceeded F_{MSY} and was used as a performance measure. In the study, DCAC performed poorly ($P_{OF} > 0.5$) for over-exploited stocks for all life-histories. DB-SRA performed poorly for under-exploited stocks with a fast life-history and for fully exploited stocks with a slow life-history.

CMSY

CMSY is an advanced implementation of the Catch-MSY method of Martell and Froese (2013) [174]. It requires prior knowledge about the depletion history, the current status, and the resilience of the stock to be assessed. It is possible to add uncertainty in the catch. The model uses the Schaefer production model to calculate annual biomasses for a given set of resilience (r) and carrying capacity (k). A Monte Carlo approach is used to detect $r - k$ pairs compatible with observed catches. If an $r - k$ pair results in a crash of the stock, or in an overshot of the carrying capacity, it will be eliminated from the range of plausible pairs. The model assumes that the parameters of the Schaefer model are constant over time. It also assumes that the knowledge about the stock status is accurate.

The CMSY model has been tested on 48 simulated stocks for WKLIFE V (ICES, 2015b [146]). Simulations covered a wide range of biomass scenarios. While CMSY gave satisfactory results for many stocks, it appeared to be less well suited for lightly exploited stocks and for species with very low resilience (e.g., sharks or deep-sea species). Part of the code is a Bayesian state-space implementation of a full Schaefer model. In case of available abundance data, it is possible to compare results of the full Schaefer model with the model based on catch data only. Additional testing were carried out on several real stocks (Table 2.2) and abundance indices were added when available (ICES, 2015b [146]). Results show that results from the catch-only model follow the same trend as results from the full Schaefer model. Nevertheless, absolute values can vary greatly, particularly when the productivity is not constant. Another drawback of CMSY is the sensitivity of the model to prior settings (Carruthers et al., 2014 [40]).

2.3.2. Catch and additional data available

SSS

It is possible to adapt the Stock Synthesis platform (Methot and Wetzel, 2013 [185]), usually used for data-rich stocks, to implement a model adapted to data-limited stocks. Simple Stock Synthesis (SSS) is a simple implementation of the Stock Synthesis platform that uses only a time series of catches (Cope, 2013 [57]). It assumes that population is influenced primarily by the production function rather than recruitment variability. This model uses the established theoretical foundation of DB-SRA, but uses an underlying age-structured model that permits the use of prior distributions on more life history parameters (e.g., parameters defining the growth curve and weight-length relationship). An artificial survey made of two "observed" values is used to mimic the assumed depletion. Priors also need to be specified for the steepness h, which represent the productivity parameters of F_{MSY} and B_{MSY}/B_0, and natural mortality M.

The strengths of SSS are the possibility to apply it on stocks with unusual life histories (e.g., sex specific life histories) and its flexibility to incorporate additional sources of uncertainty (e.g., growth variability). It is particularly adapted for category 3 stocks. If the objective is to have a temporary simple method before having enough data to move the stock to another category, then the Stock Synthesis framework might be an ideal solution. Indeed, additional data can easily be incorporated directly in the model, and it can be chosen to use it or not for the assessment. SSS therefore provides a way to assess data-limited stocks while allowing to build up stepwise towards a full stock assessment all in one modelling framework.

SSS was tested on 45 groundfish species and compared to DB-SRA (Cope, 2013 [57]). Overall, this work shows the ability of the Stock Synthesis platform to provide catch estimation in data-limited situations. SSS is based on a Beverton-Holt stock-recruitment relationship that assumes $B_{MSY}/B_0 \leqslant 0.5$, whereas DB-SRA uses a Schaefer-Pella-Tomlinson-Fletcher hybrid model that does not require this assumption. While it was not an issue for the example used in Cope (2013) [57], care should be taken for application on other species. An additional stock-recruitment formulation has been developed for Stock Synthesis to provide a way to specify the leading parameters as F_{MSY}/M and B_{MSY}/B_0, freeing the assumption that $B_{MSY}/B_0 \leqslant 0.5$ and allowing further flexibility in the exploration of productivity space (Punt and Cope, *in prep.* [213]).

CC-SRA

The initial Catch-Curve model converts length-based data into age classes using Von-Bertalanffy growth parameters. A regression line is then fitted, indicating the rate of survivorship between two age classes. The slope of the line is used to calculate the total mortality Z. The fishing mortality F is then obtained by subtracting the natural mortality M and the ratio F/M can be used as reference point for management purposes.

The Catch Curve Stock Reduction Analysis (CC-SRA) uses compositional data in recent years to achieve the goals of both catch curve and reduction analysis methods (Thorson and Cope, 2015 [252]). In addition to the catch history of the stock, age-composition sampling of the final year of catches is needed to estimate fishing mortality in the final year. If the age-composition is not available for the last year, sampling from other years can be used instead. The model assumes that fishing mortality is variable and follows no specified parametric function; that recruitment is variable around a stock-recruit relationship; and that fishery selectivity follows a logistic curve.

CC-SRA was found to be approximately unbiased for low to moderate recruitment variability, and less biased than SRA and DB-SRA given high recruitment variability. Thorson and Cope (2015) [252] therefore recommended CC-SRA as a data-poor assessment method that incorporates compositional data collection in recent years, and suggested that MSE be carried out. In their work, they assumed that abundance at age at the beginning of available catch data was from an approximately unfished state. This method might therefore not be suitable for stocks where available catch data begin several years after high exploitation levels.

SPiCT

SPiCT is a stochastic Surplus Production model in Continuous Time which incorporates dynamics in both biomass and fisheries (Pedersen and Berg, 2016 [199]). The uncertainty related to observation error in both catches and biomass indices is taken into account thanks to the state-space modeling framework. Some important assumptions are that biomass index and fisheries data have the same spatial coverage, and that commercial and survey selectivity are similar. When process and observation error cannot be separated, an additional assumption is made: process error is assumed to be equal to observation error. Instead of using the Pella and Tomlinson (1969) [200] equation, the model is based on the more stable parametrization of Fletcher (1978) [89]. The fishing mortality F_t is modeled as a separate and unobserved process and can be estimated at any time. It is the product of a random component and a seasonal component. When only annual data are available, the seasonal component is set to one. Estimates of biomass and fishing mortality obtained with SPiCT are often associated with high uncertainties. But the relative quantities F_t/F_{MSY} and B_t/B_{MSY} may be less biased and more adapted for management purposes.

The use of the improved parametrization and the use of Template Model Builder (TMB) should help improving the stability of the estimations. Nevertheless, it might not be enough to prevent biased estimates due to data scarcity and lack of contrast in the data. Residual analyses should therefore be carried out to check model fit. The authors also recommended that results be compared with those of alternative models. Informative priors can be used when information on parameter range is available, which can reduce uncertainty of estimated quantities. SPiCT was tested on several stocks (ICES, 2017b [150]). Results were similar for different life-history. The model often missed to predict an undesirable state when the stock was exploited around F_{MSY}. Prediction of an undesirable state was better when the stock was overexploited, and the model was then able to appropriately invoke the PA buffer when needed. Usually, when uncertainty cap was increased, probability of $SSB < B_{MSY}/2$ increased.

2.3.3. Length data available

LRPs

When length composition data are available, the Length-based Reference Points (LRPs) approach can provide an initial assessment of stock status (ICES, 2012d [140], 2014a [143]). This method assumes that length frequency data are representative of the catch. Indicators of exploitation can be calculated and used as proxies for stocks with unknown fishing mortality and biomass. Two estimates of mean length are calculated: one using the full length distribution (MuL) and one using only length classes above the length at first capture Lc ($MuLLc50$). More precisely, Lc is the length at which 50% of individuals are vulnerable to the fishing gear.

The median of the distribution ($Lmed$) is also estimated, as well as the 25^{th}, 75^{th} and 95^{th} percentiles, the maximum observed length in the distribution ($Lmax$), the length class contributing the most to the yield ($LMaxY$) and two estimates for length at first capture. One approach uses the 'raw' frequencies by length class (Lc), while another uses predictions of a smoother (Lc_s). The length where growth rate is maximum ($Lopt$) is empirically defined as:

$$Lopt = 2 \times L_\infty/3 \tag{2.1}$$

Lopt is also the length class which would provide maximal biomass in the unexploited population state (Cope and Punt, 2009 [59]; ICES, 2012d [140]). In addition to the empirical formulation for $Lopt$, an analytical calculation using the von Bertalanffy growth and length-weight relationship parameters can be made where $Lopt$ is the length class where the increase in growth in weight per unit time is maximal.

The mean length in the catch that would result from fishing at $F = M$ in the long term ($L_{F=M}$) can be calculated as:

$$L_{F=M} = 0.25L_\infty + 0.75Lc \tag{2.2}$$

$F = M$ is a proxy for MSY, hence $L_{F=M}$ is a length-based MSY proxy reference point that can be used to compare against current exploitation levels expressed by central metrics. The default central metric used for the comparison is MuL. The additional central metrics $MuLLc50$, $Lmed$ and $LMaxY$ can also be used and are more conservative. The length at which 50% of the fish are mature (L_m) is also needed. Table 2.1 summarizes how the ratio of the various reference points can be interpreted.

TABLE 2.1 – Length-based Reference Points ratio and associated interpretation.

Reference points ratio	**Interpretation**
L_m/Lc	If >1, a part of the catch is harvested before having the opportunity to breed.
$Lopt/MuL$	A value of 1 means that exploitation is close to the optimal level. If >1, exploitation is lower than the optimal level and if <1, exploitation is above the optimal level.
$L_{F=M}/MuL$	If <1, fishing mortality is below F_{MSY}.
$L_\infty/Lmax$	If <1, large individuals are present in the population.
L_m/Lc_s	If >1, a part of the catch is harvested before having the opportunity to breed.
$Lopt/MuLLc50$	A value of 1 means that exploitation is close to the optimal level.
$Lopt/LMaxY$	A value of 1 means that exploitation is close to the optimal level.
$L_{F=M}/Lmed$	If <1, fishing mortality is below F_{MSY}.
L_∞/L_{95}	If >1, large individuals are not well represented in the population.

LB-SPR

The Length-Based Spawning Potential Ratio (LB-SPR) is a length-based model allowing estimation of Spawning Potential Ratio (SPR). It was developed by Hordyk et al. (2015b) [131] for data-limited fisheries, where a representative sample of the size structure of catch and some information on the life history of the stock are available. The application can be freely found at: http://barefootecologist.com.au/lbspr.

The model is based on the idea that Beverton-Holt life history invariants link the exploited stock's expected length composition and its SPR. Under the assumptions of knife-edge maturation, full selectivity, and no variation of length-at-age, SPR is related to the ratios of natural mortality to growth rate (M/K), of length at maturity to asymptotic size (L_m/L_∞), and the ratio of fishing mortality to natural mortality (F/M). The length-at-age is modelled with the von Bertalanffy growth curve with increasing variability at longer lengths. Length at maturity is estimated from M/K and b, the exponent from length-weight relationship. Yield is calculated as a function of F, using numbers per recruit and length at maturity to find an optimum. Inter-individual growth variation can be computed using a normal distribution for L_∞.

According to the value of SPR, the status of the stock ranges from unfished (SPR$=1$) to fully or heavily exploited (SPR< 0.2). The caveat of this method is the high sensitivity of F/M to L_∞ value. SPR is also sensitive to the values of L_{50} and L_{95}.

LCA

Length-cohort methods using length composition data rely on the assumptions that the stock is at equilibrium, with no variation in year-class strength and in exploitation over time. Jones' (1981) [159] Length Cohort Analysis (LCA) is the method used in WKLIFE IV (ICES, 2014b [144]) to estimate fishing mortality and population size, based on length data. This method is based on Pope's age-based cohort analysis (Pope, 1972 [206]), therefore it has the same requirements to be valid: the natural mortality must be under 0.3 and the fishing mortality must be under 1.2. In order to estimate total mortality, catch at length data can be used under certain assumptions: the species' growth follows the von Bertalanffy growth model, the population is in a steady state with constant exponential mortality, there are no changes in the selection pattern of the fishery and recruitment is constant (ICES, 2014b [144]).

Cadima (2003) [37] presents two ways of conducting a length cohort analysis according to the available data. If sufficient catch at length data are available for several following years, it is possible to follow the cohorts through the length classes belonging to a same age, in a certain year, with the length classes of the next age, in the following year. The other method is based on the assumption that the distribution of individuals by length is uniform in the length classes. The length compositions are "sliced" by using the inverted length growth equation of von Bertalanffy. The catches of length classes belonging to the same age interval are thus grouped in each year. Zhang and Megrey (2010) [275] compared the values of biomass and F obtained from a biomass-based LCA with the results from a numbers-based LCA. Sensitivity to terminal F was the same for both methods. The advantage of the biomass-based LCA is that it incorporates growth and can be used in data-limited situations, for example when only one year of data is available.

2.3.4. More complex models

FLa4a

The stock assessment model framework FLa4a (Jardim et al., 2014a [154], 2014b [155]) is a non-linear catch-at-age model that can be applied rapidly to a wide range of situations with low parameterization requirements. The main objective of the assessment for all (a4a) initiative is to help fishery scientists to conduct a stock assessment and give management advice. It is based on five submodels for fishing mortality-at-age, abundance indices catchability-at-age, initial age structure, recruitment, and models for the observation variance of catch-at-age and abundance indices. Catch at ages can be obtained by converting catch at length data using the reverse Von Bertalanffy growth equation.

Each submodel can be adapted according to the specificity of the stock. The equations used are linear models and splines. Uncertainty in the submodels can be introduced through the inclusion of parameter uncertainty. This is done by making use of the parameter variance-covariance matrix, which is a correlation matrix scaled by a chosen value of CV. There are two basic types of assessments available: the management procedure fit and the full assessment fit. In the first case, no estimates of covariance are computed. In the second case, parameter estimates and their covariance are returned, taking longer time for the computation.

The statistical catch at age model is based on the Baranov catch equation (Baranov, 1918 [13]), assuming that the fish population is in a steady state over time, and that instantaneous rates of fishing and natural mortalities of fish are constant over time and age. Recruitment is modelled as a fixed variance random effect, using the following productivity models: Ricker, Beverton Holt, smooth hockey stick or geometric mean. As an alternative, the log(R) submodel can use a linear model like the other submodels.

The variance model allows the user to set up the shape of the observation variances. By default the model assumes constant variance over time and ages but it can use other models specified by the user. In linear model covariates can be used to explain part of the variance observed in the data that the 'core' model does not explain. The same can be done in the initiative a4a framework. It's for example possible to use the North Atlantic Oscillation (NAO) index to model recruitment. A set of methods allow the user to apply with more flexibility the models referred before. To merge results from several fits, using distinct models or datasets, the initiative a4a follows Millar et al. (2014) [186] recommendation to use model averaging.

Stock Synthesis

Stock Synthesis (SS) (Methot and Wetzel, 2013 [185]) is an integrated statistical catch-at-age stock assessment modelling framework. Several sources of data, as lightly processed as possible, are combined into a single analysis which accounts for the various sources of uncertainty and propagate it to the assessment results (Maunder and Punt, 2013 [177]). The use of SS has expanded over the last decade among data-rich stocks, and is also being used in data-limited situations (Cope et al., 2013 [58]; Cope, 2013 [57]; Wetzel and Punt, 2015 [269]). SS can be adapted to several types of life cycles, and can be parameterized using an age-based or size-based structure. The high adaptive potential of the framework permits the use of various sources of data and the stepwise incorporation of additional data. When SS is used in data-limited situation, availability of length-composition data is important to obtain improved results (Wetzel and Punt, 2011b [268]), even if only a few years of data are available. The user can build a model starting with only a catch history and life history information upwards to a complex model with indices of abundance and biological compositions.

2.3.5. Specific case: short lived species

Short-lived species can experience high growth rates, high natural mortality, and high recruitment variability. In the annual brown shrimp (*Crangon crangon*) North Sea fishery, Tulp et al (2016) [254] underlined that age-based stock assessment was not possible. In cephalopod species, trials using monthly VPA were made with squid (Royer et al., 2002 [235]; Challier et al., 2005 [44]) and with cuttlefish (Royer et al., 2006 [236]) but accurate age determination was considered too time consuming for routine assessments. Among the very few cephalopod stocks assessed with a full analytical model, the senegalaise octopus fishery presents an ideal situation where the catch is sorted out by commercial categories which fit quite well with monthly age groups (Jouffre and Caverivière, 2005 [160]). DCAC and DB-SRA are inappropriate for these species (Newman et al., 2014 [195]). As CC-SRA gives biased results in case of high recruitment variability, it might also not be suitable. Two examples of models adapted to short-lived species are presented in the following part.

Two-stage biomass model

Midway between simple biomass models and fully age-structured models, delay-difference models usually require relatively few data and are biologically more realistic than simple biomass models. Various population dynamics processes can be incorporated in a simple equation, allowing for time-lags due to growth and recruitment. Assuming a time-invariant catchability parameter, the model can adapt to particular life history. The drawback is that potential available age or length data can't be incorporated in the model. DB-SRA is also a type of delay-difference model, but it is based on an assumed depletion level instead of a true abundance indices time series. As the biomass levels of stocks with a fast life-history vary greatly and are highly dependent on recruitment, indicators of the real biomass level are needed.

Two-stage biomass models (Roel and Butterworth, 2000 [230]) are an example of delay-difference models, based on catch and abundance indices time series, where recruits are separated from the rest of the population. The population dynamics are described in terms of biomass with two distinct age groups, recruits or fish aged one year old, and fish that are two or more years old. Recruitment and catch are assumed to occur instantaneously as pulses, whereas growth and natural mortality operate continuously in time. Two-stage biomass models have been adapted to anchovy (Trenkel, 2008 [253]), squids (Roel and Butterworth, 2000 [230]), herring (Roel et al., 2009 [231]) and cuttlefish (Gras et al., 2014 [110]). Bayesian implementations of two-stage biomass models have also been applied on anchovy (Ibaibarriaga et al., 2008 [135], 2011 [134]; Giannoulaki et al., 2014 [105]) and cuttlefish (Alemany et al., 2017 [7]).

MAGD

Depletion models are an alternative to assess short-lived species in case of unavailable biological compositional data. This kind of models assume a closed population, and the model estimates the number of individuals entering the population, accounting for both migration and recruitment. Data required are usually total catches, a method for converting catches in weight to catches in numbers, and an estimate of natural mortality. The method was developed for real-time management. The main drawback is that biomass estimates are not related to the biological reference points. It has mainly been applied to squids (Rosenberg et al., 1990 [233]; Brodziak and Rosenberg, 1993 [30]; Royer et al., 2002 [235]; Young et al., 2004 [274]; Chen et al., 2008 [47]). Depletion models have also been implemented in a Bayesian framework in order to improve precision in parameter estimates. It has been applied to the squids (McAllister et al., 2004 [179]) and to octopus (Robert et al., 2010 [228]).

The Multi Annual Generalized Depletion model (MAGD) is an example of depletion models allowing the incorporation of high-frequency data. It has been applied to the *Loligo gahi* fishery around the Falkland Islands (Roa-Ureta, 2012 [225]) and to the Spanish mackerel (Roa-Ureta, 2014 [226]). The package CatDyn (Roa-Ureta, 2014 [226]), available on the CRAN of the software R, allows its implementation with one or two fleet(s). The model assumes that the catch in numbers at any time step is a random variable with a known distribution. A likelihood function of difference between the observed catch series and the predicted catch series is minimized to fit the model. It is only an approximated likelihood because transformation of catch in biomass to catch in numbers is ignored, and variance is eliminated from the inference (Roa-Ureta, 2014 [226]).

TABLE 2.2 – Synthesis of the data needed and the cautions to take when applying the data-limited stock assessment methods presented in this work.

Method	Required information	Particular case with risk of biased results
DCAC	Time series of catches, total sum of catches, number of years in the time-series. Estimate, probability distribution and standard deviation of depletion Δ, M and ratio F_{MSY}/M.	$M > 0.2$ year^{-1}. Time-series < 10 years. Highly depleted stock.
DB-SRA	Data required for DCAC and age at 50% maturity.	Stock close to its unfished biomass in recent years.
CMSY	Time series of catches, prior on stock resilience and level of depletion.	Non-constant productivity, reduced recruitment. Species with very low resilience (e.g., sharks). Lightly exploited stock.
SSS	Time series of catches. Priors for depletion, M, and steepness. Information on growth and weight-length relationship.	Stock close to its unfished biomass in recent years.
CC-SRA	Time series of catches, age composition data for the last year or before, and priors for life-history parameters.	High recruitment variability. Catch time series begins after the stock experienced high exploitation level. Non asymptotic fishery selection.
SPiCT	Time series of catches, index of biomass, priors for some parameters (e.g., ratio between observation and process error, shape of the production function, r, M and K).	Short time series and lack of contrast in the data.
LRPs	Fishery length composition, length at first capture, L_∞ and length at maturity.	$Lc<L_m$. Length composition not representative of the population (e.g., specific selectivity due to the fishing gear).
LB-SPR	Fishery length composition, M/k, L_∞, CV of L_∞, L_m.	Dome-shaped selectivity. High recruitment variability.
LCA	Fishery length composition, length-weight relationship, growth parameters, natural mortality.	$M > 0.3$ y^{-1} or $F > 1.2$. Lightly exploited stock.
Fla4a	Fishery age or length composition, abundance indices, life-history parameters.	
SS	Fishery age or length composition, abundance indices, life-history parameters.	
MAGD	High frequency catch and effort data. Starting value of M. Body weight frequency data are also needed if the catches are in biomass instead of numbers.	
Two-stage biomass model	Time series of catches, abundance indices, information on growth and M.	

TABLE 2.3 – Example of application of the Data-limited methods on stocks mostly within ICES waters. The stock assessment was not considered reliable for stocks highlighted in grey.

Method	Stock	Reference
DCAC	Blue ling in Subareas VI and VII and Divisions Vb and XIIb	WKLIFE (ICES, 2012d [140])
	Blackspot seabream in Subareas VI, VII and VIII	[140]
	Orange roughy in Subarea VI	[140]
	Pollack in Subareas VI and VII	WGCSE (ICES, 2016a [147])
	Nephrops in Southwest and South Portugal	WKLIFE IV (ICES, 2014b [144])
DB-SRA	Applied on 45 species of groundfishes.	Cope (2013) [57]
CMSY	Blue ling in Subareas VI and VII and Divisions Vb and XIIb	WKLIFE (ICES, 2012d [140])
	Anglerfish in Subareas IV and VI and Divisions IIa, IIIa	[140]
	Cod in Division Va	[140]
	Irish Sea herring Div. VIIa North	[140]
	Baltic flounder Div. III 22-32 (Baltic Sea)	[140]
	Northern Hake (Subareas IV, VI and VII and Divisions IIIa, VIIIa,b,d)	WKLIFE V (ICES, 2015b [146])
	Cod in Subdivisions 25-32 (Eastern Baltic Sea) and Subdivision 24	[146]
	Dab in Subdivisions 22-32 (Baltic Sea)	[146]
	Greater silver smelt in West of Scotland in Divisions Vb and VIa	[146]
	Nephrops in Southwest and South Portugal	[146]
	Haddock in Division Vb	[146]
	Saithe in Division Vb	[146]
	Cod in Division Vb2	[146]
	Blonde ray in Division IXa	WKLIFE IV (ICES, 2014b) [144]
	Sardine in Divisions VIIIa,b,d and Subarea VII	[144]
	Plaice in the North Sea	[144]
	Northern shrimp	[144]
	Nephrops in Southwest and South Portugal	[144]

	Lemon sole in Subarea IV and Divisions IIIa and VIId	[144]
	Haddock in the North Sea	[144]
	Atlantic herring	[144]
	Spurdog in Northeast Atlantic	[144]
	Atlantic cod	[144]
	Brill in Subarea IV and Divisions IIIa and VIId,e	[144]
SSS	Tested on 45 assessments and compared to DB-SRA.	Cope (2013) [57]
	Additional simulation testing.	Wetzel and Punt (2011a) [267]
CC-SRA	Simulated data	Thorson and Cope (2015) [252]
LRPs	Nephrops in Southwest and South Portugal	WKLIFE IV (ICES, 2014b [144])
	Sardine in Subareas VII and VIII	[144]
	Blonde ray in Division IXa	[144]
	Spurdog in Northeast Atlantic	[144]
	Lemon sole in the North Sea	[144]
	Northern Hake	WKLIFE V (ICES, 2015b [146])
	Pollack in Subareas VI and VII	[146]
LB-SPR	MSE	Hordyk et al. (2015a) [130]
	Pollack in Subareas VI and VII	WKLIFEV (ICES, 2015b [146]) and WKProxy (ICES, 2016b [148])
LCA	Lobster around the UK and Ireland	Cefas (2015b) [42]
	Edible crab around the UK and Ireland	Cefas (2015a) [41]
	Nephrops in Southwest and South Portugal	WKLIFE IV (ICES, 2014b [144])
	Blonde ray in Division IXa	[144]
	Lemon sole in Subarea IV and Division IIIa and VIId	[144]
	Sardine in Divisions VIIIa,b,d and Subarea VII	[144]
	Seabass in Divisions VIIIa,b	IBPNew (ICES, 2012b [138])
SPiCT	Black-bellied anglerfish in Divisions VIIb-k and VIIIa,b,d	WKProxy (ICES, 2016b [148])
	Anglerfish in Subareas IV, VI and Division III.a	[148]

	Haddock in Division VIIa	[148]
	Megrim in Divisions VIIb-k and VIIIa,b,d	[148]
	Plaice in Divisions VIIf,	[148]
	Plaice in Division VIIa	[148]
	Nephrops in Southwest and South Portugal	WKLIFE V (ICES, 2015b [146])
	Cod in Subdivisions 25-32 (Eastern Baltic Sea) and Subdivision 24	[146]
	Dab in Subdivisions 22-32 (Baltic Sea)	[146]
	Cod in Division IIIa East	[146]
	Greater silver smelt in Division Va	WKLIFE VI (ICES, 2017b [150])
	Cod in Division Va	[150]
	Dab in Subdivisions 22-32 (Baltic Sea)	[150]
	Herring in Subdivision 31	[150]
	Nephrops in North Galicia	[150]
	Plaice in Subdivisions 22-32 (Baltic Sea)	[150]
	Pollack in Subarea VIII and Division IXa	[150]
	Sandeel in Divisions IVa,b	[150]
	Turbot in Subarea IV	[150]
	Whiting in Division VIa	[150]
	Witch in Subarea IV and Divisions IIIa and VIId	[150]
Fla4a	European hake in the Gulf of Lion	FAO/GFCM (2015) [85]
SS3	Sea bass in Divisions IVb,c and VIIa,d-h	WGCSE (ICES, 2016a [147])
	Hake in Division IIIa, VIIIa,b,d and Subareas IV, VI	WGHMM (ICES, 2013 [142])
MAGD	*Loligo gahi* fishery (Falkland Islands)	Roa-Ureta (2012) [225]
	Spanish mackerel in Saudi waters of the Arabian Gulf	Roa-Ureta (2014) [226]
	Striped red mullet and cuttlefish in the western Mediterranean	Maynou (2015) [178]
	Cuttlefish in Divisions VIId,e (English Channel)	Alemany et al. (2015) [6]
Two-stage biomass model	South African chokka squid	Roel and Butterworth (2000) [230]

European anchovy in the Bay of Biscay	Ibaibarriaga et al. (2008) [135]; Trenkel (2008) [253]; Ibaibarriaga et al. (2011) [134]
Anchovy in the Aegean Sea (Eastern Mediterranean)	Giannoulaki et al. (2014) [105]
Herring in Division VIIa, North	Roel et al. (2009) [231]
Cuttlefish in Divisions VIId,e (English Channel)	Gras et al. (2014) [110]; Alemany et al. (2017) [7]

2.4. Third step: sensitivity analysis and model averaging

Once a set of possible models has been selected, regarding available data and models' assumptions, an advice should be given on stock status. In fisheries science, a single model is often selected, and stock assessment is then conducted following the same method. However, when only one method is used, stock assessments for data-limited stocks can be based on less data than what is really available. According to the method used, the signal of a stock depletion might take more or less time before being detected by the model. Using several stock assessment methods can help increasing confidence in models results.

For each method, priors and assumed values are needed on certain parameters. Expert judgement or independent data can bring information, but there are uncertainties associated with each assumption. As highlighted by Chen et al. (2003) [48], the uncertainty in stock assessment usually increases with decreasing data quantity and quality. It is therefore important to conduct sensitivity analysis to test alternative assumed values (eg. other values for M). This will allow to have a larger and more accurate spectrum of the possible results and will help management decision process.

It is usual to assess a data-limited stock without taking into account recreational fishery because no information is available. That amounts to saying that recreational catches are negligible compared to the uncertainty or lack of quality of the commercial catch data. This is therefore an additional assumption, thus sensitivity analysis should be carried out. Having several alternative models might complicate the following step of management advice. To summarize all results and associated uncertainties, model averaging can be considered.

The underlying idea of model averaging is that a model is a possible representation of reality, which will never be reality itself. By selecting a single "best" model to conduct a stock assessment, other models are rejected and therefore considered as false. There is an uncertainty associated with this selection which is usually not taken into account. Ignoring uncertainties involved in model selection can lead to too optimistic inference results. Furthermore, different models require different assumptions which should sometimes not be rejected (Millar et al., 2014 [186]). Model averaging can be done between similar models or similar derived model outputs. The aim is to avoid rejecting models which could be a source of further information, but also incorporate model-selection error in the result.

In Frequentist model average (FMA), weights from model selection (e.g., AIC, BIC) are used (Wang et al., 2009 [265]). In Bayesian model averaging (Hoeting et al., 1999 [128]; Hoeting, 2002 [127]), the list of models used is specified, and prior probabilities for all models and all parameters are set. Then the posterior distribution of the parameter of interest is simulated. Bayesian model averaging (BMA) has been used by Jiao et al. (2009) [158] in stock recruitment modeling for Lake Erie walleye fishery (*Sander vitreus*). They suggest that model selection uncertainty be considered and the BMA be applied to other stock assessment models and even in the fisheries management decision making in the future. Millar et al. (2014) [186] also suggest a change in the typical stock assessment procedure by moving toward a model averaging method. They highlight the importance of a good estimation of uncertainty both in model and in parameters.

But BMA is criticized by some scientists because it would account for uncertainty about which model is correct but still operates under the assumption that only one of them is, leading to an implicit model selection procedure (Monteith et al., 2011 [188]). The use of Bayesian model combination (BMC) instead of BMA is therefore recommended. BMC is an algorithmic correction to BMA. Instead of sampling each model in the ensemble individually, it samples from the space of possible ensembles (with model weightings drawn randomly from a Dirichlet distribution having uniform parameters). This modification overcomes the tendency of BMA to converge toward giving all of the weight to a single model. Although BMC is somewhat more computationally expensive than BMA, it tends to yield dramatically better results than BMA. At last, one should not forget the warning message of Hilborn and Walters (1992) [125]: "Beware of methods that average sources of information that are contradictory".

2.5. Final step: management considerations and evaluation of the data needed

The final step consists in giving advice on stock management according to the stock assessment results. When time is available, it is worthy conducting a management strategy evaluation (MSE) prior to the implementation of a harvest control rule. It helps determining the relative importance of various factors in relation to achieving management goals (Punt, 2008 [212]). One big issue in data-limited fish stock assessment is the workforce limit. The DLMtool developed by Carruthers et al. (2014) [40] is a huge progress in this field. It is an option to conduct MSE with pre-defined or self-implemented harvest control rules. SPiCT is also useful to conduct MSE, but additional harvest control rules should be implemented. SPiCT based management procedure and DLMtool gave similar results in the WKLIFE VI report (ICES, 2017b [150]).

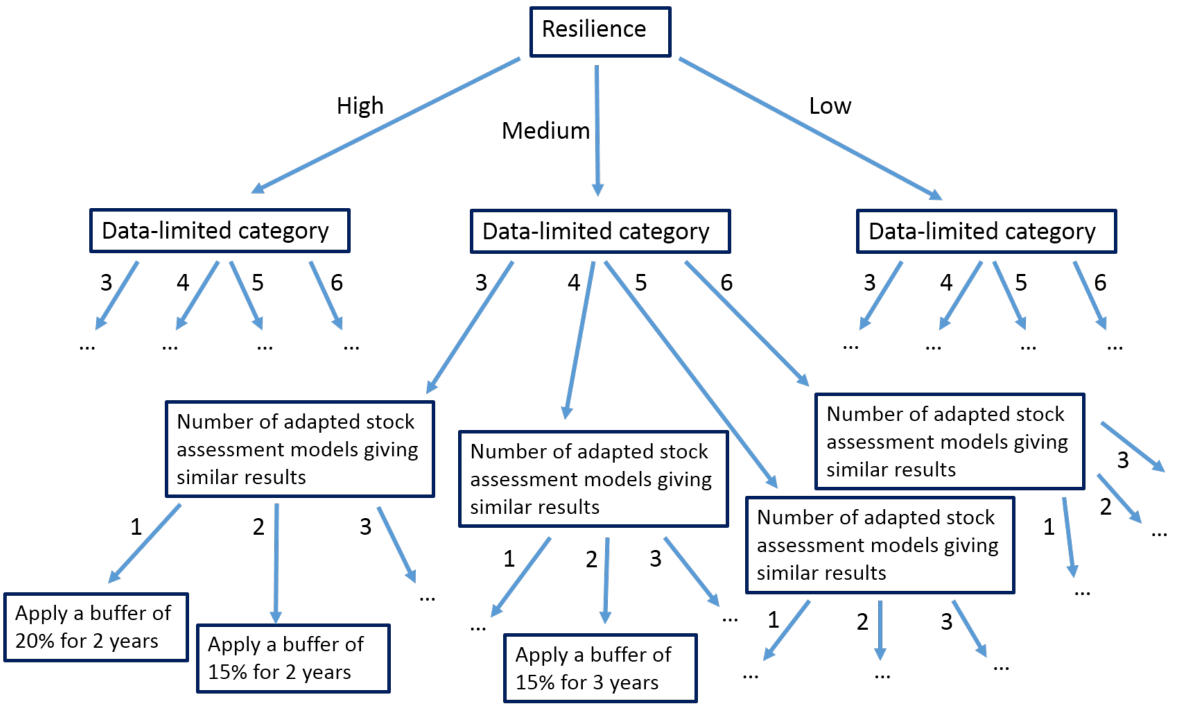

FIGURE 2.3 – Example of a simple decision tree for setting precautionary buffer. Resilience level is based on expert knowledge, stocks are classified in DLS categories according to ICES (2012d) [140] and precautionary approach buffers decrease when more models give similar results.

The aim of stock assessment is to provide good management advice in order to achieve sustainable harvest rates. This advice is needed as quickly as possible and there is a trade-off between accuracy and speed. In case of uncertain assessment, which is often the case for data-limited stocks, precautionary buffer are usually applied. The detailed methodology used by ICES to infer harvest control rules for data-limited stocks can be found in the ICES DLS guidance report (ICES, 2012a [137]). Recently, harvest control rules based on length reference points have been tested (ICES, 2017b [150]). The use of the reference point $L_{F=M}$ has proven to be not conservative enough, and the precautionary reference point $L_{F=0.75M}$ should be used instead. The DLS guidance report recommend the application of a 20% precautionary buffer in case of strong uncertainties. The magnitude of this buffer and the time frame of application are not always clear. We propose an example of a decision tree (Fig. 2.3) that could be adapted regarding results of MSE and used to better standardize the process of management advice.

If possible, it is also important to evaluate the data needed to improve the stock assessment and the management advice. This must be discussed regarding available funding and workforce. Even when management advice is given for a data-limited stock, further investigation should be carried out to improve the assessment and the management. As highlighted by Bentley (2014) [17], the availability of data-limited stock assessment methods should not prevent the collection of additional data. Methods adapted to data-limited stocks are useful and necessary to give management advice with available data, but the main objective should be to improve the stock assessment and reduce uncertainty of the estimates.

2.6. Discussion

The recognition of the need for data-limited stock assessment and management methods has increased over the last decade. Several working groups and symposiums focusing on data-limited stock assessment methods have emerged. The need to find a balance between using a general framework and adapting a specific model was highlighted at the 30^{th} Lowell Wakefield Fisheries Symposium "Tools and Strategies for Assessment and Management of Data-Limited Fish Stocks" which took place in Anchorage in May 2015. Warning was also given about the danger of applying a model without understanding it, which could be a possible consequence of the development of generic tools to conduct stock assessment, such as the DLM package (Carruthers et al., 2014 [40]).

Methods presented in this work did not account for extreme data-poor stocks such as many elasmobranchs, which are usually by-catch species. We consider it dangerous to recommend a standardized method for this kind of stocks, as there are usually specific issues for each stock (e.g., species-specific identification, greater uncertainties in life history data). However, applications of Bayesian methods have increased in stock assessment science and have proven to be particularly adapted in a data limited context (Chrysafi and Kuparinen, 2016 [51]). A Bayesian framework permits the use of different sources of information, and the propagation of estimates' uncertainties through the model. Information from data-rich stocks can also be used to better assess data-limited stocks, as described by Punt et al. (2011) [217] with the "Robin Hood" approach. The use of Bayesian hierarchical models can improve knowledge on these data-poor stocks.

Data gathering is dependent on available time and money. It is therefore useful to improve the efficiency of data collection by determining which models would give best results and adapt the kind of data needed. Quantifying the gain in certainty when additional data is gathered would also help in decision making. Furthermore, it is always useful to get the more precise knowledge about life history parameters of the stock. As these parameters shouldn't evolve too quickly for long-lived species, an update every five or six years could be considered. This would meet the requirement of accurate biological parameters without increasing drastically management costs.

The scientific community working on data-limited fish stock assessment usually has to face two main types of communication challenge. The first one relates to the fishing community who does not always understand the scientific advice. For example, the precautionary buffer set in case of uncertain stock assessment can prompt a mitigated response among fishermen. The second one concerns the management decisions taken as a result of the scientific advice. The gap between scientific recommendation and political decisions on fishing limits is a well-known issue, which applies for both data-rich and data-limited fisheries. To address these challenges, more effort on communication could be considered. While the development of several methods is helpful to face the many particularities of data-limited stocks, it seems important to have a common generalized framework which brings more credibility to the advice. There is a need for the scientific community to speak with a clear voice. A coherent and convincing discourse is the key to gain both government and fishermen trust.

CHAPITRE 3

CHAPITRE 3 : Comparaison de modèles d'évaluation du stock de seiche de Manche

"*Mieux vaut comprendre peu que comprendre mal.*"

Anatole France (1937), dans **Lettres à L'ashram.**

Présentation des articles "Stock assessment models for the English Channel stock of cuttlefish" et "A Bayesian two-stage biomass model for stock assessment of data-limited species: an application to cuttlefish (*Sepia officinalis*) in the English Channel"

Nous avons vu dans le chapitre précédent que des modèles particuliers sont nécessaires pour évaluer les stocks des espèces à vie courte. Au cours de ce troisième chapitre, nous allons nous intéresser à l'un des cas d'étude de cette thèse, le stock de seiche de Manche, à travers deux articles.

Dans le premier article, un modèle de biomasse à deux stades est adapté dans un cadre Bayésien et les résultats sont comparés avec le modèle initial développé par Gras et al. (2014) [110]. Les données utilisées sont les captures totales des pêcheries anglaises et françaises, deux séries de LPUE, et deux séries d'indice d'abondance, l'une provenant de la campagne anglaise BTS et l'autre de la campagne française CGFS. Le modèle est construit autour d'une simplification du cycle de vie de la seiche de Manche. Les seiches sont supposées éclore au 1er juillet. Seule la dynamique de population des individus de plus d'un an est modélisée. La campagne BTS, qui a lieu en juillet, informe le modèle sur l'abondance des seiches de un an au début de la saison de pêche. La campagne CGFS d'octobre informe sur l'évolution de l'abondance au cours des trois premiers mois. Les captures sont supposées se produire de manière groupée au milieu de la saison de pêche, au 1^{er} janvier. Les seiches se reproduisent à la fin de leur deuxième année, et le modèle considère qu'elles meurent toutes lorsqu'elles atteignent l'âge de deux ans.

Le modèle MAGD (Roa-Ureta, 2012 [225], 2014 [226]) est un modèle de déplétion multi-annuel qui a ici été adapté à un pas de temps mensuel. Les données mensuelles de captures et d'effort étaient requises, ainsi que les poids individuels moyens des seiches par mois afin de convertir les captures en poids en captures en nombre. Ces données n'étant cependant disponibles que pour la pêcherie française, les résultats d'estimation de biomasse doivent être standardisés avant de pouvoir être comparés aux résultats du modèle de biomasse à deux stades. Le package CatDyn (Roa-Ureta, 2012 [225]) a été utilisé pour appliquer le modèle MAGD.

Un meilleur ajustement des indices d'abondance des campagnes scientifiques est observé pour le modèle de biomasse à deux stades initial que pour le modèle Bayésien. En revanche, l'ajustement des deux séries de LPUE est meilleur pour le modèle Bayésien. Aucun des deux modèles ne parvient à estimer les plus fortes valeurs des campagnes BTS et CGFS (observées en 2000 et 2002 pour les deux campagnes, et en 2006 pour la campagne CGFS). Les estimations de biomasse du modèle initial et du modèle Bayésien de biomasse à deux stades sont proches. Cependant, les sorties du modèle Bayésien montrent une moins grande ampleur de variation que le modèle initial. Les estimations de taux d'exploitation sont également proches, avec une forte diminution entre 2006 et 2008. Aucune relation n'est identifiée entre le niveau de biomasse de géniteurs et le recrutement qui suit.

La mortalité par pêche estimée par le modèle MAGD augmente progressivement entre 1992 et 2004 avant de chuter entre 2006 et 2009. Ce résultat concorde avec la diminution du taux d'exploitation estimé par le modèle de biomasse à deux stades sur la même période. Les estimations de biomasse standardisées obtenues pour les trois modèles suivent une même tendance. Cependant, les sorties du modèle MAGD montrent des variations de moindre ampleur. La comparaison des sorties des trois modèles permet une première validation des tendances générales obtenues pour la biomasse et le taux d'exploitation du stock de seiche de Manche.

En revanche, le modèle MAGD est basé uniquement sur les données des chalutiers français, et les indices d'abondance des campagnes scientifiques ne sont pas pris en compte. Il semblerait plus judicieux d'exploiter l'ensemble des données disponibles, ce que la structure du modèle MAGD ne permet pas pour ce stock. Le modèle de biomasse à deux stades initial présente l'inconvénient de reposer sur un paramètre de croissance de biomasse fixé g dont la valeur influence grandement les résultats. Ce même modèle adapté en Bayésien permet une prise en compte de l'ensemble des incertitudes dans les sorties du modèle, mais les résultats restent sensibles à la valeur de g. De plus, avoir un paramètre g fixé et identique chaque année reste une hypothèse irréaliste pour un stock dont la croissance est dépendante des variations des conditions environnementales.

Le modèle Bayésien s'avère être une voie prometteuse à condition d'être amélioré, avec un travail particulier sur ce paramètre g. C'est justement l'objectif du deuxième article, dans lequel le modèle Bayésien de biomasse à deux stades est repris dans un cadre hiérarchique Bayésien. Le modèle de référence M1 modélise la dynamique de population des individus d'un an et plus et repose sur un paramètre $g_{1,y}$ à variations interannuelles. Un prior informatif est construit pour $g_{1,y}$ à partir de données de fréquences de taille du programme Obsmer. Le modèle de référence est ensuite décliné en trois variations. Le modèle M2 repose sur un paramètre g_1 fixé, et le modèle M4 s'ajuste uniquement sur les indices d'abondance issus des campagnes scientifiques BTS et CGFS. La construction du modèle M3 se différencie du modèle de référence par l'inclusion de la dynamique de population des individus de moins d'un an. Pour cela, le paramètre de croissance de biomasse $g_{0,y}$ spécifique du groupe 0 est introduit et un prior informatif est construit à partir des fréquences de taille issues de la campagne scientifique CGFS.

Contrairement aux résultats du modèle Bayésien construit dans la première partie de ce chapitre, l'ensemble des données observées est compris dans les intervalles de confiance à 95% des distributions a posteriori du modèle de référence. De 2002 à 2014, les résultats montrent une diminution de la biomasse des individus entamant leur deuxième année (B_1), tandis que l'évolution des estimations de biomasse des individus de 2 ans (B_2) ne présente aucune tendance claire. Les estimations de $g_{1,y}$ fluctuent entre 0.64 et 0.83 de 1992 à 2008, puis augmentent jusqu'en 2011. L'estimation la plus élevée est de 1.16 en 2014. Le taux d'exploitation varie entre 0.4 et 0.64 entre 1992 et 2008, et une forte baisse est estimée en 2009 avec un taux de 0.25. Les valeurs les plus élevées sont estimées en 2001 et 2011 (respectivement 0.64 et 0.62).

Un meilleur ajustement est obtenu avec le modèle de référence M1 qu'avec le modèle M2, mais les estimations des deux modèles diffèrent peu. Bien que le modèle M3 requière davantage de données et d'hypothèses, il ne surpasse pas le modèle M1 en termes de qualité d'ajustement concernant le groupe 1+ de la population. L'inclusion du groupe 0+ dans la modélisation n'apporte donc pas de réel avantage, et certaines hypothèses formulées pour la construction du prior sur $g_{0,y}$ s'avèrent problématiques. Par exemple, Royer et al. (2006) [236] ont détecté la présence de deux micro-cohortes parmi le groupe 0+. Dans leur étude, un premier recrutement a été observé en octobre, et un deuxième en avril. Ce phénomène, qui n'est apparemment pas systématique, pourrait biaiser le calcul de croissance basé sur les fréquences de taille de la campagne CGFS.

La question qui se pose alors est de savoir jusqu'à quel niveau de complexité de modèle il est possible de monter au vu des données disponibles. S'il est vrai qu'une complexité accrue peut permettre un meilleur réalisme du modèle, le manque de données implique la nécessité de poser des hypothèses qui risquent alors de biaiser les résultats. Dans notre étude, nous avons conclu que le modèle M1 était le plus adapté face au niveau de données disponibles. En complément, le modèle M4 permet de prédire le niveau de biomasse non exploitée en hiver à partir des données des campagnes scientifiques. Ainsi, si l'évaluation du stock au milieu de la saison de pêche indique un fort déclin de biomasse, des mesures de gestion pourraient être envisagées.

Parmi les différentes méthodes de gestion existantes, les quotas de pêche semblent être un choix peu avisé pour le stock de seiche. En effet, les stocks de céphalopodes sont soumis à de fortes variations de niveau de biomasse, ce qui rend difficile la mise en place d'une gestion par quotas (Caddy, 1983 [35]; Beddington et al., 1990 [14]). Nous avons vu dans le premier chapitre que le stock de seiche de Manche était géré par des mesures locales, et que l'interdiction de chalutage dans la bande des 3 milles était parfois levée. En règle générale, cette levée d'interdiction intervient deux semaines à la fin du mois d'Août et six semaines au printemps. Un exemple concret de mesure de gestion serait de ne pas lever l'interdiction de chaluter dans la zone des 3 milles, à titre exceptionnel, en cas d'estimation de biomasse faible au milieu de la saison de pêche. Ceci permettrait de préserver un niveau minimal de biomasse de géniteurs et de protéger les jeunes stades.

3.1. Stock assessment models for the English Channel stock of cuttlefish

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Abstract

Among the English Channel fishery, the importance of cuttlefish stock has increased, following the cephalopods global landings and market trend. The stock is currently managed at regional scale but not by European regulations, although it is a shared resource. The species is targeted by French and British fishing fleets at several stages of its life-cycle and across much of its distributional range. An assessment of this stock was conducted in June 2014 by fitting a two-stage biomass model on a 22 years' time-series (1992-2013). As the assumptions of the model are based on a simplified life-cycle, it would be appropriate to compare the results with outputs from other models in order to obtain reliable biomass estimations. The final aim is to produce reliable management rules to assure a sustainable harvest rate. The use of a Bayesian framework is particularly adapted for decision making, allowing the propagation of uncertainty in the model and the use of prior knowledge on some parameter distributions. Therefore, we implemented the two-stage biomass model into a Bayesian framework and compared the results with the outputs of the initial fit. We also applied a multi-annual generalized depletion model to the English Channel cuttlefish stock. We found similar trends of biomass estimates for the various models. The Bayesian model outputs showed a smaller range of variation than the initial fit. These results allow a first comparison of the initial model outputs. But the Bayesian model could be improved and particular attention should be paid to the growth parameter g because of the high sensitivity of model outputs to its value.

Keywords: stock assessment, short-lived species, data-limited, cuttlefish, *Sepia officinalis*, English Channel, two-stage biomass model, depletion model, Bayesian methods

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Cette partie de chapitre fait l'objet d'un article scientifique qui a été soumis dans une revue scientifique à comité de lecture.

Résumé

L'importance du stock de seiche au sein des pêcheries de la Manche a augmenté, suivant ainsi la tendance générale du marché et des débarquements de céphalopodes. Le stock est actuellement géré à l'échelle régionale mais n'est soumis à aucune règle Européenne spécifique, bien qu'il s'agisse d'une ressource partagée. L'espèce est ciblée par les flottilles françaises et anglaises à plusieurs étapes de son cycle de vie et sur une grande partie de son aire de répartition. Une évaluation a été réalisée pour ce stock en juin 2014 en ajustant un modèle de biomasse à deux stades à une série de données de 22 années (1992-2013). Puisque les hypothèses du modèle reposent sur un cycle de vie simplifié, il serait pertinent de comparer les résultats avec les sorties d'autres modèles afin d'obtenir des estimations de biomasses fiables. L'objectif final serait de produire des règles de gestion fiables afin d'assurer un niveau d'exploitation durable. L'utilisation d'un cadre Bayésien est particulièrement adaptée pour la prise de décision, permettant la propagation de l'incertitude dans le modèle et l'utilisation de connaissances a priori sur la distribution de certains paramètres. Nous avons donc adapté le modèle de biomasse à deux stades dans un cadre Bayésien et avons comparé les résultats avec les sorties du premier ajustement. Nous avons également appliqué un modèle de déplétion généralisée multi-annuel au stock de seiche de Manche. Des tendances similaires d'estimation de biomasse ont été obtenues pour les différents modèles. Les sorties du modèle Bayésien ont montré des variations moins grandes que l'ajustement initial. Ces résultats permettent une première comparaison des sorties du modèle initial. Cependant, le modèle Bayésien pourrait être amélioré, et une attention particulière devrait être portée au paramètre de croissance de biomasse g à cause de la grande sensibilité des sorties du modèle à sa valeur.

Mots clés: évaluation de stock, espèce à vie courte, données limitées, seiche, *Sepia officinalis*, Manche, modèle de biomasse à deux stades, modèle de déplétion, méthodes Bayésiennes

3.1.1. Introduction

Stock assessment for short-lived species is a delicate matter because of the difficulty of swift data collection as well as the challenge of modelling population dynamics. Cephalopod populations are fast growing short-lived ecological opportunists. Age based methods in these species are hampered by time consuming age determination with statoliths. In spite of trials with a wide range of models (Pierce and Guerra, 1994 [204]) there is no routine stock assessment in most of cephalopods fisheries, although a precautionary approach is often advocated (Rodhouse et al., 2014 [229]).

The English Channel cuttlefish stock is one of the most important resource for the Channel fisheries and is exploited by French and English fishermen (Dunn, 1999a [77]; Engelhard et al., 2012 [80]). The inshore exploitation is managed by local rules, but no EU regulation is applied to the whole stock. It experiences a short life-span (considered of 2 years in the English Channel) and performs seasonal migrations. Cuttlefish concentrates in the central western Channel during winter and in coastal areas during spring and summer (Boucaud-Camou and Boismery, 1991 [25]).

One argument for an English Channel stock unit was that migration takes place almost entirely within the English Channel (Dunn, 1999b [78]). Boundaries of the stock were set as ICES division VIId and VIIe, which was also coherent with the concentration of high Catch Per Unit Effort (CPUE) inside these boundaries (Wang et al., 2003 [266]).

Analytical methods have been used to occasionally assess the stock (Royer et al., 2006 [236]), but because of the difficulty to correctly describe catch structure, less data-demanding models were sought (Gras et al., 2014 [110]), which could be used routinely. The two-stage biomass model (Roel and Butterworth, 2000 [230]) is not too much data-demanding and is therefore well suited for data-limited stocks. It assumes that the exploited population can be observed at two different stages: recruitment and full exploitation. It has been adapted to the English Channel cuttlefish stock (Gras et al., 2014 [110]), based on a simplification of cuttlefish life-cycle, and with bootstrap estimated uncertainties. Ibaibarriaga et al. (2008) [135] highlights the advantage of using Bayesian methods for estimating uncertainties in these models and to face the lack of data. The main idea of the Bayesian inference is to use the initial knowledge (prior distribution), update it with the most recent information (observed data, interpreted via the likelihood function) and form the posterior distribution, which is the new understanding about the studied phenomenon (Pulkkinen, 2015 [210]).

This study presents the evolution of biomass estimates from 1992 to 2012 using a Bayesian implementation of the two-stage biomass model from Gras et al. (2014) [110].

Outputs are compared with the initial fit. Another model designed for data limited stocks is also applied: the multi-annual generalized depletion model (MAGD) from Roa-Ureta (2014) [226]. The aim is to improve the two-stage biomass model, which uses catch, effort and survey data, and compare it with the MAGD model using catch, effort and mean individual weight by month. This study is a first step in the construction of good management tools for short-lived species in data-limited situations, and further work will be done as explained in the discussion part.

3.1.2. Materials and methods

3.1.2.1. Data used in the models

The implementation of the two-stage biomass model required the abundance indices from the Bottom Trawl Survey (BTS) and the Channel Ground Fish Survey (CGFS), as well as the landings and the effort data from the French and the UK trawlers, and the total catch of cuttlefish among the English Channel ($C_{1+,y}$). The BTS abundance indices and the data from the UK trawlers were extracted by the Centre for Environment, Fisheries and Aquaculture Science (Cefas), and the data from the CGFS survey and from the French trawlers were extracted by the French Research Institute for Exploitation of the Sea (Ifremer). The BTS survey is carried out each year in July (when cuttlefish recruitment occurs), and the CGFS survey is carried out in the eastern English Channel one quarter later, in October. The trawling lasts approximately 30 minutes at each station for both surveys (Carpentier et al., 2009 [39]). The effort data consists on the number of trawling hours for the trip considered and the engine power of the vessel considered. The weight of the specimens of one year old and more caught in the English Channel was also required. This last information could be estimated from sale data, by calculating the percentage of cuttlefish belonging to the commercial categories 1 or 2 (i.e. animals above 300g).

For the MAGD model, the catch and the effort data from the French Bottom Otter Trawls (OTB) were aggregated at a monthly scale. A time series of mean individual weight was also needed. The University of Caen has conducted monthly cuttlefish sampling by commercial categories between 1997 and 2013 at Port-en-Bessin (Normandy). Not all months could be sampled (193 months sampled instead of 204 months), and July was often missing. Mean weight could be calculated for each commercial category. The mean individual weight by month was obtained by weighing the weight of each category by the proportion of the category among landings, and by dividing the resulting total weight by the number of cuttlefish sampled.

3.1.2.2. Two-stage biomass model

A package with the version of a two-stage biomass model adapted to cuttlefish was coded in R (Gras, 2014 [109]). The model (Gras et al., 2014 [110]) assumes a simplified life cycle of cuttlefish. It assumes that the exploited population can be observed at two different stages: recruitment and full exploitation. The recruited biomass (B_1) is estimated with the abundance indices from the BTS and the CGFS surveys. The spawning stock biomass (B_2) is estimated with the Landings Per Unit Effort (LPUE) from the French and the UK bottom trawl fisheries. A biomass growth parameter g is fixed externally. It is composed by the natural mortality rate assumed to be equal to 1.2 (Royer et al., 2006 [236]; Gras et al., 2014 [110]), and by the growth rate derived from the mean weight at age calculated from historical data collected by the University of Caen.

A first step is to calculate the standardized LPUE, using the delta-glm function of the cuttlefish.model package. The LPUE variability is explained by 4 variables: fishing season, month, ICES rectangle and engine power of the vessel.

Each fishing season y extends from the 1^{st} July to the 30^{th} June of the following year. The total catch of one year old cuttlefish ($C_{1+,y}$) is assumed to happen as a pulse in the middle of the fishing season (on 1^{st} January). The spawning stock biomass $B_{2,y}$ of the fishing season y at the end of the life cycle is therefore expressed as:

$$B_{2,y} = \left(B_{1,y}e^{-g/2} - C_{1+,y}\right)e^{-g/2} \tag{3.1}$$

Where g is the biomass growth rate parameter which includes the individuals growth in weight and the natural mortality of cuttlefish. The abundance $B_{1,y}$ at the beginning of the fishing season can be estimated with the BTS and the CGFS survey indices:

$$S_y^1 = k_1 B_{1,y} e^{\varepsilon_y} \;;\; S_y^2 = k_2 B_{1,y} e^{-g/4} e^{\delta_y} \tag{3.2}$$

Where S_y^1 is the BTS survey index for the fishing season y, k_1 is the BTS survey catchability, ε_y is the observation error for the fishing season y, S_y^2 is the CGFS survey index, k_2 the CGFS survey catchability, and δ_y is the observation error.

The LPUE are modelled based on the mean biomass in the fishing season. The UK standardized LPUE (U_y^{uk}) and the French standardized LPUE (U_y^{fr}) can be expressed as:

$$\begin{aligned} U_y^{uk} &= \frac{1}{2} q_{uk}\left[B_{1,y}e^{-g/4} + (B_{1,y}e^{-g/2} - C'_{1+,y})e^{-g/4}\right] \\ U_y^{fr} &= \frac{1}{2} q_{fr}\left[B_{1,y} + (B_{1,y}e^{-g/2} - C_{1+,y})e^{-g/2}\right] \end{aligned} \tag{3.3}$$

Where q_{uk} is the catchability of UK trawlers, q_{fr} the catchability of French trawlers, and $C'_{1+,y}$ the landings from July, year Y to April, year Y+1, considering that UK trawlers exploit cuttlefish only in autumn and winter. The model is finally fitted by minimizing the sum of squares residuals.

The exploitation rate can be expressed as the total landings of the fishing season y divided by the biomass estimated on 1^{st} January ($B_{1.jan}$), in fishing season y:

$$E_y = C_{1+,y}/B_{1,y}e^{-g/2} \tag{3.4}$$

The model used by Gras et al. (2014) [110] was implemented into a Bayesian framework and the software Openbugs was used. The Bayesian fit required prior distributions for B_1 and for the catchability rates. The priors were the same each year. We chose normal distributions, with a mean of 15000 and a CV of 2.5 for B_1, and a mean of 0.0001 and a CV of 0.0067 for the catchability rates to stay close to the work of Gras et al. (2014) [110]. We also used the same value for g as in Gras et al. (2014) [110]: $g = -1.01$. The posterior distribution of B_1 was obtained by combining the likelihood function with the prior distribution.

The chain convergence was checked with the BGR diagnostic suggested by Brooks and Gelman (1998) [31] and a sensitivity analysis was conducted on B_1 prior distribution and g value. A 20% variation was applied on the mean of B_1 prior distribution, and values of $g = -0.5$ and -1.5 were tested to compare the results with the sensitivity analysis conducted in Gras et al. (2014) [110]. The initial and the Bayesian fit of the two-stage biomass model were applied on years 1992-2013. 1000 iterations were conducted for the initial model with a bootstrap method, and 100 000 iterations for the Bayesian model using a Markov chain Monte Carlo (MCMC) method.

3.1.2.3. MAGD model

Generalized depletion models require catch in numbers by month and equally long time series of monthly mean body weight. The package CatDyn (Roa-Ureta, 2012 [225]), available on the CRAN of the software R, allows an implementation of a MAGD model with one or two fleet(s). The package BB (Varadhan and Gilbert, 2009 [258]) is also required to fit the model with a numerical optimizer. The conjugate gradient (CG) and the spectral projected gradient (spg) numerical methods happen to work well on nonlinear recursive regression (Roa-Ureta, 2014 [226]) and are more likely to be successful with large optimization problems (Nash and Varadhan, 2011 [193]). These two methods were therefore preferred to others.

The formula used by the model is the following (Roa-Ureta et al., 2015 [227]):

$$\begin{aligned} C_t &= kE_t^{\alpha} N_t^{\beta} e^{-M/2} \\ &= kE_t^{\alpha} \left(N_0 e^{-Mt} - e^{-M/2} \sum_{i=1}^{i=t-1} C_i e^{-M(t-i-1)} + \sum_{i=1}^{i=t} P_i e^{-M(t-i)} \right)^{\beta} e^{-M/2} \end{aligned} \tag{3.5}$$

Where C_t is the catch in numbers of individuals per short time step (t is the month in our study), E is the fishing effort, N is the fish abundance and k is the catchability factor. Perturbations P_i are interpreted as regular pulses of annual recruitment occurring at a particular month. Parameter β defines the relationship between fish abundance and the response of catch-per-unit effort. In case of proportionality, it would be estimated near 1. If β is estimated at higher than 1, catchability varies more than population number (hyper-depletion). If it is estimated at less than 1, the opposite occurs (hyper-stability). The model also accounts for nonlinear effects in the relation between catch and effort through parameter α. An estimation near 1 means proportionality. In case of saturated gear, α would be estimated at less than 1, and at higher than 1 in case of synergistic gear.

The monthly fishing mortality rate F_t can be expressed as:

$$F_t = kN_t^{1-\beta} E_t^{\alpha} \tag{3.6}$$

We applied a one fleet MAGD model with the package Catdyn from Roa-Ureta (Roa-Ureta, 2014 [226]), version 1.0-6 (built on 2015-01-16) on the same time series used for the application of the two-stage biomass model. The model accounted for 22 perturbations, totalling 27 parameters. The numerical algorithm methods *CG* and *spg* as well as the normal and the lognormal models were tested.

The landings in weight of French bottom otter trawls (OTB) were aggregated at monthly scale. The fishing effort was measured as the sum of fishing hours per month. The cuttlefish mean individual weight data were used to transform the catch in weight to catch in numbers. To select the starting values of the perturbation timings, the perturbations in the catch spike S_t were selected visually a priori using a convenient statistic for graphical display of perturbations:

$$S_t = 10 \left(\frac{x_t}{max(x_t)} - \frac{E_t}{max(E_t)} \right) \tag{3.7}$$

Where x_t is the observed catch in numbers. This statistic shows high positive values in case of catch spikes not explained by effort spikes. The perturbations were interpreted as regular pulses of annual recruitment resetting the depletion process. It occurred in September of each year, as offshore migration of cuttlefish takes place.

The model assumes that the catch in numbers at any time step is a random variable with a known distribution. A likelihood function of difference between the observed catch series and the predicted catch series is minimized to fit the model. It is only an approximated likelihood because the transformation of catch in biomass to catch in numbers is ignored, and the variance is eliminated from the inference (Roa-Ureta, 2014 [226]). According to the analysis of the residuals and the Akaike information criterion (AIC) values, a measure of the relative quality of statistical models, the normal model using the numerical optimizer *spg* was selected.

The model outputs include an estimate of the biomass vulnerable to the fishing gear, at a monthly scale. The mean annual biomass was obtained by averaging the monthly biomass for each year. The annual fishing mortality rates were obtained by doing the sum of F_t for each year, assuming separable fishing mortality rates, as in Smith et al. (2009) [245].

To compare the trends in the evolution of biomass estimates from the two-stage biomass model and from the MAGD model, the biomass estimates were standardized by dividing them by the mean biomass of the time-series for each model outputs.

3.1.3. Results

The evolution of the estimated abundance indices (Fig. 3.1) shows a better fit of the initial model for BTS and CGFS surveys, but a better fit of the Bayesian model is observed for French and UK LPUE. The models do not succeed in estimating high values of BTS and CGFS abundance indices (e.g. 2000, 2002 for both surveys, and 2006 for CGFS survey). The survey abundance indices in 2012 pull the model fit downward, whereas the LPUE abundance indices pull it upward.

The evolution of the recruited biomass estimates (Fig. 3.2.a.) and the spawning stock biomass estimates (Fig. 3.2.b) are similar between the initial fit and the Bayesian fit of the two-stage biomass model. However, the outputs from the Bayesian fit show a smaller range of variation than the initial fit. The confidence intervals are smaller for the Bayesian fit, except during years of small biomass estimate (i.e. 1994, 1997 and 2001). Similar trends of exploitation rate are observed for both fits of the two-stage biomass model (Fig. 3.2.c.). An important decrease in the exploitation rate is observed between 2006 and 2008 for both fit, but the following 2011 spike predicted by the Bayesian fit is not as high as the one predicted by the initial fit. No stock-recruitment relationship was observed for the

Bayesian fit (Fig. 3.2.d.), nor for the initial fit. In Gras et al. (2014) [110], the minimum estimated B_2 (11 000 tons) was proposed as Blim for English Channel cuttlefish, based on the precautionary principle. According to the Bayesian fit outputs, Blim would be 13 690 tons.

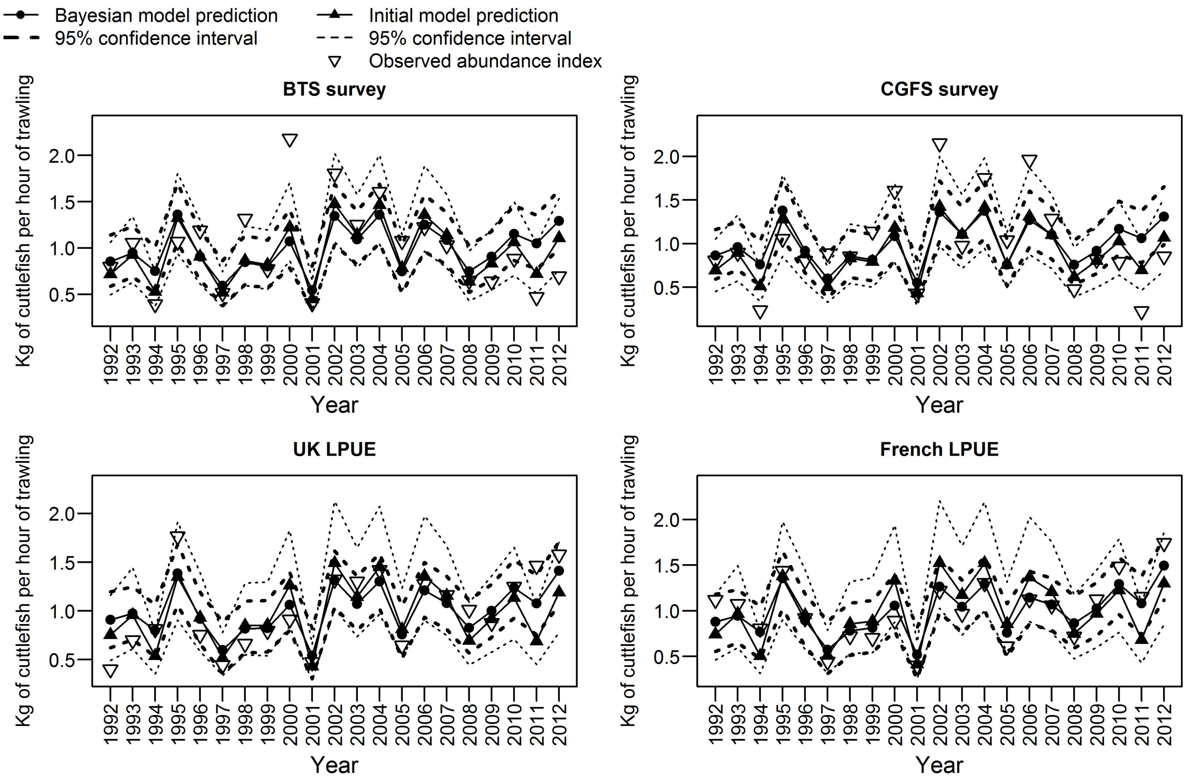

FIGURE 3.1 – Time series of the observed and predicted abundance indices for initial model and Bayesian model fit with 95% confidence interval from 1992 to 2012.

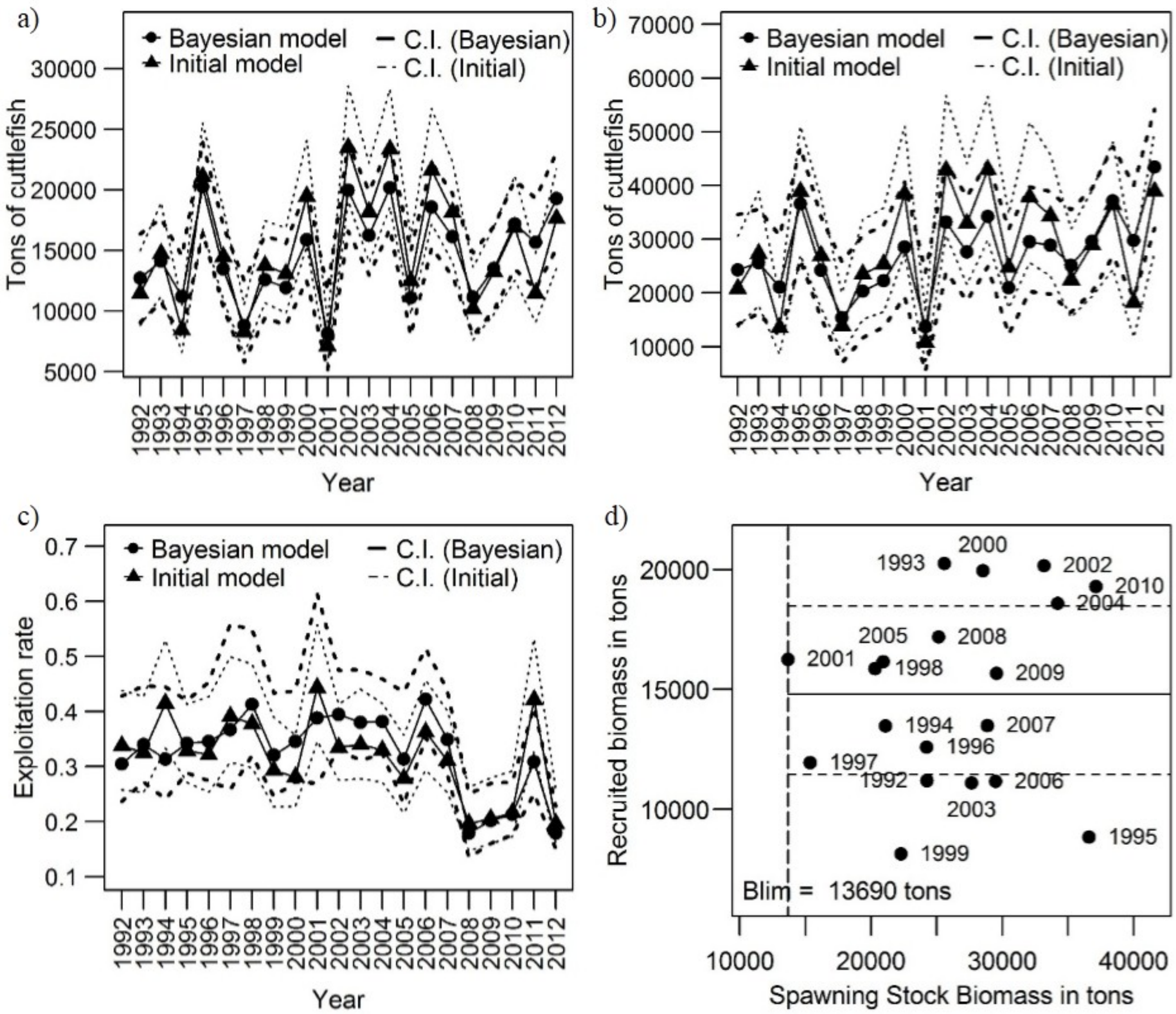

FIGURE 3.2 – Comparison of a) the evolution of recruited biomass B_1, b) the spawning stock biomass B_2 and c) the exploitation rate for the initial and the Bayesian fit of the two-stage biomass model. d) Stock-recruitment relationship for the Bayesian fit of the two-stage biomass model, with the average annual recruitment (solid line) and its 95% confidence interval (dashed lines). Years plotted are recruitment years.

The catchability rates estimated by the Bayesian model are higher than the estimations from the initial fit (Table 3.1), from +3.3% to +12.6%. The biggest differences between the two fits are observed for the CGFS catchability rate (k_2). Table 3.2 shows the percentage of variation between the outputs from the Bayesian and the outputs from the initial fit of the two-stage biomass model. In average, the biggest differences between both fits are observed for the exploitation rate.

TABLE 3.1 – Variability between the initial model and the Bayesian model estimates of catchability rates (in percentage).

k_1	k_2	q_{uk}	q_{fr}
7.258	12.64	7.197	3.253

k_1 = catchability rate of BTS survey, k_2 = catchability rate of CGFS survey, q_{fr} = catchability rate of French trawlers, q_{uk} = catchability rate of UK trawlers.

TABLE 3.2 – Percentage of variation between the Bayesian model outputs and the initial model outputs.

Fishing season	B_1	B_2	$B_{1.jan}$	E
1992	10.89	10.84	16.45	-9.802
1993	-4.283	-4.311	-6.332	4.513
1994	32.43	32.42	55.59	-24.49
1995	-3.977	-3.959	-5.866	4.138
1996	-6.940	-6.925	-10.14	7.444
1997	6.548	6.576	10.91	-6.136
1998	-8.488	-8.494	-13.57	9.289
1999	-8.695	-8.669	-12.20	9.491
2000	-18.56	-18.55	-25.77	22.77
2001	14.25	14.27	25.79	-12.46
2002	-15.04	-15.04	-22.58	17.69
2003	-10.62	-10.64	-16.05	11.88
2004	-13.64	-13.66	-20.31	15.81
2005	-11.14	-11.11	-15.34	12.52
2006	-14.07	-14.06	-22.06	16.38
2007	-11.00	-11.00	-15.93	12.38
2008	9.677	9.725	12.16	-8.846
2009	1.698	1.686	2.176	-1.639
2010	1.504	1.515	1.938	-1.476
2011	36.43	36.46	63.07	-26.73
2012	9.375	9.364	11.67	-8.558
Mean variation	-0.1742	-0.1695	0.6482	2.103
SD	14.95	14.59	24.22	13.67

B_1 = Recruited biomass, B_2 = spawning stock biomass, $B_{1.jan}$= biomass estimated on 1^{st}January in the middle of the fishing season, E= exploitation rate, SD = standard deviation.

The results of the sensitivity analysis conducted on the Bayesian two-stage model (Table 3.3) show that B_2 estimates are very sensitive to the variation of g. A change of 20% in the mean value of B_1 prior distribution leads to 30% variation of B_2 estimates. The estimates of exploitation rates are most sensitive to the underestimation of B_1 prior distribution and to the overestimation of g. The survey catchability estimates are most sensitive to the variation of B_1 prior distribution, whereas the UK and French fleet catchability estimates are most sensitive to the variation of g.

TABLE 3.3 – Sensitivity analysis of the Bayesian two-stage biomass model. Percentages of variation between the results of the initial model and the results of the alternative models.

	B1_ mean = 12000	**B1_ mean = 18000**	$\boldsymbol{g = -0.5}$	$\boldsymbol{g = -1.5}$
B_1	-19.96	20.06	-2.657×10^{-2}	2.249×10^{-3}
B_2	-29.72	29.87	-48.56	80.64
$B_{1.jan}$	-19.96	20.06	-22.53	27.77
E	24.95	-16.71	29.09	-21.73
k_1	-25.02	16.67	0.0742	0.0297
k_2	-24.98	16.71	13.7	-11.5
q_{uk}	-30.44	20.69	35.9	-34.2
q_{fr}	-35.03	18.95	45.6	-26.4

B1_mean = value of the mean for B_1 normal prior distribution.

Fig. 3.3 shows the evolution of the mean annual biomass and the annual fishing mortality rate estimated by the MAGD model. The biomass estimates show high inter-annual variations with no clear general trend. The fishing mortality increases from the beginning of the time-series to 2004, and shows an important decrease from 2006 to 2009. This decrease is consistent with the decrease in exploitation rate observed for the two-stage biomass model. The evolution of the standardized biomass estimates (Fig. 3.4) show similar trends for both models, but the MAGD model outputs show a smaller range of variation. The fit of the MAGD model is presented on Fig. 3.5.

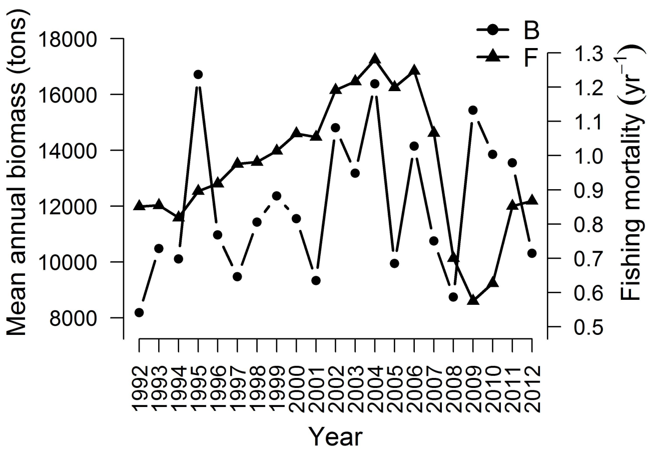

FIGURE 3.3 – Evolution of mean annual biomass and annual fishing mortality estimates of the MAGD model.

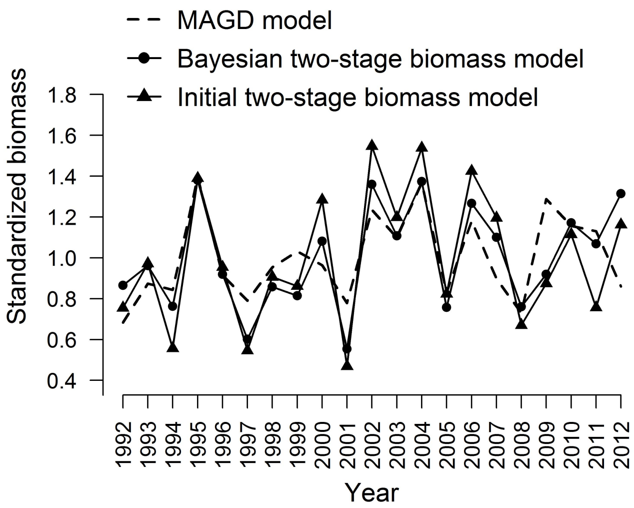

FIGURE 3.4 – Evolution of standardized biomass estimates for MAGD model and initial and Bayesian fit of the two-stage biomass model.

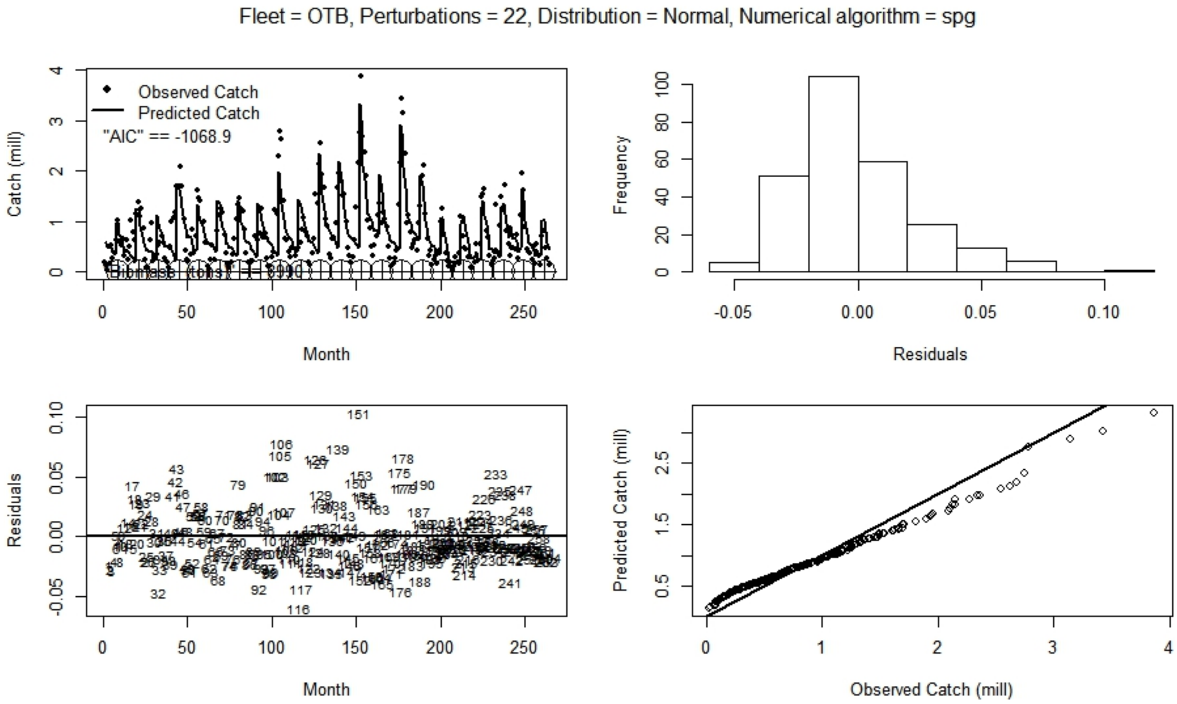

FIGURE 3.5 – Stock assessment predictions from the MAGD model and model residuals. Model predicted catch versus observed catch (top left), residual empirical distribution (top right), residual scatter plot (bottom left) and quantile-quantile plot of generalized depletion model. Perturbation timing configuration is represented as target symbol (top left).

Table 3.4 shows the values of the model parameters estimates. The initial population was estimated at 18.3 million individuals, with regular peaks of recruits varying from 18.3 million to 61.9 million individuals. The monthly natural mortality was estimated at 0.1. The parameter α was estimated at 0.65, meaning that the studied fleet shows a saturation effect. According to the value of the β parameter (<1), we face a regime of rather hyper-stability.

TABLE 3.4 – Stock assessment results of the multi-annual generalized depletion model applied to the monthly catch and effort data of the English Channel stock of cuttlefish.

Parameter	**Timing**	**MLE**	**CV (%)**
M (month^{-1})		0.0998	10.26
N0 ($\times 10^6$)		18.32	16.08
P1 ($\times 10^6$)	Sep. 1992	20.27	15.10
P2 ($\times 10^6$)	Sep. 1993	30.42	16.42
P3 ($\times 10^6$)	Sep. 1994	27.02	17.21
P4 ($\times 10^6$)	Sep. 1995	49.26	17.44
P5 ($\times 10^6$)	Sep. 1996	29.39	18.99
P6 ($\times 10^6$)	Sep. 1997	26.57	17.51
P7 ($\times 10^6$)	Sep. 1998	28.73	16.95
P8 ($\times 10^6$)	Sep. 1999	27.01	16.51
P9 ($\times 10^6$)	Sep. 2000	40.36	15.69
P10 ($\times 10^6$)	Sep. 2001	27.87	17.05
P11 ($\times 10^6$)	Sep. 2002	42.93	15.13
P12 ($\times 10^6$)	Sep. 2003	35.59	15.36
P13 ($\times 10^6$)	Sep. 2004	61.87	16.92
P14 ($\times 10^6$)	Sep. 2005	24.88	17.10
P15 ($\times 10^6$)	Sep. 2006	54.00	16.62
P16 ($\times 10^6$)	Sep. 2007	28.56	16.92
P17 ($\times 10^6$)	Sep. 2008	19.22	17.76
P18 ($\times 10^6$)	Sep. 2009	35.72	18.12
P19 ($\times 10^6$)	Sep. 2010	42.39	18.62
P20 ($\times 10^6$)	Sep. 2011	37.39	19.48
P21 ($\times 10^6$)	Sep. 2012	28.11	18.42
P22 ($\times 10^6$)	Sep. 2013	18.34	17.84
k (effort^{-1})		5.713×10^{-5}	0.7257
alpha		0.6501	–
beta		0.8986	1.802

MLE = maximum likelihood estimates, CV = coefficients of variation (model failed to produce one standard error, indicated by "–").

3.1.4. Discussion

In a first step, we wanted to implement the two stage biomass model in a Bayesian framework and to compare the results. The estimates obtained with the initial fit (Gras et al., 2014 [110]) and with the Bayesian fit of the two-stage biomass model showed similar trends. However, the model still doesn't succeed in estimating some values of abundance indices (Fig. 3.1). The outputs of the Bayesian fit showed a high sensitivity to the prior distribution of B_1 and to the g value. The need to give good prior estimations is a common issue of Bayesian methods. Gras et al. (2014) [110] identified a significant positive correlation between the sea surface temperature during the third quarter (summer) of the year before the recruitment and B_1. This result could be a starting point to investigate a Bayesian model including environmental factors, in order to give better prior distributions on B_1.

The high sensitivity of the results to g was already highlighted by Gras et al. (2014) [110] and further work also needs to be done on this particular point. Growth used for the two-stage biomass model is assumed to be the same for each year, which is a strong assumption for cephalopod species. One possibility would be to build an informative prior for g, using meta-analysis on other cephalopod stocks. Ideally, variations of g in other stocks could be used to infer g annual variations of the English Channel cuttlefish stock in the Bayesian fit. But this information might be hard to obtain, as no regular evaluation of growth seem to be conducted for cephalopods stocks in the English Channel.

The parameter g could also vary with the season, as suggested in Dunn (1999a) [77]. He found that fastest growth in length took place between July and October in males, and between August and October in females. The slowest growth rates were recorded from the winter before spawning in the spawning period. If we could for example find a relationship between sea surface temperature and cuttlefish growth, we could use this link to infer information on annual growth variation. Finally, size frequency data could be an additional source of information on growth variation.

The analysis of the residuals from the MAGD fit (Fig. 3.5) shows that the model overestimates catch for small catch values and underestimates it for high catch values. The quantile-quantile plot presented in Roa-Ureta (2014) [226] shows the same characteristics. This can explain why the variation range observed with the MAGD model is smaller than the variation range observed with the initial two-stage biomass model.

The parameter α of the MAGD model was estimated at less than 1 (Table 3.8), meaning that the studied gear shows a saturation effect. The accumulation of fishes in the trawl can narrow the meshes because of the weight, creating a backward flow and leading to a decreasing catchability rate with increasing fishing time. The monthly natural mortality was estimated at 0.1 by the MAGD model, which was in accordance with Royer et al. (2006) [236] results. They estimated the natural mortality by an empirical method (Caddy, 1996 [36]), and a monthly rate of 0.1 was obtained for the exploited stage. Gras et al. (2014) [110] used an annual natural mortality rate of 1.2, following the assumption of Royer et al. (2006) [236]. According to the outputs of the MAGD model, we would also have an annual natural mortality of 1.2.

The timing used for the MAGD model was September of each year, which was not consistent with Royer et al. (2006) [236] assumptions. They found that the main period of recruitment to the fishery was October-November as young of the year migrate offshore to wintering grounds, and that a second group of recruits was observed in March-April as the stock migrates to inshore areas. It would be necessary to try setting perturbations at other dates to see if results differ a lot. It could also be interesting to set two pulses of annual recruitment (44 perturbations) to better model reality.

The absolute values of biomass estimates were different between the two-stage biomass model and the MAGD model. The first reason is that the data used for the MAGD model implementation differ from the data used for the two-stage biomass model. The comparison could be easier if UK data were included. The mean individual weight by month for UK trawlers would then be necessary. Another reason is that the two-stage biomass model estimates the biomass at a specific time of the fishing season, whereas the MAGD model estimates the biomass at a monthly level, which is then averaged at an annual scale.

The advantage of the MAGD model is that it requires really few data. It also allows the implementation of a two-fleet model. In the case of cuttlefish, not only trawlers impact the cuttlefish stock, but also fishing pots. It could be interesting to apply the MAGD model on both OTB and fishing pot fishery, but there is a lack of individual weight data for the pot fishery. The disadvantage of the MAGD model is that it relies only on catch and effort data, so if a trend detected by the survey abundance indices is not detectable in the catch per unit effort, the results could be biased. For example in our study, the biomass estimates of the two-stage biomass model show an increase from 2011 to 2012 (Fig. 3.3), whereas the MAGD model outputs show a decrease. The analysis of the abundance indices (Fig. 3.1) show that the survey and the LPUE data indicate different trends. In this case the two-stage model is likely to better predict reality.

A possible next step could be to apply a hierarchical statistical framework to combine generalized depletion models and biomass dynamic models in the stock assessment, as developed by Roa-Ureta et al. (2015) [227]. They implemented a random effects state-space model, using the biomass estimates from the MAGD model to infer prior values of biomass for the Pella and Tomlinson's (1969) [200] model. This kind of production models was used in assessments of *Sepia* in the Arabian Sea (Sato and Hatanaka 1983 [238]), making the equilibrium assumption. Usual surplus production models assume a stock-recruitment relationship, which is inconsistent with cephalopod stocks. However, surplus production models were fitted without the equilibrium hypothesis in Mediterranean Cephalopod stocks (Stefanie Keller, Instituto Español de Oceanografía, Palma de Mallorca, Spain, 2015, *pers. comm.*).

Another idea is to use the Stock Synthesis (SS) framework (Methot and Wetzel, 2013 [185]) to compute an adapted model, using all available information, including data used by the two-stage biomass model, as well as mean individual weight by month and length composition data. This framework offers many possibilities to use different sources of data and can be adapted to complex life histories. The model can account for a time-varying growth, as well as a cohort specific growth rate, environmental factors, and could also include migration. An SS model has for example been adapted for bigeye tuna *Thunnus obesus*, using five areas (Aires-da-Silva and Maunder, 2012 [3]).

In Gras et al. (2014) [110], an exploitation rate below 40% is recommended, and a threshold of 11 000 tons is proposed for the spawning stock biomass. Setting quotas to manage the English Channel cuttlefish stock is unlikely to be efficient because of the high variability in cephalopod stock sizes (Caddy, 1983 [35]; Beddington et al., 1990 [14]). Currently, the stock is managed at a regional scale. In Normandy, the fishing of cuttlefish is forbidden within the 3-miles inshore zone, except during 2 weeks at the end of August, and during another 6 weeks in spring. In order to better manage the stock, simulations could be conducted. A reduction of effort at specific times or in specific areas could be tested. Better management rules could thus be predicted, with good uncertainty estimates, thanks to the Bayesian framework.

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3.2. A Bayesian two-stage biomass model for stock assessment of data-limited species: an application to cuttlefish (*Sepia officinalis*) in the English Channel

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Abstract

Cuttlefish is a key commercial species in the English Channel fishery in terms of landings and value. Age-based assessment methods are limited by time-consuming age determination with statoliths and the lack of stock assessment models tailored to this data-limited species. A two-stage biomass model is developed in the Bayesian state-space modelling framework that allows inferences to be made on the stock biomass at the start, middle and end of each fishing seasons between 1992 and 2014, while accounting for both process and measurement errors and to assimilate various sources of information. A method that uses ancillary length-frequency data is developed to provide an informative prior distribution for the biomass growth rate parameter g (E=0.89) and its annual variability (CV=0.1). The new model is a substantial improvement on the existing stock assessment method used by the International Council for the Exploration of the Sea. Taking into consideration a time-varying g parameter provides a more ecologically meaningful model with regard to the sensitivity of the cuttlefish population dynamics to environmental fluctuations and improves model fit. The model also provides predictions of the unexploited biomass in winter, which is based on survey data, and helps manage the stock in the event of strong depletion.

Keywords: English Channel, cuttlefish, *Sepia officinalis*, Bayesian state-space model, data-limited stock, two-stage biomass model

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Résumé

La seiche est une espèce commerciale de grande importance dans les pêcheries de Manche tant en termes de débarquement qu'en valeur. Les méthodes d'évaluation de stock structurées en âge sont limitées par une lecture d'âge à partir de statolithes coûteuse en temps et par l'absence de modèles d'évaluation de stock adaptés à cette espèce à données limitées. Un modèle de biomasse à deux stades est développé dans un cadre de modélisation Bayésien qui permet de faire des inférences sur la biomasse du stock au début, au milieu et à la fin de chacune des saisons de pêche entre 1992 et 2014, tout en prenant en compte les erreurs de processus et de mesure et en assimilant des sources d'information variées. Une méthode utilisant des données de fréquence de taille complémentaires est développée pour fournir une distribution de prior informatif sur le paramètre de croissance de la biomasse g (E=0.89) et sur sa variabilité interannuelle (CV=0.1). Le nouveau modèle est une amélioration considérable de la méthode d'évaluation de stock existante utilisée par le Conseil International pour l'Exploration de la Mer. La prise en compte d'un paramètre g à variation interannuelle améliore l'ajustement du modèle et permet un meilleur réalisme écologique au vu de la sensibilité de la dynamique de population de la seiche aux fluctuations environnementales. Le modèle fourni également des prédictions sur la biomasse inexploitée en hiver à partir des données de campagnes scientifiques, et aide à gérer le stock en cas de forte diminution d'abondance.

Mots clés: Manche, seiche, *Sepia officinalis*, modèle Bayésien, stock à données limitées, modèle de biomasse à deux stades

3.2.1. Introduction

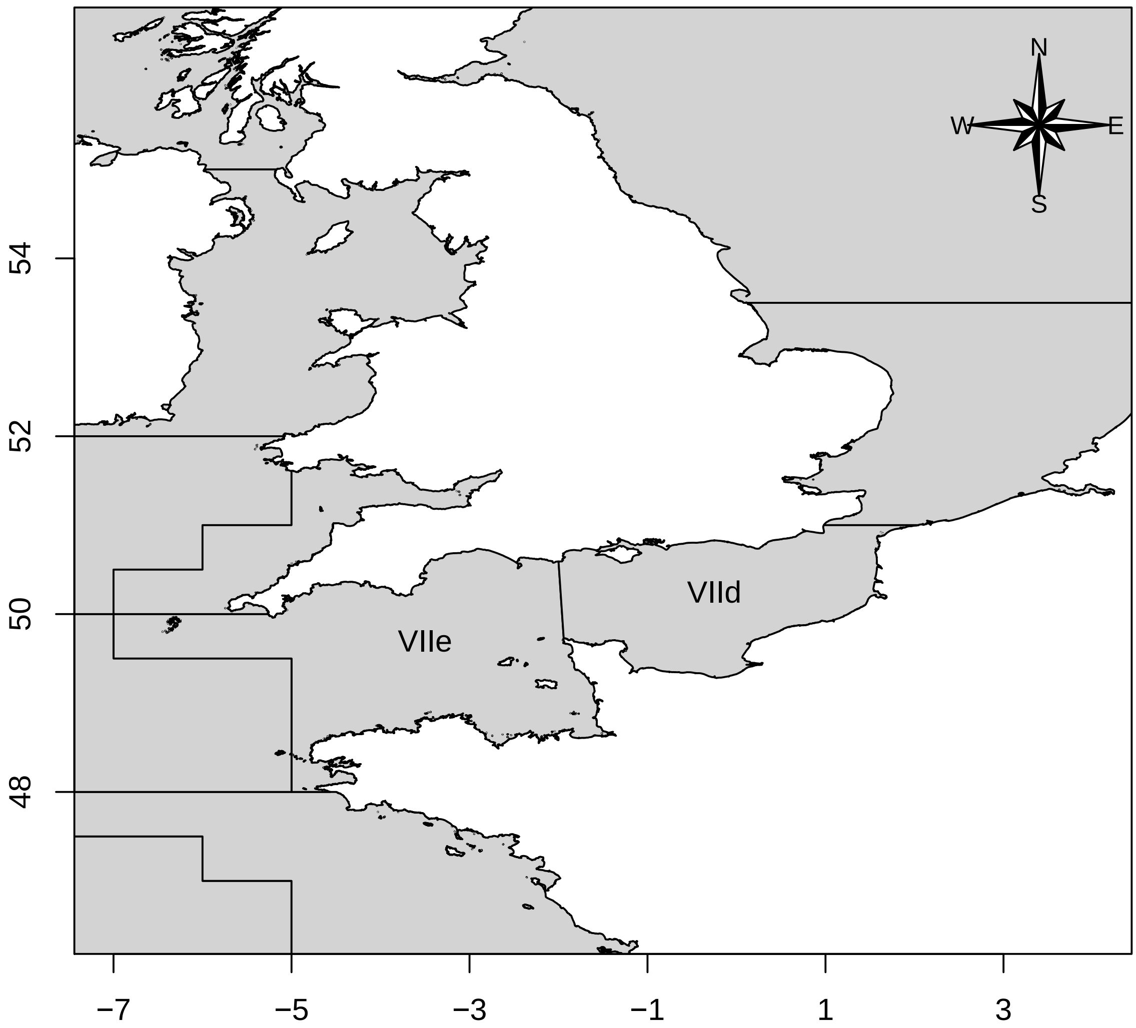

FIGURE 3.6 – Location of the stock studied. The English Channel is composed of ICES divisions VIId and VIIe.

Cephalopods stocks are difficult to assess and require specific models to be developed (Pierce and Guerra, 1994) because of the nature of their life cycle, including short life span and highly variable growth, and because of the difficulty of age determination (Lipinski et al., 1998; González et al., 2000; Bettencourt and Guerra, 2001). The lack of routine stock assessment methods for short-lived species restricts sharing of information and comparing status among stocks, and reinforces the need for a precautionary approach (Rodhouse et al., 2014).

The cuttlefish stock in the English Channel (Fig. 3.6) is data-limited. This stock is assumed to be a single unit because of high catch-per-unit-effort concentration in International Council for the Exploration of the Seas (ICES) divisions VIId and VIIe (Wang et al., 2003 [266]). It is a shared resource exploited by French and English fishermen (Engelhard et al., 2012 [80]). No European regulations apply to this stock despite its importance in terms of landings and value. The French inshore exploitation is managed by local rules such as minimum landing weight and mesh size. In England, no minimum landing size and no restrictions on the fishing season have been established for cuttlefish (Pierce et al., 2010 [203]).

The English Channel cuttlefish population is semelparous with a two-year lifespan. Migration outside the Channel is suspected to be very low (Boucaud-Camou and Boismery, 1991 [25]). Adults spawn inshore in shallow waters in spring and die. Hatching peaks in summer, and juveniles stay inshore until autumn. Recruitment into the fishery starts in October of the first year, and the annual cohort is fully recruited at the start of the second summer of life, i.e. one year after hatching. Tagging experiments have shown inshore-offshore seasonal migrations: cuttlefish concentrate offshore in the deeper central western part of the Channel during winter, and move inshore in spring for coastal feeding and spawning (Boucaud-Camou and Boismery, 1991 [25]). Seasonal migrations are mainly triggered by temperature, although day-length also influences pre-adult sexual maturation (Richard, 1971 [219]).

The stock has been assessed using a Thomson and Bell model based on monthly catch-at-age data (Royer et al., 2006 [236]), but the method, based on monthly length frequencies, was too data-demanding for a routine stock assessment. Furthermore, conversion of length frequencies into age is highly uncertain because growth and timing of migration might vary substantially according to seasons and years. A much less data demanding two-stage biomass model (Roel and Butterworth, 2000 [230]) was proposed for this stock (Gras et al., 2014 [110]). The model developed by Gras et al. (2014) [110] represents the biomass of group 1+ individuals only, and assumes two stages among the exploited population: recruitment and full exploitation. Recruited biomass (B_1; evaluated on the first of July) is estimated using abundance indices from the Bottom Trawl survey (BTS) and the Channel Ground Fish Survey (CGFS). Spawning stock biomass (B_2) is then estimated using Landings Per Unit Effort (LPUE) from French and United Kingdom (UK) bottom trawl fisheries. The model is fitted to the time series of catches and abundance indices using a maximum likelihood framework that assumes observation errors only, and uncertainties about estimates are quantified using bootstrapping. The model suffers from several weaknesses. Firstly, it considers observation errors only and hence ignores process errors in the biomass dynamics. It also suffers from a lack of flexibility to change model assumptions and/or to assimilate other sources of available information or data. Secondly, the growth rate parameter g (between 12 and 23 months old cuttlefish) is assumed to be known and constant from year to year even though the growth rate of cephalopods is known to be highly sensitive to environmental fluctuations (Rodhouse et al., 2014 [229]). The parameter g includes natural mortality (set to 1.2 yr^{-1}) and a mean growth rate in weight (based on historical data from Medhioub (1986) [180] and set to 2.2 yr^{-1}), which are assumed to be constant in time and known without uncertainty. However, Gras et al. (2014) [110]) showed a high sensitivity of model outputs to the growth rate parameter, and advocated the use of more recent data that would provide a more accurate estimate of this parameter. Thirdly, the model only captures the dynamics of the 1+ component of the population. The time series of abundance indices from the CGFS survey is assumed to be based mainly on group 1+ individuals, although length frequencies suggest a mixture of 0+ and 1+. Indeed, the CGFS survey occurs in October, when cuttlefish migrate offshore. Some of the group 0 individuals are 3 months old at this time of the year and form the lower part of the survey length frequencies. Therefore, using the CGFS time series without processing the data to separate out the two cohorts might provide a biased estimate of group 1+ cuttlefish biomass.

In this work, we have perfected the two-stage biomass model adapted for cuttlefish, based on three substantive new contributions:

(a) The model is developed in a Bayesian state-space framework (Rivot et al., 2004 [223]; Buckland et al., 2007 [33]; Parent and Rivot, 2013 [196]), thus allowing for a comprehensive integration of the different sources of uncertainty by considering both process errors in the biomass dynamics and observation error in the data.

(b) We develop an informative prior (Hilborn and Liermann, 1998 [124]) on the biomass growth rate that takes advantage of various sources of available data to quantify the average growth rate and provide a credible range of variability over the years.

(c) We improve the quality of the data and the demographic realism of the model by explicitly considering that two separate age classes (0+ and 1+) can compose the abundance indices and the exploited biomass.

We first build a model considering the dynamics of 1+ only and a time-varying g parameter. We then evaluate the benefit of a time-varying g parameter instead and evaluate the sensitivity of the results to the amount of data used and the predictive capacity of the model. Finally, we explore the feasibility of considering the dynamics of the two cohorts (0+ and 1+) in the same model.

3.2.2. Materials and methods

We first describe the data used for stock assessment and provide details about the data processing. Then we detail the process equations for the biomass dynamics and the observation equations. Thirdly, we detail the method used to construct an informative prior distribution on the biomass growth rate parameter (denoted $g_{0,y}$ and $g_{1,y}$ for 0 and 1+ groups respectively). Finally, we outline our strategy to analyze the sensitivity of the results to the hypotheses about between-year variation of critical parameters, to the age-structure and the data sources. All parameters used in the model are summarized in Table 3.5, and variants of the baseline model are summarized in Table 3.6.

TABLE 3.5 – The priors.

	Parameter	**Description**	**Distribution**
	μ_{B1}	Grand mean of $B_{1,y}$	Lognormal(μ = 15000, CV = 0.1)
	σ^2_{B1}	Variance of $B_{1,y}$	InverseGamma(0.05, 0.05)
	μ_{g_1}	Grand mean of $g_{1,y}$	Lognormal(μ = 0.89, CV = 0.1)
	σ^2_{g1}	Variance of $g_{1,y}$	InverseGamma(0.05, 0.05)
	$E_{1,y}$	Exploitation rate for group 1+	Beta(α = 1.5, β = 1.5)
	$CV_{process}$	CV used for the lognormal process errors	Exponential(λ = 6)
	CV_{C1}	CV used for the catch of group 1+	Exponential(λ = 8)
	$\log(q_{bts})$	Catchability of the BTS survey	Uniform(a = -15, b = 3)
	$\log(q_{cgfs})$	Catchability of the CGFS survey	Uniform(a = -15, b = 3)
	$\log(q_{lpue1})$	Catchability of the group 1+ French LPUE	Uniform(a = -15, b = 3)
	σ^2_{bts}	Variance of observation errors for BTS survey	InverseGamma(0.05, 0.05)
	σ^2_{cgfs}	Variance of observation errors for CGFS survey	InverseGamma(0.05, 0.05)
	$\sigma^2_{lpue\ 1}$	Variance of observation errors for group 1+ French LPUE	InverseGamma(0.05, 0.05)
Parameters specific to model M3	μ_{B0}	Grand mean of $B_{0,y}$	Lognormal(μ = 5000, CV = 0.5)
	μ_{g_0}	Grand mean of $g_{0,y}$	Lognormal(μ = 0.97, CV = 0.1)
	$E_{0,y}$	Exploitation rate for group 0	Beta(1.5, 1.5)
	$\log(q_{lpue0})$	Catchability of the French LPUE for group 0	Uniform(-15, 3)
	σ^2_{B0}	Variance of $B_{0,y}$	InverseGamma(0.05, 0.05)
	σ^2_{g0}	Variance of $g_{0,y}$	InverseGamma(0.05, 0.05)
	CV_{C0}	CV of observation errors for group 0 catches	Exponential(λ = 8)
	$\sigma^2_{lpue\ 0}$	Variance of observation errors for the group 0 French LPUE	InverseGamma(0.05, 0.05)

TABLE 3.6 – Model hypotheses.

Model	Exploited biomass	*g* parameter	Abundance indices used
M1	Group 1+ only	Time-varying ($g_{1,y}$)	BTS, CGFS, LPUE (1+)
M2	Group 1+ only	Fixed (g_1)	BTS, CGFS, LPUE (1+)
M3	Group 0 and 1+	Time-varying ($g_{0,y}$ and $g_{1,y}$)	BTS, CGFS, LPUE (1+), LPUE (0)
M4	Group 1+ only	Time-varying ($g_{1,y}$)	BTS, CGFS

3.2.2.1. Data sources and data processing

We used total catch data from the English and French fisheries, and abundance indices from the English BTS and French CGFS surveys, with additional information to separate group 0 and group 1+ animals. The BTS abundance indices and UK catch and effort data were obtained from the Center for Environment Fisheries and Aquaculture Science (CEFAS). The French CGFS abundance indices, French catch and effort, and length data were obtained from the French Research Institute for Exploitation of the Sea (IFREMER). BTS abundance indices were used to model the biomass of 1+ age group only. This group of 0 individuals represents a very small proportion of the BTS survey data because the survey occurs around July just after hatchlings are born, and because the research vessel does not fish too close to the coast where juveniles are found (Carpentier et al., 2009 [39]). BTS abundance indices were calculated as catch-per-unit-effort, using trawling time as effort, and scaled so that the first value of the time series equals 1.

The CGFS survey data were used to provide indices of abundance for the 0+ and 1+ age groups. The CGFS occurs each year during October (Coppin et al., 2002 [60]). Some cuttlefish of the group 0 are already 3 months old at this time of the year and are potentially caught during the CGFS. The following procedure was used to separate the two cohorts (0 and 1+) and to provide a more reliable abundance index for the 1+ group only. The package mixdist (Macdonald et al., 2011 [171]) was applied to the CGFS length frequency data to calculate the mean length and the percentage of number of individuals older than one year-old ($\%N_{1+,y}$) for each fishing season y (Appendix A). Mean length was converted into mean weight using the Dunn (1999a) [77] length-weight relationship. Percentage in weight of group 1+ individuals was calculated as follows:

$$\%w_{1+,y} = [\%N_{1+,y} \times \bar{w}_{1+,y}] \,/\, [\bar{w}_{1+,y} \times \%N_{1+,y} + \bar{w}_{0,y} \times (1 - \%N_{1+,y})] \qquad (3.8)$$

where $\bar{w}_{0,y}$ and $\bar{w}_{1+,y}$are the mean weight of group 0 and group 1+ individuals for the fishing season y. $\%w_{1+,y}$ was then applied to CGFS catch data to calculate the catch in weight of group 1+ individuals. From 2005 to 2014, group 1+ individuals represented on average 91.5% of the CGFS catch-in-weight, with a very small between-year CV of 0.056.

As length data for CGFS survey were available from 2005 only, we used this mean value to calculate the pre-2005 catch-in-weight of 1+ individuals. The catch of 1+ individuals was then divided by trawl swept area for each haul. The resulting CPUE were averaged per strata s with surfaces A_s (ICES rectangles). CPUE by stratum $U_{y,s}^{cgfs}$ were then raised to the VIId area (Fig. 3.6), and scaled so that the first value of the time series equals 1:

$$\%U_y^{cgfs} = \frac{\sum_s A_s \times U_{y,s}^{cgfs} / \sum_s A_s}{\sum_s A_s \times U_{1,s}^{cgfs} / \sum_s A_s} \tag{3.9}$$

The French LPUE were calculated using commercial data that provide information about the percentage in weight of one year-old cuttlefish by year and month. Following (Gras et al., 2014 [110]), cuttlefish of commercial categories 1 and 2 (animals above 300g) were assumed to be 1+ year old. We applied these percentages to separate group 0 and group 1+ in the catches. The zero-inflation in the data was analysed using a Delta-GLM (Lo et al., 1992; Stefánsson, 1996 [247]; Fletcher et al., 2005 [88]; Gras et al., 2014 [110]) applied to each of the time series (aggregated by trip) with ICES statistical rectangle, vessel power, fishing season and month as factors. A year effect on the expected abundance indices was extracted and considered as a time series of abundance indices (Appendix B). The UK LPUE was not used in the model because no information was available to separate the 0 and 1+ age groups in the English catch.

In the two-stage biomass model, the time series of total catch by age group (from both French and UK vessels) were also needed. The same method as for the LPUE was used to estimate the percentage of the two age groups in the French catches for each year and quarter. For UK catches, the mean percentage of group 1+ individuals from 1992 to 2012 was applied from 2013 to 2015 to complete the time series.

3.2.2.2. The two-stage biomass model

The model is based on a simplified cuttlefish life cycle (Fig. 3.7): we consider an exclusive 2 years lifespan, with massive natural mortality occurring shortly after spawning on June 30^{th}. Each fishing season extends from July 1^{st} (when one year-old individuals are recruited to the fishery) to June 30^{th} of the following year (one year later, remaining individuals are mature and have spawned). We use subscript y to refer to the fishing season. Catch of cuttlefish of the two age groups 0+ and 1+ (denoted $C_{0,y}$ and $C_{1,y}$ for 0+ and 1+ group, respectively) is assumed to happen as a coordinated pulse in the middle of the fishing season (on January 2^{nd}).

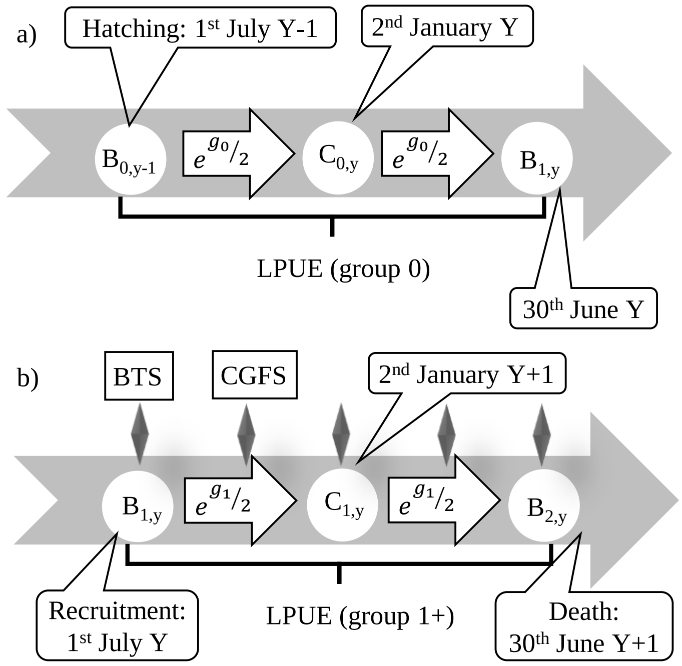

FIGURE 3.7 – The simplified life cycle of the English Channel stock of cuttlefish. For models M1, M2 and M4, only group 1+ individuals are modeled (b). For model M3, a cohort of group 0 individuals is added (a). The total catch of French and English fishery occurs as a pulse in the middle of the fishing season: $C_{0,y}$ for group 0 individuals, and $C_{1,y}$ for group 1+ individuals.

We first define the baseline model M1 for the English Channel cuttlefish stock, and then the variants M2, M3 and M4. The model M1 captures the dynamics of group 1+ individuals only. It assumes an intrinsic biomass growth rate parameter $g_{1,y}$ specific to group 1+, based on mortality and growth coefficients specific to this class. A hierarchical structure is assumed for the $g_{1,y}$'s to capture variation among years. The model is fitted to time series of total catches, and BTS, CGFS and French LPUE abundance indices, where CGFS, French LPUE and total catch are processed to account for 1+ age group only. Models M2, M3 and M4 are constructed to assess the sensitivity of results to alternative model structures and sources of data (Table 3.6).

3.2.2.2.1. Baseline model M1 with one single cohort (1+ age group)

Biomass dynamics

Let $B_{1,y}$ be the biomass of the 1+ group at the start of the fishing season. A hierarchical lognormal structure is set on the $B_{1,y}$'s to capture variation among years:

$$log(B_{1,y}) \sim N(log(\mu_{B1}) - \frac{1}{2}\sigma^2_{B1}, \sigma^2_{B1}) \tag{3.10}$$

with a grand mean μ_{B1} a priori drawn from an informative lognormal prior distribution and a variance σ^2_{B1} a priori drawn from an uninformative prior distribution (Table 3.5). The unexploited biomass estimated on 1^{st} October ($B_{1.oct,y}$) without catch removals is defined as follows:

$$log(B_{1.oct,y}) \sim N\left(log\left(B_{1,y}e^{\frac{g_{1,y}}{4}}\right) - \frac{1}{2}\sigma^2_{process}, \sigma^2_{process}\right) \tag{3.11}$$

where $g_{1,y}$ is the biomass growth rate parameter of group 1+ individuals, and lognormal process errors $\sigma^2_{process} = log(CV^2_{process} + 1)$, with $CV_{process}$ drawn from an informative prior distribution (see Table 3.1).

The unexploited biomass estimated on 1^{st} January ($B_{1.jan,y}$) without catch removals is defined as follows:

$$log(B_{1.jan,y}) \sim N\left(log\left(B_{1.oct,y}e^{\frac{g_{1,y}}{4}}\right) - \frac{1}{2}\sigma^2_{process}, \sigma^2_{process}\right) \tag{3.12}$$

The spawning stock biomass $B_{2,y}$ of fishing season y is expressed as:

$$log(B_{2,y}) \sim N\left(log\left([B_{1.jan,y}(1 - E_{1,y})]\, e^{\frac{g_{1,y}}{2}}\right) - \sigma^2_{process}, 2 \times \sigma^2_{process}\right) \tag{3.13}$$

where $E_{1,y}$ is the exploitation rate for group 1+ individuals and the process error variance is twice the $\sigma^2_{process}$ to account for the fact that the time step is twice that given in Eqns (3.11) and (3.12).

Observation equations

The expected values of the catches are calculated as the biomass in the middle of the fishing season ($B_{1.jan,y}$) multiplied by the exploitation rate $E_{1,y}$. Catches of 1+ animals are then assumed to be observed with lognormal observation errors with a coefficient of variation CV_{C1}. An informative prior distribution that favors small values of CV is specified in order to imitate the prior expectation that catches are assumed to be well known for trawlers (see Table 3.1).

$$log(C_{1,y}) \sim N\left(log(E_{1,y}B_{1.jan,y}) - \frac{1}{2}\sigma^2_{C1}, \sigma^2_{C1}\right) \tag{3.14}$$

As the BTS survey occurs in July, the BTS abundance indices provide information on the biomass of one-year old cuttlefish at the start of the fishing season ($B_{1,y}$). The CGFS survey occurs three months later, so abundance indices are assumed to be noisy observation of the biomass of group 1+ individuals one quarter after the beginning of the fishing season ($B_{1.oct,y}$). The BTS and CGFS survey indices (denoted U_y^{bts} and U_y^{cgfs}, respectively) are assumed to be an indirect observation of the biomasses $B_{1,y}$ and $B_{1.oct,y}$ with catchabilities q_{bts} and q_{cgfs} and lognormal observation errors with variances σ^2_{bts} and σ^2_{cgfs}, drawn from a non-informative prior distribution (Table 3.5):

$$\begin{aligned} log(U_y^{bts}) &\sim N\left(log(q_{bts}B_{1,y}) - \frac{1}{2}\sigma^2_{bts}, \sigma^2_{bts}\right) \\ log(U_y^{cgfs}) &\sim N\left(log(q_{cgfs}B_{1.oct,y}) - \frac{1}{2}\sigma^2_{cgfs}, \sigma^2_{cgfs}\right) \end{aligned} \tag{3.15}$$

Two different observation error variances are used in Eqn (3.15) because the CGFS data are supposed to be less reliable before 2005, with CV before 2005 being twice that after 2005. Finally, the French standardized LPUE for group 1+ animals (U_y^{lpue1}) is assumed to be a lognormal observation of the mean of the biomass between the start and the end of the fishing season (with catchability q_{lpue1}) with variance σ^2_{lpue1}:

$$log(U_y^{lpue1}) \sim N\left(log\left(\frac{1}{2}q_{lpue1}[B_{1,y} + B_{2,y}]\right) - \frac{1}{2}\sigma^2_{lpue1}, \sigma^2_{lpue1}\right) \tag{3.16}$$

3.2.2.2.2. Priors

We developed a prior for the intrinsic biomass growth rate parameter $g_{1,y}$ for the group 1+ individuals defined as the difference between the mean growth coefficient (Gr) and the natural mortality rate (M) (Appendix A). A lognormal hierarchical structure with grand mean μ_{g1} (drawn from an informative lognormal prior distribution; Table 3.5) and variance σ^2_{g1} (drawn from a non-informative prior distribution; Table 3.5) is defined on the $g_{1,y}$'s:

$$log(g_{1,y}) \sim N\left(log(\mu_{g1}) - \frac{1}{2}\sigma^2_{g1}, \sigma^2_{g1}\right) \tag{3.17}$$

The exploitation rate is drawn a priori from a weakly informative beta prior distribution, allowing $E_{1,y}$ to take any value between 0 and 1. The variances of the observation errors for the abundance indices, σ^2_{bts}, σ^2_{cgfs} and σ^2_{lpue1} are all drawn from uninformative inverse-gamma distributions.

A sensitivity of the baseline model M1 to the prior distribution of $g_{1,y}$ and on B_1 was evaluated. A percentage of $+/-$ 20% was applied to the mean values used for the construction of both priors. The sensitivity to the variation coefficient controlling the a priori inter-year variation in catch was also evaluated (Table 3.7).

3.2.2.2.3. Alternative model structure and sensitivity analysis

Model M2 is an alternative to the baseline model M1 that assumes that g is constant over the years, with a value of 0.89. Comparing the results between M1 and M2 allows us to quantify the benefits of considering inter-year variability in g (Table 3.6; Eqn 3.17).

Model M3 explores the feasibility of modeling both the 0+ and the 1+ cohorts using an additional LPUE index calculated for 0+ age group. The results from Model 3 are compared to those from model M1 to evaluate the influence of considering the dynamics of group 0 and 1+ individuals (instead of 1+ only for M1). The cohort dynamics start with a lognormal hierarchical prior on the biomass of group 0 animals (denoted $B_{0,y}$) with grand mean μ_{B0} and variance σ^2_{B0} drawn from an informative and non-informative prior distribution respectively (see Table 3.5):

$$log(B_{0,y}) \sim N\left(log(\mu_{B0}) - \frac{1}{2}\sigma^2_{B0}, \sigma^2_{B0}\right)) \tag{3.18}$$

The biomass of the 0+ group then grows with growth rate $g_{0,y}$ to provide the biomass of 0+ group in October then in January when they can be exploited with harvest rate $E_{0,y}$ before being recruited as 1+ group in July at the start of the fishing season y+1:

$$log(B_{0.oct,y}) \sim N\left(log\left(B_{0,y}e^{\frac{g_{0,y}}{4}}\right) - \frac{1}{2}\sigma^2_{process}, \sigma^2_{process}\right) \tag{3.19}$$

$$log(B_{0.jan,y}) \sim N\left(log\left(B_{0.oct,y}e^{\frac{g_{0,y}}{4}}\right) - \frac{1}{2}\sigma^2_{process}, \sigma^2_{process}\right) \tag{3.20}$$

$$log(B_{1,y+1}) \sim N\left(log\left([B_{0.jan,y}(1 - E_{0,y})]e^{\frac{g_{0,y}}{2}}\right) - \sigma^2_{process}, 2 \times \sigma^2_{process}\right) \tag{3.21}$$

A lognormal hierarchical prior with a grand mean μ_{g0} and variance σ^2_{g0} (Table 3.5) is set for $g_{0,y}$:

$$log(g_{0,y}) \sim N\left(log(\mu_{g0}) - \frac{1}{2}\sigma^2_{g0}, \sigma^2_{g0}\right) \tag{3.22}$$

Additional observation equations (Eqns 3.23 and 3.24) are needed to incorporate information from the French LPUE and the catches of group 0 cuttlefish:

$$log(U^{lpue0}_y) \sim N\left(log\left(\frac{1}{2}q_{lpue0}\left[B_{0,y} + B_{0,y}e^{g_{0,y}}(1 - E_{0,y})\right]\right) - \frac{1}{2}\sigma^2_{lpue0}, \sigma^2_{lpue0}\right) \tag{3.23}$$

$$log(C_{0,y}) \sim N\left(log\left(E_{0,y}B_{0,y}e^{\frac{g_{0,y}}{2}} - \frac{1}{2}\sigma^2_{C0}, \sigma^2_{C0}\right)\right) \tag{3.24}$$

where q_{lpue0} is the catchability of French trawlers for group 0 individuals, and σ^2_{lpue0} is the unknown variance of the lognormal observation errors, drawn from an uninformative prior distribution (Table 3.5). Catches of 0+ animals are assumed to be observed with lognormal observation errors with variance σ^2_{C0} derived from the informative prior distribution on the coefficient of variation CV_{C0} (Table 3.5). The sensitivity of the results of model M3 to the prior distribution of $g_{0,y}$ and of B_0 was evaluated. A percentage of $+/-$ 20% was applied to the mean values used for the construction of both priors. Sensitivity to the variation coefficient controlling the a priori inter-year variation in catch was also evaluated (Table 3.7).

Model M4 is similar to Model M1, but does not include the French LPUE abundance indices, and therefore enabled us to assess the sensitivity of the results to the data and to explore the capacity of the model to forecast the biomass of age-1 group at the start of the year, $B_{1.jan}$.

TABLE 3.7 – Alternative priors explored in sensitivity analyses.

	Parameter	Alternative priors tested	Name of the model run
M1	μ_{B1}	Lognormal(μ = 12000, CV = 0.1)	Smaller μ_{B1}
	μ_{B1}	Lognormal(μ = 18000, CV = 0.1)	Higher μ_{B1}
	μ_{g1}	Lognormal(μ = 0.71, CV = 0.1)	Smaller μ_{g1}
	μ_{g1}	Lognormal(μ = 1.07, CV = 1.07)	Higher μ_{g1}
	CV_{C1}	CV_{C1} ~ Exp (4)	Higher CV_{C1}
M3	μ_{B0}	Lognormal(μ = 4000, CV = 0.5)	Smaller μ_{B0}
	μ_{B0}	Lognormal(μ = 6000, CV = 0.5)	Higher μ_{B0}
	μ_{g0}	Lognormal(μ = 0.78, CV = 0.1)	Smaller μ_{g0}
	μ_{g0}	Lognormal(μ = 1.16, CV = 0.1)	Higher μ_{g0}
	CV_{C0}	CV_{C0} ~ Exp (4)	Higher CV_{C0}

3.2.2.3. Model comparison

The deviance information criterion (DIC) and the normalized root mean-squared error (NRMSE) were used to compare the models. The DIC is a Bayesian measure of fit, which includes a penalty term for model complexity, and was used to compare models fitted to the same data sets (M1 versus M2 and sensitivity analysis on M1 and M3). A difference of 7 between the models was assumed to provide strong evidence in favor of the model with the smaller DIC (Spiegelhalter et al., 2002). The capacity to fit the abundance indices time series was evaluated using NRMSE, which compares the difference between the observed abundance indices with posterior replicates of abundance indices. For each time series of length L, a NRMSE is calculated as follows:

$$NRMSE = \frac{1}{S}\sum_{j=1}^{j=S}\sqrt{\frac{1}{L}\sum_{i=1}^{i=L}\left(\frac{y_i - \tilde{y}_i^{(j)}}{\bar{y}}\right)^2} \tag{3.25}$$

where y_i is the observed value of the abundance index i (in log scale), $\tilde{y}_i^{(j)}$ is a replicated value drawn from the posterior predictive distribution (log scale), $\bar{y}$ is the mean of the time series of observed abundance indices (log scale) and S is the size of the MCMC sample. The average over a large MCMC sample size enabled us to integrate over the posterior distribution of replicated abundance indices. Lower NRMSE values indicate a better fit to the time series.

We also calculated the posterior predictive p-values (Gelman et al., 2014 [102]) to evaluate how the model a posteriori fitted to the data (see an example in Archambault et al. (2016) [10] for details on calculation). p-values concentrating near 0 or 1 indicate that the observed pattern would be unlikely to be seen in replications of the data if the model were true, and thus indicate lack of model fit.

3.2.2.4. Computational details

Three chains of 200,000 Markov Chain Monte Carlo (MCMC) samples were simulated using OpenBUGS (OpenBUGS V3.2.3 ; Lunn et al., 2009 [169]). A burn-in period of 10,000 samples was used to avoid dependence of the MCMC samples on the initial conditions, and each chain was thinned by 30 to reduce autocorrelation. Convergence of the MCMC simulations to the posterior distribution was checked using the Brooks-Gelman-Rubin (BGR) convergence diagnostic (Brooks and Gelman, 1998 [31]).

3.2.3. Results

3.2.3.1. Results from the baseline model M1

Results are plotted with years at the start of the fishing seasons on the x-axis. Therefore, for a year t, estimates of B_1 are for July t, estimates of $B_{1.jan}$ are for January t+1, and estimates of B_2 are in June t+1 even if the same fishing season y is considered.

All observed abundance indices were within the range of 95% Bayesian credible intervals of posterior replicates for French LPUE (Fig. 3.8.b), BTS survey (Fig. 3.8.c) and CGFS survey (Fig. 3.8.d). The posterior predictive p-values (Table 3.8) ranged from 0.51 to 0.7, showing that there were no strong discrepancies between the model fitted a posteriori and the data. The model tended to slightly overestimate the CGFS abundance indices (p-values > 0.5). Posterior predictive p-values for BTS, LPUE and Catch were close to 0.5, indicating that the model is well able to reproduce these data. The fitted and observed catches were very similar (Fig. 3.8.a), with high inter-year variability with no clear trend until 2006, and then a decreasing trend from 2006 to 2014.

Estimates (median of posterior distributions) of B_1 showed a decreasing trend from 2002 to 2014 (Fig. 3.9.a). Estimates of B_2 showed no clear trend (Fig. 3.9.b). Estimates of $g_{1,y}$ from model M1 fluctuated between 0.64 and 0.83 from 1992 to 2008 with no particular trend and increased from 0.72 in 2008 to 1 in 2011. The highest value was estimated at 1.16 in 2014 (Fig. 3.9.c). The exploitation rate varied between 0.4 and 0.64 from 1992 to 2008, and a drop to 0.25 occurred in 2009 (Fig. 3.9.d). The highest values were obtained for the fishing seasons 2001 and 2011 (respectively 0.64 and 0.62) and were associated with low estimates of recruited biomass B_1 and spawning stock biomass B_2 in 2001, and high estimate of $g_{1,y}$ in 2011.

TABLE 3.8 – Comparison of deviance information criterion (DIC) value, normalized root mean-squared error (NRMSE) and Bayesian p-values for all model runs.

Model run	**DIC**	**NRMSE**						***p*-value**					
		BTS	CGFS	LPUE		Catch		BTS	CGFS	LPUE		Catch	
Model M1	422	0.73	0.78	0.72		0.55		0.55	0.7	0.54		0.51	
Smaller μ_{B1}	422	0.74	0.78	0.7		0.54		0.54	0.7	0.54		0.51	
Higher μ_{B1}	422	0.74	0.77	0.74		0.57		0.57	0.7	0.54		0.51	
Smaller μ_{g1}	425	0.74	0.77	0.72		0.55		0.54	0.7	0.54		0.51	
Higher μ_{g1}	420	0.73	0.77	0.73		0.56		0.56	0.7	0.55		0.51	
Higher CV_{C1}	442	0.74	0.77	0.72		0.59		0.55	0.71	0.54		0.54	
		BTS	CGFS	0	1+	0	1+	BTS	CGFS	0	1+	0	1+
Model M3	818	0.76	0.81	0.81	0.71	0.46	0.54	0.54	0.7	0.53	0.55	0.51	0.51
Smaller μ_{B0}	816	0.76	0.81	0.81	0.7	0.46	0.53	0.53	0.7	0.52	0.55	0.51	0.51
Higher μ_{B0}	815	0.76	0.81	0.81	0.7	0.47	0.53	0.54	0.71	0.51	0.54	0.51	0.51
Smaller μ_{g0}	816	0.77	0.81	0.8	0.7	0.46	0.53	0.54	0.71	0.52	0.55	0.51	0.51
Higher μ_{g0}	818	0.76	0.81	0.8	0.7	0.46	0.54	0.54	0.7	0.52	0.54	0.52	0.51
Higher CV_{C0}	837	0.76	0.81	0.8	0.7	0.51	0.54	0.54	0.71	0.5	0.54	0.53	0.51

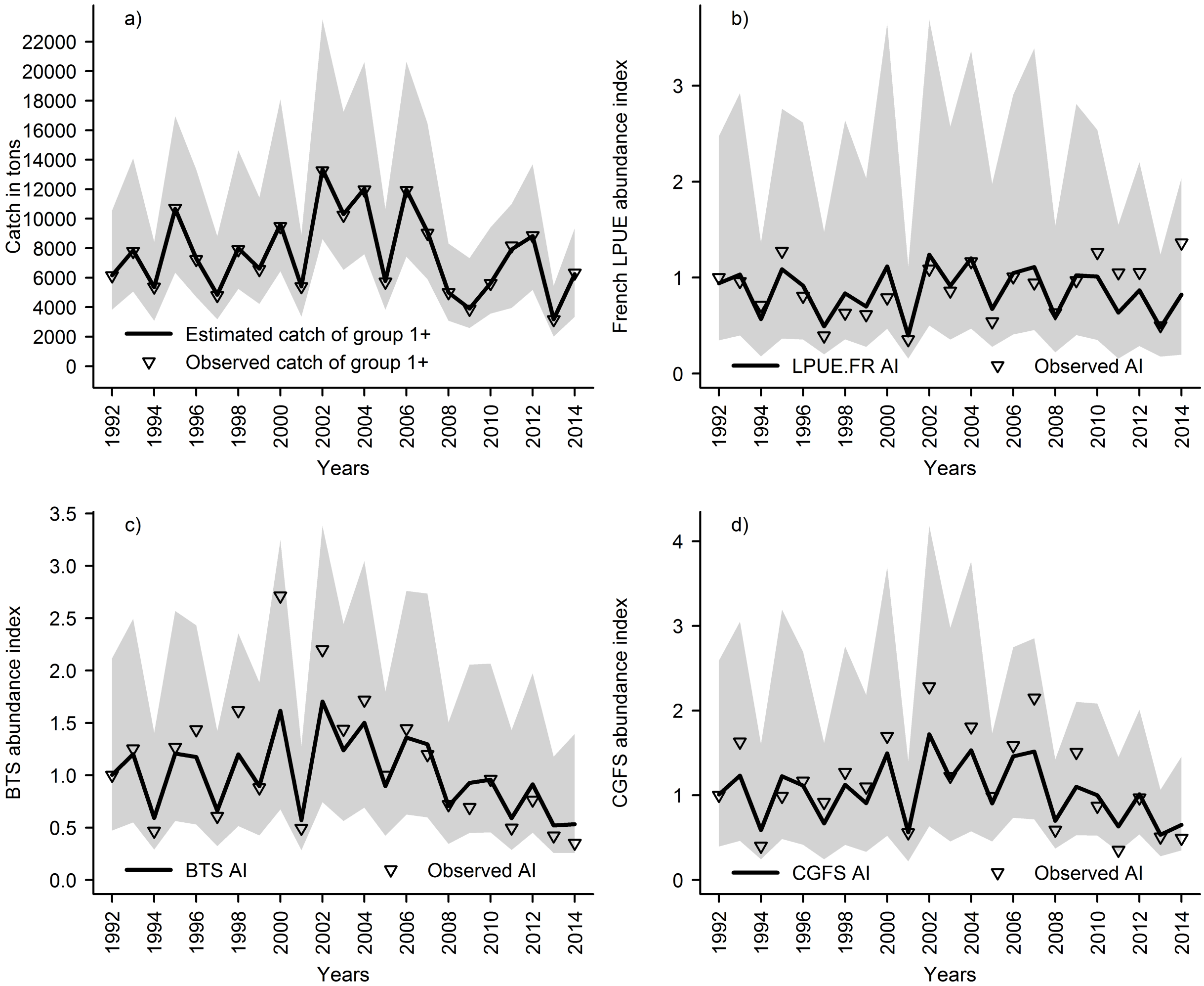

FIGURE 3.8 – A comparison of model M1 posterior median estimates with observed values for catch (a) and LPUE (b), BTS (c) and CGFGS (d) abundance indices. Solid lines: posterior medians. Shaded areas: 95% Bayesian credible intervals.

3.2.3.2. Sensitivity of M1 estimates to the priors

Overall, the results of model M1 were only slightly sensitive to modifications to the priors for key parameters (Table 3.9). B_1, $B_{1.jan}$ and B_2 were sensitive to the mean value of the prior distribution of B_1, varying by up to 14%. Changes to the mean value of the prior on $g_{1,y}$ impacted mainly the estimates of $g_{1,y}$ and B_2, with respectively up to 17% and 11% variation. Exploitation rate estimates were mostly sensitive to the choice of prior distribution of the grand mean with variation up to 8%. The sensitivity of the catches were less than 1% for all model runs and are consequently not shown.

The only significant difference of DIC value was observed for the model run with higher CV on catches (Table 3.8) and indicates a better fit of the base model M1 compared to the model with higher CV on catches. The NRMSE showed no noticeable differences of fit for the three abundance index time series during the various trials.

TABLE 3.9 – Mean percentage of variation between posterior means from model M1 and posterior means from the other model runs. The mean of percentages from all fishing seasons is given for each parameter and each model run. The CV related to the variation between fishing seasons is specified in brackets.

		Smaller μ_{B1}	**Higher μ_{B1}**	**Smaller μ_{g1}**	**Higher μ_{g1}**	**Higher CV_{C1}**
M1	B_1	-10.7 (0.4)	8.1 (0.4)	3.4 (1)	-3.5 (0.8)	0.67 (0.8)
	$B_{1.jan}$	-8.3 (0.3)	5.9 (0.3)	-2.6 (0.5)	2.2 (0.5)	1.8 (1)
	B_2	-14.3 (0.17)	9.6 (0.2)	-10.4 (0.6)	10.9 (0.7)	1.1 (1.8)
	g_1	1.7 (1)	-0.8 (1.1)	-17.1 (0.2)	15.5 (0.3)	0.9 (1.5)
	E_1	8.1 (0.3)	-4.5 (0.3)	2.2 (0.6)	-1.7 (0.7)	0.8 (1.3)
		Smaller μ_{B0}	**Higher μ_{B0}**	**Smaller μ_{g0}**	**Higher μ_{g0}**	**Higher CV_{C1}**
M3	B_0	-0.38 (1.5)	0.9 (0.54)	14.3 (0.08)	-11.7 (0.07)	1.34 (0.4)
	B_1	-0.3 (1.2)	-0.04 (13.3)	-1.6 (0.4)	1.37 (0.8)	0.13 (3.7)
	B_2	0.19 (7.9)	-0.4 (3.6)	-2.2 (1)	2.2 (1)	0.88 (1.5)
	g_0	0.12 (4)	-0.9 (0.5)	-19.4 (0.03)	18.1 (0.03)	-0.8 (0.6)
	g_1	0.67 (1.1)	-0.02 (40)	1.1 (0.9)	-0.69 (1.4)	0.03 (24.6)
	E_0	0.18 (2.9)	-0.5 (0.7)	-3.9 (0.2)	3.8 (0.3)	0.5 (2.4)
	E_1	0.09 (7.5)	0.17 (2.6)	1 (0.8)	-0.95 (0.8)	-0.32 (1.3)

3.2.3.3. Assuming a constant g_1 (models M1 versus M2)

Model M1, which assumed a time-varying $g_{1,y}$ outperformed the model with a constant value of g_1 over the years (M2) because a lower DIC value was obtained for model M1 (Table 3.10) and a lower value of NRMSE was observed for LPUE for model M1, indicating a better fit to the data. p-values for BTS, LPUE and catch were not impacted by the change from model M1 to model M2.

Estimates of $g_{1,y}$ from model M1 were smaller than the grand mean (0.89), except for years 2011 and 2014 (Fig. 3.9.c). B_1 estimates were very close for both models M1 and M2 (Fig. 3.9.a), but model M2 provided slightly higher estimates of B_2 (Fig. 3.9.b). Posterior estimates of exploitation rates followed the same trend, but estimates from model M1 were slightly higher (Fig. 3.9.d).

The limited effect of setting a time-varying $g_{1,y}$ on B_1 and E estimates (Figs 3.9.a and 3.9.d) is in accordance with the sensitivity analysis conducted on the mean value used for the prior distribution of $g_{1,y}$ (Table 3.9). Changes to the mean value for $g_{1,y}$ prior distribution had little effect on the estimates of B_1 and E, but a higher effect on B_2. Differences between B_2 values estimated by models M1 and M2 ranged from 128 to 4,080 tons (Fig. 3.9.b).

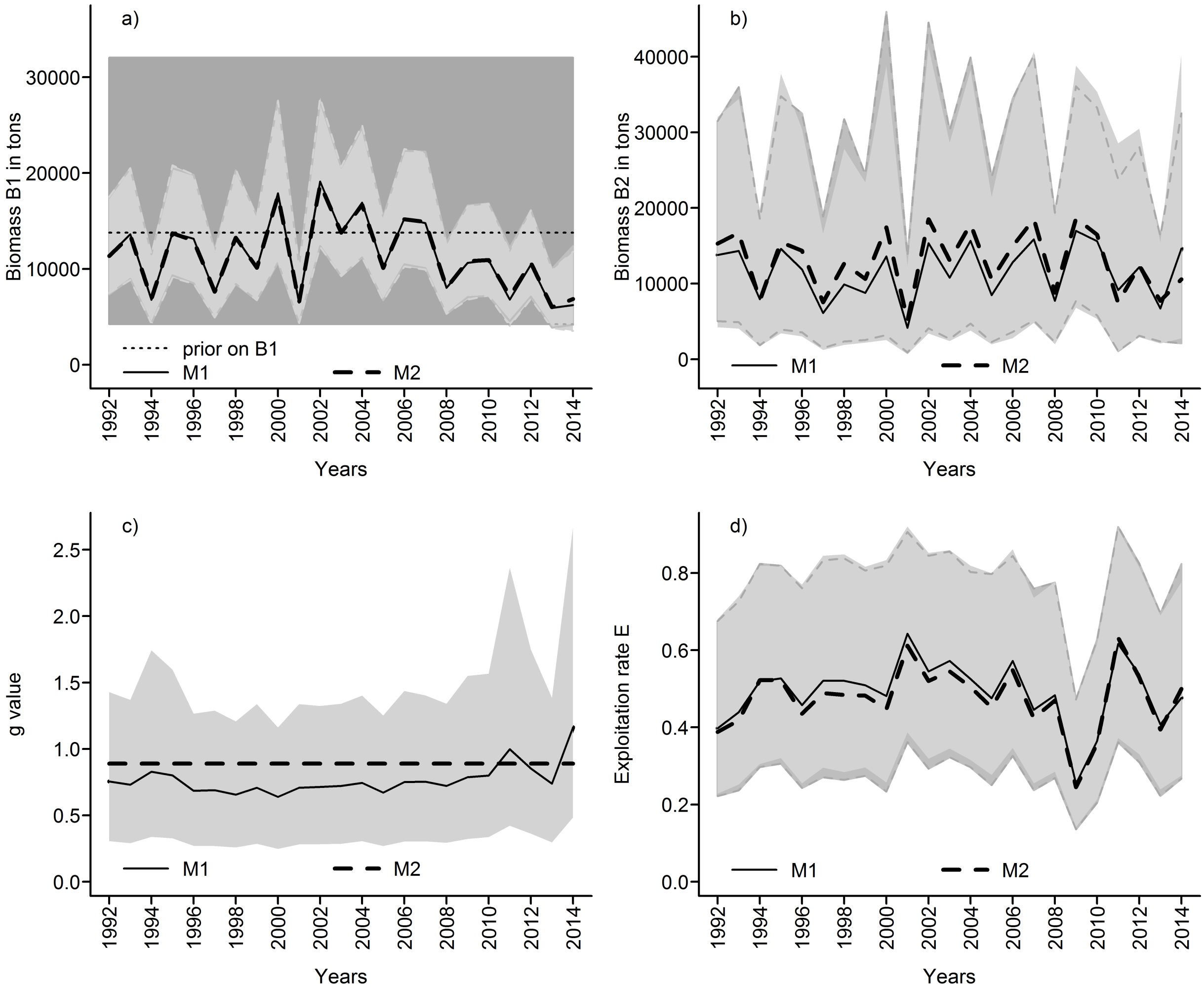

FIGURE 3.9 – A comparison of B_1 (a), B_2 (b), g (c) and E (d) for models M1 and M2. Solid lines: posterior medians for model M1. Dotted lines in bold: posterior medians for model M2. Dotted line (a): B_1 prior medians. Shaded areas: 95% Bayesian credible intervals (Lightgrey for model M1, grey for model M2, and darkgrey for the prior distribution of B_1).

3.2.3.4. Including the 0+ group in the dynamics (models M1 versus M3)

Overall, extending the model to include the 0+ group did not improve the fit of 1+ group category of the model (the one that is common to models M1 and M3). Differences in p-values between models M1 and M3 were weak for all abundance indices (Table 3.10). NRMSE values for BTS and CGFS were slightly lower for model M1 than for model M3 (Table 3.10; Figs 3.10.c and 3.10.d), indicating a better fit to the data. NRMSE values for model M3, for the LPUE of group 1+ individuals were smaller than for the LPUE of group 0 individuals, indicating a better fit to the LPUE of group 1+ individuals (Table 3.10; Fig. 3.10.b).

TABLE 3.10 – Comparison of deviance information criterion (DIC), normalized root mean-squared error (NRMSE) and Bayesian p-values for all models.

		M1	M2	M3	M4
DIC		422	430	-	-
NRMSE	BTS	0.73	0.74	0.76	0.74
	CGFS	0.78	0.77	0.81	0.76
	LPUE (Group 0+)	-	-	0.81	-
	LPUE (Group 1+)	0.72	0.76	0.71	-
	Catch (Group 0+)	-	-	0.46	-
	Catch (Group 1+)	0.55	0.56	0.54	0.33
***p*-value**	BTS	0.55	0.55	0.54	0.59
	CGFS	0.7	0.7	0.7	0.74
	LPUE (Group 0+)	-	-	0.53	-
	LPUE (Group 1+)	0.54	0.53	0.55	-
	Catch (Group 0+)	-	-	0.51	-
	Catch (Group 1+)	0.51	0.51	0.51	0.51

Estimates of B_0 for model M3 showed little variation (Fig. 3.11.a), but were sensitive to the prior distribution of $g_{0,y}$ (Table 3.9). Estimates of B_1 and B_2 were smaller for model M3 than for model M1 (Figs 3.11.a and 3.11.b). Estimates of $g_{1,y}$ were similar for models M1 and M3. Estimates of $g_{0,y}$ were sensitive to the prior distribution of $g_{0,y}$ with up to 19% variation in posterior means (Table 3.9; Fig. 3.11.c). The exploitation rate estimated for group 1+ individuals followed the same trend for models M1 and M3, but model M3 had higher estimates. The exploitation rate of group 0 individuals increased greatly between 1992 and 2000, as well as the catch of group 0 individuals (Figs 3.10.a and 3.11.d).

The sensitivity analysis conducted on model M3 showed that changes to the prior distribution of $B_{0,y}$ or to the prior distribution of $g_{0,y}$ had little effect on DIC, NRMSE and the p-values (Table 3.8). However, the model with a higher CV on catches was associated with higher DIC and NRMSE values for the catch of group 0 animals, indicating a better fit of the model M3 with baseline priors (Table 3.8).

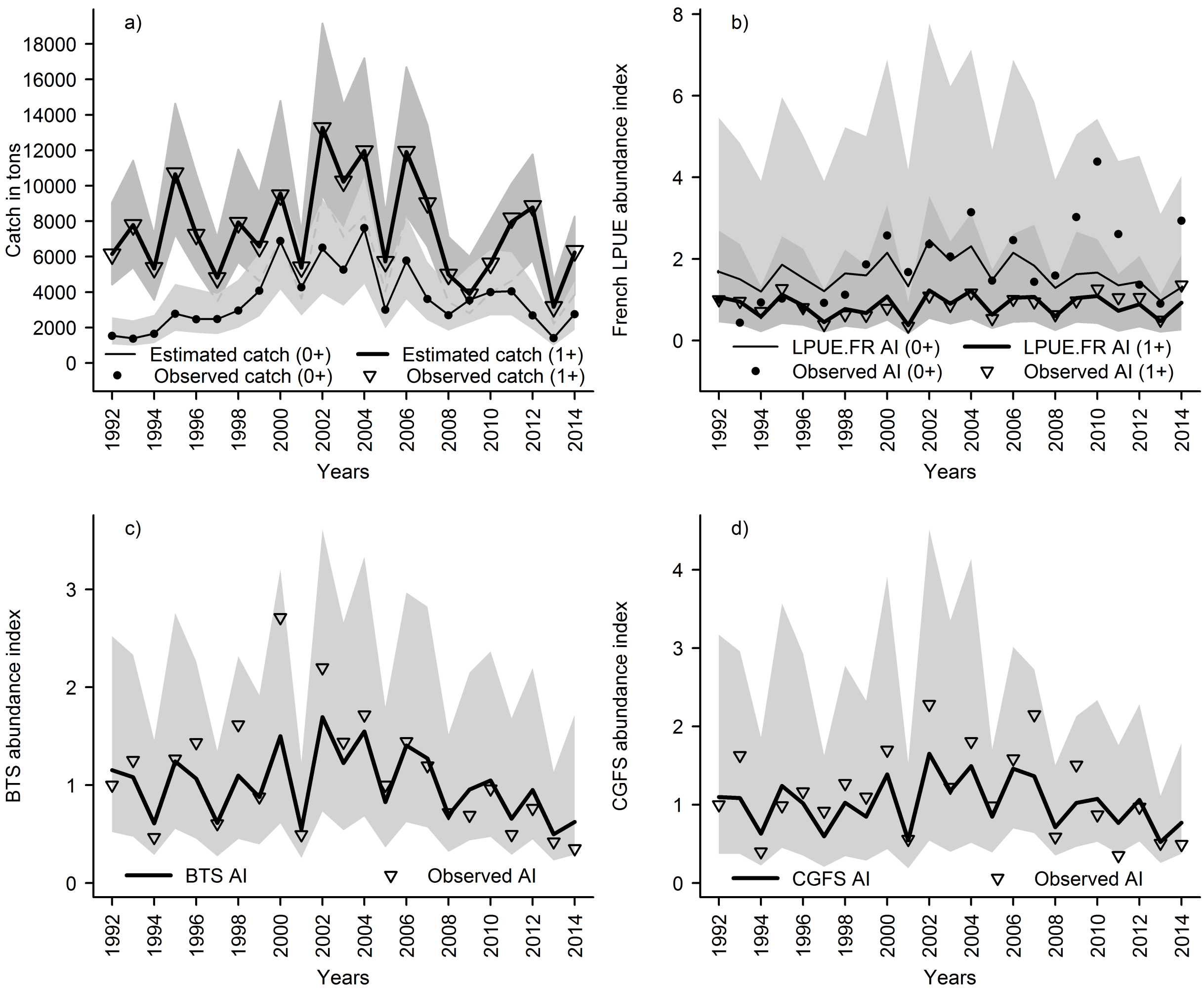

FIGURE 3.10 – A comparison of model M3 posterior median estimates with observed values for catch (a) and LPUE (b), BTS (c) and CGFGS (d) abundance indices. Solid lines: posterior medians. Shaded areas: 95% Bayesian credible intervals.

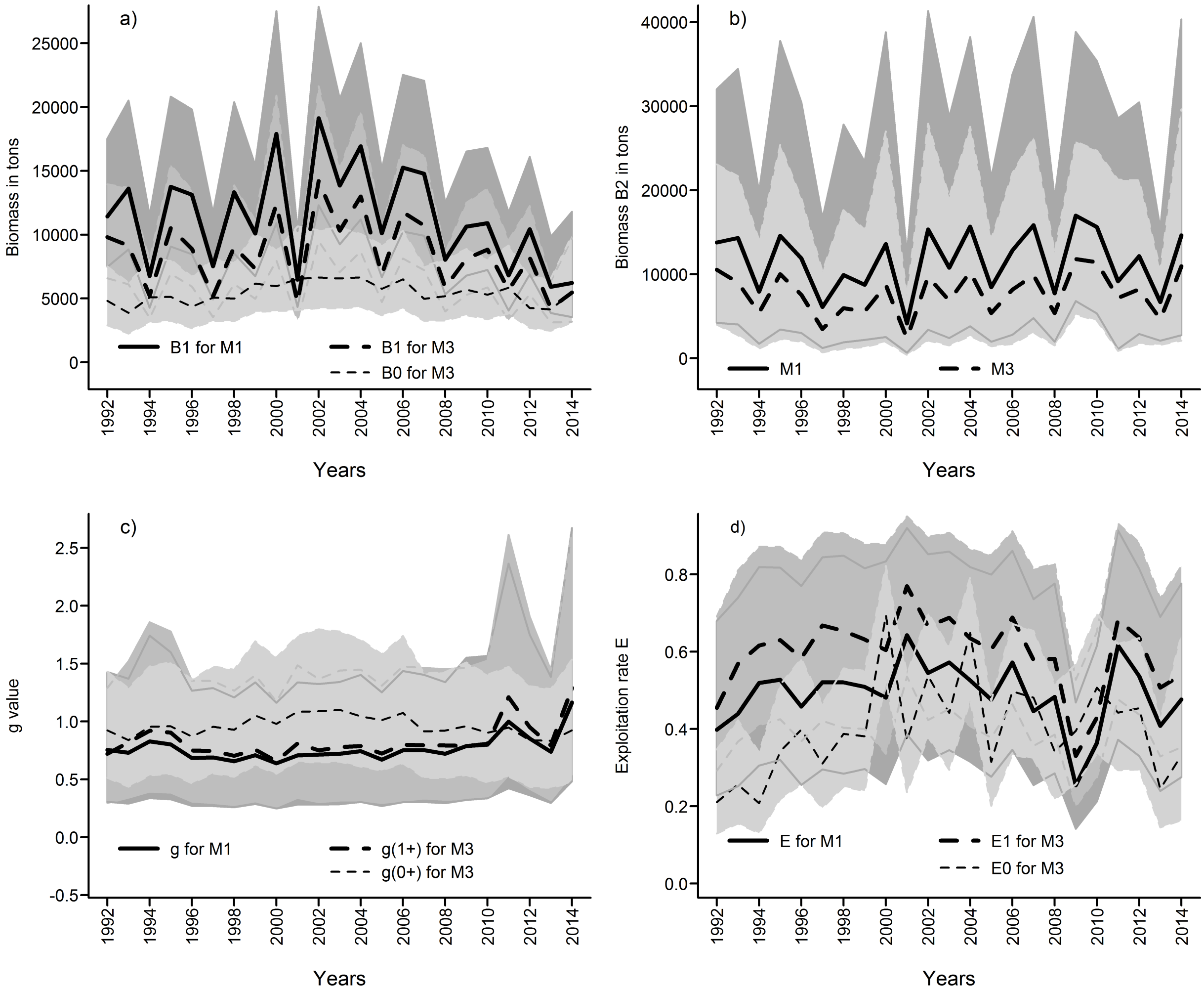

FIGURE 3.11 – A comparison of B_1 (a), B_2 (b), g (c) and E (d) for models M1 and M3. Solid lines: posterior medians for model M1. Dotted lines: posterior medians for model M3. Shaded areas: 95% Bayesian credible intervals (Light grey for model M1 and grey for model M3).

3.2.3.5. Effect of deleting the French LPUE abundance indices (models M1 versus M4)

Overall, model M4 did not show any improved performance with regards to model M1. NRMSE values of catch were smaller for model M4 than for model M1, indicating a better fit. However, the p-values for the BTS and CGFS were higher for model M4 than for model M1, indicating a better fit of model M1 (Table 3.10). Model M4 provided less variable estimates of $g_{1,y}$ (Fig. 3.12.c), but more variable estimates of the exploitation rate (Fig. 3.12.d) than model M1. The lower variability of the estimates of $g_{1,y}$ in model M4 is in accordance with lack of information from the LPUE to update the prior distribution of $g_{1,y}$. The estimates of B_1 and $B_{1.jan}$ (Figs 3.12.a and 3.12.b) followed the same trend as for models M1 and M4. Because the French LPUE abundance indices were higher than survey abundance indices for the last five fishing seasons (Figs 3.8.b, 3.8.c and 3.8.d), results of model M4 showed a slightly greater decreasing trend between 2002 and 2014 than in model M1.

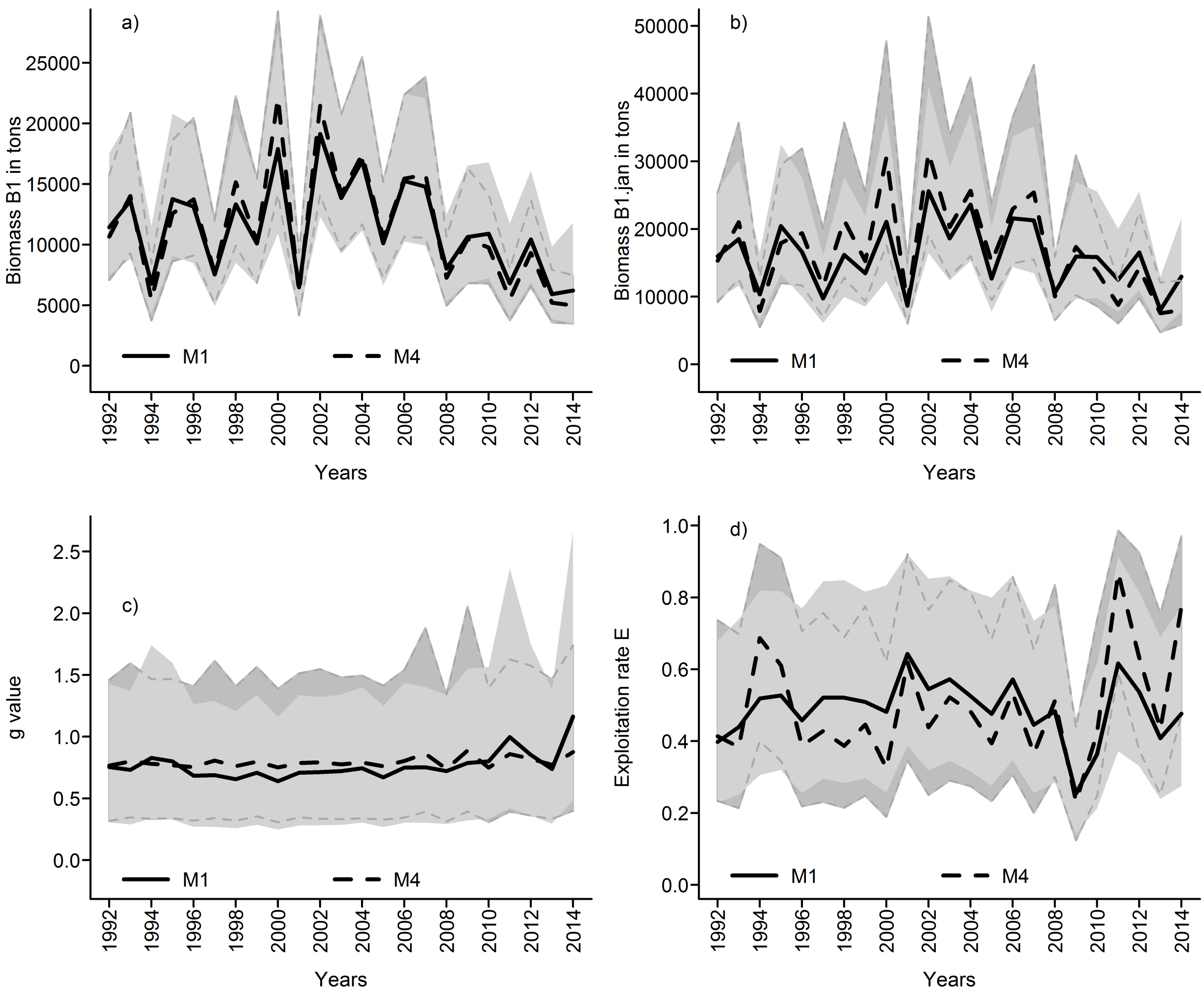

FIGURE 3.12 – A comparison of B_1 (a), $B_{1.jan}$ (b), g (c) and E (d) for models M1 and M4. Solid lines: posterior medians for model M1. Dotted lines: posterior medians for model M4. Shaded areas: 95% Bayesian credible intervals (Light grey for model M1 and grey for model M4).

3.2.4. Discussion

3.2.4.1. A new two stage biomass dynamic model for cuttlefish in the Eastern Channel

The Bayesian state-space two-stage biomass dynamics model provided a substantial contribution to the existing assessment method for the English Channel cuttlefish stock.

A Leslie-Delury depletion model was applied by Dunn (1999b) [78] based on data from the UK beam trawl fleet only, but French landings were not taken into account in this model, although they are higher than English landings. Royer et al. (2006) [236] have developed a monthly VPA, but the method could not be applied routinely because of the inconsistency of size structures.

The two-stage biomass model is an alternative for short-lived species with a lack of reliable age-data (Roel and Butterworth, 2000 [230]; Roel et al., 2009 [231]; Giannoulaki et al., 2014 [105]). In particular, the model developed in this study provides substantial extension to that developed by Gras et al. (2014) [110] inter alia because it is developed in a state-space modelling framework that allows for a comprehensive integration of several sources of uncertainty in the biomass dynamics and in the data. The Bayesian framework also allows use of prior information on the biomass growth rate parameter. Finally, the flexibility of the state-space modelling framework allows us to easily expand the model and to test for the benefits of considering both 0+ and 1+ age groups in the biomass dynamics.

Model M1, based on a time-varying biomass growth rate and BTS, CGFS and LPUE time series and specific to group 1+ individuals, was found as the best trade-off between ecological significance, data requirement and transferability to other stocks, and is therefore the one we advocate for the English Channel cuttlefish stock.

The hypothesis of a time-invariant biomass growth rate parameter (model M2) was clearly rejected by our analysis because model M1 outperformed model M2 in terms of model fit, with a smaller DIC and a smaller NRMSE for the LPUE. This result is in accordance with published literature on cephalopods, which are known to experience high inter-annual growth variation (Challier, 2005 [44]; Domingues et al., 2006 [73]).

We found no clear advantages to including the 0+ group in the model (model M3). Model M3 did not outperform M1 in terms of quality of fit, and including an additional 0+ group in the model required additional data and information that increased the sensitivity of model outputs. Hypotheses related to the prior distribution of the growth rate parameter $g_{0,y}$ can be questioned, as environmental variability might have a stronger impact on group 0 individuals than on group 1+ individuals. In fact, temperature and nutrient availability are known to affect both growth and natural mortality of cuttlefish, particularly during the juvenile phase (Moltschaniwskyj and Martinez, 1998 [187]). Calculation of growth of 0+ group might be biased because of micro-cohort issues. For example, Royer et al. (2006) [236] indicates the presence of two micro-cohorts of cuttlefish in the English Channel, with a first recruitment around October, and a second around April. As the CGFS takes place in October, the mean growth calculated for group 0 animals might be biased for years when there were two micro-cohorts: only the first micro-cohort would be represented in the data of age class 0 in year t, whereas both micro-cohorts would be represented for age class 1 in year t+1.

Our model also illustrates the capacity of the framework to forecast biomass dynamics while propagating posterior uncertainty in forecasting. Model M4 provided predictions of the unexploited biomass in winter based on survey data, and could help manage the stock in the event of strong depletion.

3.2.4.2. Limits of the approach

The approach provides a framework for structuring further research and data collection. It is based on the assumption of a single population for the English Channel stock of cuttlefish. This assumption is supported by several authors (Dunn, 1999b [78]; Le Goff and Daguzan, 1991 [163]; Pawson, 1995 [198]; Wang et al., 2003 [266]). However, stock boundaries are still not clearly defined and other research supports a substantial gene flow between the English Channel and the northern Northeast Atlantic (Gulf of Biscay, France) (Pérez-Losada et al., 2007 [207]). Wolfram et al. (2006) [272] also showed there is an extensive gene flow among weakly structured cuttlefish populations from the Bay of Biscay into the North Sea. Investigating the spatial structure of cuttlefish populations in the Channel and Gulf of Biscay and its impact on stock assessment and management should form the basis for future research.

The results were sensitive to some of prior assumptions. Results from model M1 showed that B2 and g1,y were the most sensitive variables (Table 3.9). The sensitivity of the exploitation rate to the prior distribution of $g_{1,y}$ was low, therefore this variable should be a good indicator of stock status, as proposed by Gras et al. (2014) [110]. Future research is needed to improve knowledge on the biomass growth rate and on the length-weight relationship. The method we developed to construct an informative prior on g made use of data from Dunn (1999b) [78] that ignores the variability over the years and within years of growth parameters. Future research should investigate the variation of the growth rate and length-weight relationship of cuttlefish, both over the years and within the years (e.g. through tag-recapture experiments).

3.2.4.3. Management implications

The estimates of exploitation rates differ noticeably from those of Gras et al. (2014) [110]. Specifically, Gras et al. (2014) [110] did not detect any trend in exploitation rates between 1992 and 2008. Our study added six years of data, and estimated a decreasing trend of exploitation rate from 2001 to 2009.

Our model can be used to help define in-season assessment and management to limit the risk of overexploitation (Rosenberg et al., 1990 [233]; Pierce and Guerra, 1994 [204]). In France, the minimum landing weight of cuttlefish is 100 g and otter trawl nets are not allowed to use mesh size <80mm. For pot fishery, there is also a limited number of fishing licenses. In Normandy, trawlers are allowed to fish cuttlefish spawners six weeks in spring inside 3 nautical miles as an exemption, which is decided each year around April. Another exemption allows them to target hatchlings for two weeks in the summer. Predictions of the unexploited biomass in winter ($B_{1.jan}$) from model M4 could be used as information to authorize or alternatively to close those exemptions in the event of a very low biomass predicted for the fishing season.

3.2.4.4. Applicability of the model to other stocks

Beyond the case study of the English Channel cuttlefish stock, the approach provides general insights to improve cephalopod assessment models that can be transferred to other stocks of *S. officinalis*, in France or abroad, or even to other cephalopods species.

Some European cuttlefish stocks monitored by the ICES Working Group on Cephalopod Fisheries and Life History have not been assessed. For most of them, data required for the two stage biomass dynamic model are available. An assessment of *S. officinalis* in the Bay of Biscay was conducted by Gi Jeon (1982) [104], who used a VPA with a monthly time-scale and two age groups, based on data from years 1978-1979. A series of the French standardized LPUE can be calculated. Scientific data are available from Ifremer EVHOE survey (Evaluation of Fishing Resources in Western Europe), but the reliability of those data to construct an abundance index for cuttlefish abundance remains questionable because the survey occurs offshore in November, and therefore catches cuttlefish only if the migration has already happened.

Another stock of *S. officinalis* is found around Spain and Portugal. A time series of LPUE for Spanish trawlers is available, as well as a time series of survey abundance indices. The Moroccan Dakhla (2001-2006) stock, the Cape Blanc (1990-2006) stock in Mauritania-Morocco, and the Senegal-the Gambia stocks (1993-2006) have been assessed through a one stage Schaefer biomass production model (FAO/CECAF, 2007 [84]). As both catch and abundance indices from the survey and/or CPUE are available for all those

S. officinalis stocks, developing a two-stage biomass model for those stocks would mean taking an interesting direction of research.

Other species of cuttlefish have been assessed (in India: Nair et al., 1993 [192]; Rao et al., 1993 [218]; off the Arabian Sea coast of Oman: Mehanna et al., 2014 [181]; and in the Gulf of Suez: Mehanna and Amin, 2005 [182]; Mehanna and El-Gammal, 2010 [183]). All these studies use length-based cohort analysis, which requires the very strong and not realistic assumption of a constant age-length relationship (Forsythe and Heukelem, 1987 [90]; Saville, 1987 [239]) and it could be worth developing more parsimonious two-stage biomass models.

Our results highlighted the key role of the informative priors on biomass growth rate parameters in the two stage model. Developing a meta-analysis to populate estimates of those parameters across many cuttlefish stocks (e.g., through hierarchical Bayesian models) could help improve the precision of informative priors and transfer information to stocks where only little information is available.

Some model assumptions should be tailored to fit some stock specificities. For stocks in warmer waters, we could expect a higher value of Gr (Richard, 1971 [219]). Cuttlefish experience a slower growth rate in the English Channel than in South Brittany, and a water temperature effect is suspected (Le Goff and Daguzan, 1991 [163]). The model presented here is developed under the assumption of an exclusive two-year life cycle which would no longer be valid. The model should be modified to take into account the co-existence of several reproduction strategies with various durations, as suggested for the Bay of Biscay stock that exhibit a mixture of 1 and 2 year life cycles.

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CHAPITRE 4

CHAPITRE 4 : Amélioration de l'évaluation et de la gestion du stock de lieu jaune

"*Sustainability, ensuring the future of life on Earth, is an infinite game, the endless expression of generosity on behalf of all.*"

Paul Hawken (2007), from **Blessed Unrest: How the Largest Movement in the World Came into Being and Why No One Saw It Coming.**

Présentation des articles "Quantifying stock status of the relatively data-limited stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion using a flexible age-structured modelling framework" et "Setting catch limit in a data-limited situation, case study of the stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion"

Le chapitre précédent se penchait sur les méthodes d'évaluation de stocks à données limitées dans le cas d'une espèce à cycle de vie court. Nous allons à présent étudier le cas d'une espèce à cycle de vie long, le lieu jaune. La première partie du quatrième chapitre se concentre sur l'estimation du statut du stock en comparant les résultats d'un modèle Stock Synthesis et d'un modèle LB-SPR (« Length-Based Spawning Potential Ratio »).

Les modèles de type Stock Synthesis (Methot and Wetzel, 2013 [185]) sont des modèles d'évaluation de stock intégrés pouvant être paramétrés à partir de données structurées en âge ou en taille. Toutes les données disponibles sont incorporées dans une unique analyse par des fonctions de vraisemblance, et l'incertitude associée aux différentes sources de données est propagée aux sorties finales du modèle (Maunder and Punt, 2013 [177]).

Les principaux pays exploitant le stock de lieu jaune étudié sont la France, le Royaume-Uni et l'Irlande. La série historique des pêches du Royaume-Uni est complète et s'étend de 1950 à 2015, tandis que les données des autres pays comportent des années manquantes. Trois scénarios de captures commerciales sont construits, ainsi que cinq scénarios de captures récréatives. Deux séries de captures par unité d'effort sont calculées à partir des données des chalutiers Français et Irlandais. Les données de fréquence de taille disponibles pour la France et l'Irlande sont également utilisées dans le modèle. Une valeur de mortalité naturelle de 0.34 années -1 est obtenue à partir de méthodes basées sur les traits d'histoire de vie du stock. Cette valeur est employée pour le modèle de référence, et des analyses de sensibilité sont menées.

Les résultats du modèle de référence montrent une diminution de l'estimation de biomasse de géniteurs de 36 815t en 1950 à 9 749t en 1991. De 1991 à 2013, la biomasse augmente à 16 513t et semble stable sur les deux dernières années. La biomasse relative de géniteurs, qui indique le statut du stock, diminue de 1 en 1950 à 0.265 en 1991, avant de remonter à 0.449 en 2013 et de se stabiliser sur les deux dernières années. La valeur finale de biomasse relative est de 0.44 en 2015, ce qui indique un bon état du stock.

Les analyses de sensibilité montrent qu'un modèle basé sur une valeur de mortalité naturelle de 0.2 années^{-1} estime une valeur finale de biomasse relative de 0.25. L'estimation du statut du stock est donc sensible à la valeur de mortalité naturelle employée. De même, les modèles alternatifs basés sur les différents scénarios de captures récréatives peuvent aboutir à une estimation du statut du stock éloignée du résultat du modèle de référence. En revanche, les résultats sont peu sensibles à la valeur du paramètre h (paramètre déterminant l'inclinaison de la pente dans la relation stock-recrutement) et à la taille de première maturité sexuelle. Si les estimations de biomasse de géniteurs et de biomasse relative diffèrent entre le modèle de référence et les modèles basés sur les différents scénarios de captures commerciales, l'estimation du statut du stock reste très proche pour les dernières années. Une analyse de sensibilité est également menée afin d'évaluer l'influence des différentes composantes de la fonction de vraisemblance sur l'estimation finale du statut du stock. La suppression des données de taille entraîne la plus forte modification des résultats, avec une estimation plus optimiste du statut final du stock et une plus grande incertitude associée aux résultats.

La comparaison des résultats du modèle Stock Synthesis avec ceux du modèle LBSPR montre une estimation de la fonction de sélectivité similaire pour les données de taille des chalutiers. La valeur moyenne du ratio de géniteurs potentiels est également très proche pour les deux méthodes (0.43 pour le modèle Stock Synthesis et 0.41 pour le modèle LB-SPR).

Pour finir, une méthode de modélisation d'ensemble est appliquée. Les résultats des modèles considérés comme les plus plausibles sont synthétisés afin de faciliter la lecture globale des résultats en prenant en compte les incertitudes engendrées par les différentes hypothèses. Les résultats de la modélisation d'ensemble sont très proches des résultats du modèle de référence. Cependant, les incertitudes associées aux estimations de biomasse relative sont plus grandes pour la modélisation d'ensemble que pour le modèle de référence entre 1950 et 1980.

Cette étude propose une première évaluation du statut du stock de lieu jaune de Manche-Mer Celtique, en incluant l'ensemble des données disponibles dans le modèle d'évaluation. Les résultats des analyses de sensibilité soulignent à la fois l'importance d'employer les données de fréquence de taille disponibles et la nécessité d'utiliser une valeur de mortalité naturelle la plus fiable possible. Une prochaine étape serait de pousser l'analyse à la détermination de niveaux de captures permettant une exploitation durable du stock. C'est l'objet du deuxième article qui compare différentes méthodes permettant de déterminer une limite de captures dans des situations de données limitées. Le modèle Stock Synthesis construit dans la première partie de ce chapitre et incluant l'ensemble des données disponibles est repris et les résultats sont cette fois interprétés avec un objectif de gestion.

Deux autres modèles de type Stock Synthesis nécessitant moins de données sont construits à partir de ce modèle complet : un modèle extended Simple Stock Synthesis (XSSS) (Cope et al., 2013 [58]; Wetzel and Punt, 2015 [269]) pour lequel les données de fréquences de taille sont supprimées, et un modèle Simple Stock Synthesis (SSS) (Cope, 2013 [57]) pour lequel les indices d'abondance calculés avec les données de captures et d'effort sont supprimés. Pour ces deux modèles basés sur une quantité de données moindre, la connaissance a priori du niveau de déplétion du stock est intégrée sous forme d'un indice d'abondance fictif. Les valeurs de déplétion testées sont inspirées des valeurs employées par le groupe de travail européen WGCSE (ICES, 2016a [147]) pour l'application du modèle DCAC.

Outre les modèles de type Stock Synthesis, plusieurs méthodes simples sont testées grâce au DLMtool. Cet outil développé par Carruthers et al. (2014) permet d'appliquer simultanément plusieurs méthodes d'évaluation de stocks adaptées aux cas de données limitées. Il est également possible de mener une évaluation de stratégies de gestion (MSE pour « Management Strategy Evaluation ») à l'aide du DLMtool.

Au cours de cette étude, les résultats des différents modèles sont comparés. Des analyses de sensibilité sont également menées sur la valeur de mortalité naturelle et sur la connaissance a priori du niveau de déplétion du stock. Une MSE est réalisée avec une projection de 20 ans afin d'évaluer les effets à long terme des méthodes testées avec le DLMtool. Les performances sont mesurées en termes de probabilité pour la biomasse d'être en dessous du B_{MSY} et de probabilité pour la mortalité par pêche d'être au-dessus du F_{MSY}.

Les estimations de biomasse relative de géniteurs sont similaires pour les modèles SS et XSSS, bien que de plus grandes incertitudes soient associées aux résultats du modèle SS. Le modèle SSS estime une plus grande biomasse relative et aboutit à une estimation du statut final du stock plus optimiste. Les valeurs de F_{MSY} obtenues pour les modèles SSS et XSSS sont proches (0.33 et 0.31 respectivement), tandis qu'une plus grande valeur est obtenue pour le modèle SS ($F_{MSY} = 0.46$).

L'ensemble des valeurs de MSY calculées avec le DLMtool a été synthétisé en une unique distribution de fréquence autour d'une valeur moyenne qui s'est avérée être plus conservatrice que les résultats des modèles de type Stock Synthesis. Une valeur médiane de MSY d'environ 7 900 t est estimée par les modèles XSSS et SS. En revanche, le modèle SSS résulte en une estimation moins conservatrice. Les résultats de la MSE montrent qu'après 20 ans de projection, aucune des méthodes testées avec le DLMtool ne résulte en une probabilité supérieure à 50% pour la biomasse d'être en dessous de $0.2 \times B_{MSY}$. Ainsi, aucune de ces méthodes ne présente une probabilité supérieure à 50% de conduire à un effondrement du stock.

Le détail des résultats fait ressortir trois méthodes du DLMtool particulièrement performantes pour la gestion du stock étudié : Itarget1, curE75 et matlenlim. Ces trois méthodes présentent une probabilité inférieure à 10% pour la biomasse d'être en dessous de B_{MSY} et une probabilité inférieure à 10% pour l'effort de pêche d'être au-dessus de F_{MSY} après 20 ans de projection. La méthode Itarget1 consiste en une diminution progressive de l'effort de pêche jusqu'à l'atteinte d'un objectif d'indice d'abondance relatif. La méthode curE75 consiste en une mesure de gestion impliquant un maintien de l'effort de pêche à un niveau égal à 75% de l'effort actuel. Enfin, la méthode matlenlim agit sur la sélectivité afin qu'elle se calque sur la courbe de maturité. Concrètement, pour le lieu jaune, cette dernière mesure reviendrait à augmenter la taille de capture minimale qui est actuellement bien inférieure à la taille de maturité.

La probabilité pour un stock d'aboutir à une situation de surexploitation est plus élevée lorsque qu'une forte incertitude est associée au statut du stock et à l'estimation du niveau de captures permettant une exploitation durable du stock (Rosenberg et al., 2007 [232]; ICES, 2012d [140]). Parmi les composantes de cette incertitude, la part due à l'absence d'information sur la pêche récréative peut être considérable. Au cours de cette étude, nous avons construit notre analyse sur un scénario de pêche récréative où les captures augmentent progressivement de 1950 à 2015 pour atteindre les 2 000 t en 2015. Mais ce scénario est subjectif, et souligne l'importance de l'acquisition de données relatives à la pêche récréative.

Contrairement au modèle SSS, le modèle Stock Synthesis complet ne requiert pas de connaissance a priori sur le niveau de déplétion du stock. En revanche, une valeur de mortalité naturelle M est nécessaire pour les deux modèles, et les résultats du modèle SS sont plus sensibles à la valeur de M que les résultats du modèle SSS. Une plus faible valeur de M résulte en une plus faible estimation de MSY. Ce résultat peut être dû à une plus faible productivité du stock interprétée par le modèle. Dans les situations de stocks à données limitées, la valeur de M peut être déduite des paramètres d'histoire de vie du stock, ce qui a été réalisé pour le stock étudié. Cependant, lorsque les données disponibles sont disparates, le calcul des paramètres biologiques du stock peut être incertain. Il est alors judicieux de mettre à profit les avantages du cadre de modélisation Bayésien. La méthode de « Robin des Bois » décrite par Punt et al. (2011) [217] qui consiste à emprunter des données aux stocks « riches » pour donner aux stocks « pauvres » peut être un bon moyen d'optimiser toute l'information disponible. Cette méthode sera développée dans le chapitre suivant.

4.1. Quantifying stock status of the relatively data-limited stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion using a flexible age-structured modelling framework

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Abstract

"Data-limited" remains the most common descriptor of global fish stocks despite impressive technical advances in data-rich stock assessments. A variety of methods have recently been developed and tested in order to provide ways to derive important management quantities in data-limited situations. The stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion has a variety of data sources that vary in quantity and quality, and thus is considered relatively data-limited. There is currently no information on stock status and a high uncertainty on sustainable removals. We apply the flexible Stock Synthesis framework to incorporate all available data in a variety of model configurations to estimate stock status. Different catch scenarios are specified and several sensitivity analysis are run to quantify uncertainty in model specification. We identify a set of plausible models and apply an ensemble modeling approach to describe stock status while accounting for within and among model uncertainty. We also compare the results with the Length-Based Spawning Potential Ratio (LB-SPR) method, a prominent data-limited method which uses only length composition and life history data and does not include an underlying dynamics model. Results demonstrate the benefit of both quantifying uncertainty across model specification while also comparing results across different approaches that use common data, but different underlying assumptions. The final stock status estimates are not very sensitive to the assumptions made on the historical commercial catches, but are sensitive to the assumptions on the recreational fishery and on natural mortality.

Keywords: data-limited, stock assessment, stock status, pollack, *Pollachius pollachius*, Stock Synthesis, LBSPR, length-based methods

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Cette partie de chapitre fait l'objet d'un article scientifique qui sera soumis dans une revue scientifique à comité de lecture.

Résumé

Malgré les progrès dans les modèles d'évaluation des stocks de poissons dits « riches en données », la majorité des stocks de poissons restent peu ou pas évalués du fait de manque de données et sont qualifiés de stocks à « données limitées ». De nombreuses méthodes ont récemment été développées et testées afin d'estimer des niveaux de prélèvement permettant une exploitation durable des stocks dans les situations de données limitées. Le stock de lieu jaune (*Pollachius pollachius*) de la mer Celtique est classifié comme un stock à données limitées par le Conseil International pour l'Exploration de la Mer. Néanmoins, plusieurs sources de données existent et méritent d'être mieux exploitées pour l'évaluation du stock. Le statut du stock est actuellement inconnu, et une forte incertitude persiste quant au niveau de captures permettant une exploitation durable. Nous utilisons la plateforme de modélisation flexible Stock Synthesis afin d'inclure toutes les données disponibles dans différentes configurations d'un modèle de base pour estimer le statut du stock. Différents scénarios de captures sont spécifiés et plusieurs analyses de sensibilité sont menées afin de quantifier l'incertitude autour des spécifications du modèle. Nous identifions un ensemble de modèles dont les hypothèses sont considérées comme plausibles et appliquons une approche de « modélisation d'ensemble » pour décrire le statut du stock en prenant en compte à la fois l'incertitude interne au modèle et l'incertitude entre les modèles. Nous comparons également les résultats obtenus avec la méthode LB-SPR qui calcule le ratio de géniteurs potentiels à partir de la composition en tailles des captures et des données d'histoire de vie. L'estimation du statut du stock sur les dernières années s'avère peu sensible aux hypothèses faites sur l'historique des captures commerciales, mais est très sensible aux hypothèses sur les captures récréatives et sur la mortalité naturelle.

Mots clés: données limitées, évaluation de stock, statut du stock, lieu jaune, *Pollachius pollachius*, Stock Synthesis, LBSPR, méthodes basées sur les tailles

4.1.1. Introduction

Fishery stock assessment of data-limited stocks (DLS) is a rising issue in fishery sciences. Stocks can be considered data-limited or "data-poor" when quantity or quality of the data is considered insufficient to run a standard, quantitative assessment that estimates changes in population biomass through time (Smith et al., 2009a [244]; Honey et al., 2010 [129]). More than 80% of global catches come from non-formally assessed fisheries (Costello et al., 2012 [61]), thus the magnitude of this situation is large. Fisheries scientists are asked to provide advice on an increasing number of stocks, including DLS. Approaches devised for data-limited situations typical require many assumptions, therefore quantifying uncertainty in the results is imperative (Hilborn, 1997 [123]).

In this paper, we use the Stock Synthesis framework to build a model adapted to the stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion. Stock Synthesis models (Methot and Wetzel, 2013 [185]) are integrated statistical age-structured stock assessment models that can be parameterized using an age-based structure or size-based structure. In integrated analysis, all available data are used in a single analysis through likelihood functions. The uncertainty associated with the various data sources can be propagated to final model outputs (Maunder and Punt, 2013 [177]). Widely used in complex data situations, Stock Synthesis can also be applied in data-limited situations (Cope, 2013 [57]; Cope et al., 2013 [58]; Wetzel and Punt, 2015 [269]). The flexibility of the framework allows the user to build a model starting with only a catch history and life history information upwards to a complex model with indices of abundance and biological compositions. Stock Synthesis model is able to use both weight, length and age composition data — including conditional age-at-length data — as components in an overall likelihood function (Maunder and Punt, 2013 [177]). But its application in situations wherein that information is lacking is an exciting new application (Cope 2013 [57]).

Pollack (family Gadidae) is a cosmopolitan benthopelagic fish most effectively caught by trawls and gillnets. According to reported landings in English and French waters, the highest densities of pollack are found in the western English Channel, with around 60% of pollack landings reported in that region (ICES, 2016a [147]). Juveniles of pollack are mostly found in shallow waters (around 10m deep), and adults reside at depths of 40-100m (Pawson, 1995 [198]; Suquet, 2001 [248]). The maximum reported age for pollack is 15 years (Suquet, 2001 [248]). FAO reports a maximum length at 130 cm and maximum weight at 18.1 kg. First sexual maturity seems to occur at about 3 years and 1.5 kg (Suquet, 2001 [248]) and spawning occurs around March and April, leading to high density spawning aggregations (Moreau, 1964 [189]). Fisheries target these aggregations and obtain the highest catch rates during this time (Suquet, 2001 [248]).

Despite the wide distribution, population differentiation may exist. Charrier et al. (2006) [46] found a significant genetic differentiation between individuals originating from the western English Channel and the Bay of Biscay. But as the differentiation was weak, the results would need to be confirmed by further investigations. For now, even if stock identity of pollack is not clear (ICES, 2014 [143]), pollack from subarea VI and VII (Figure 4.1) are managed as one advisory unit. In this work we focus on pollack from these subareas and assume one population.

In Europe, marine recreational fishery survey data are sparse, and few stock assessments account for recreational fishing impacts despite its potentially substantial contribution. Many fish stocks are assessed by working groups consisting of experts from several countries. In France, the most recent study conducted in 2011-2013 by Levrel et al. (2013) [165] estimated 3301 tons of yearly recreational fishery catches of pollack, among which 2274 tons would be kept. The average length of individuals caught is 47.5 cm and the average length of individuals kept is 50.5 cm, both above the legal catch size of 30 cm. When trying to put together a removal history, the amount of recreational catch is a big source of uncertainty for pollack. Until now, recreational catches have not been taken into consideration in the stock assessment.

Data used in stock assessments in Europe are provided by countries as a response to an official data call from the International Council for the Exploration of the Sea (ICES). But the type of data requested depends on the stock assessment model used by the European working group, therefore it can be difficult to gather all existing data. The current method applied to pollack in the Celtic Seas Ecoregion is the Depletion Corrected Average Catch (DCAC) method (MacCall, 2009 [170]). It requires a portion of the catch time series (the period of most intense removals) and assumptions on stock status and productivity. Results from this simple model are greatly dependent on the average catch calculated and the stock status assumed (Wetzel and Punt, 2011a [267]). For pollack in area VI and VII, the ICES report from the Working Group WGNEW (ICES, 2014 [143]) highlights that some length–frequency data are available for recent years, but area specific data on life-history parameters are missing. According to this report, the DCAC method could be improved by including the significant removals from the recreational fisheries. The advice is to gather data on recreational fisheries in order to better manage the stock.

In this paper, our aim is to better estimate stock status, instead of assuming what it is, and move beyond catch-only models by using all available information. We build a model adapted to the studied stock, using the Stock Synthesis framework. We set various catch scenarios, and conduct several sensitivity analysis on different assumptions made in model construction. We also apply a method using only the length-based data and compare results of stock status. Finally, we take an ensemble modelling approach by combining plausible models that reflect important axes of uncertainty.

4.1.2. Materials and methods

4.1.2.1. Catch data processing and catch history construction

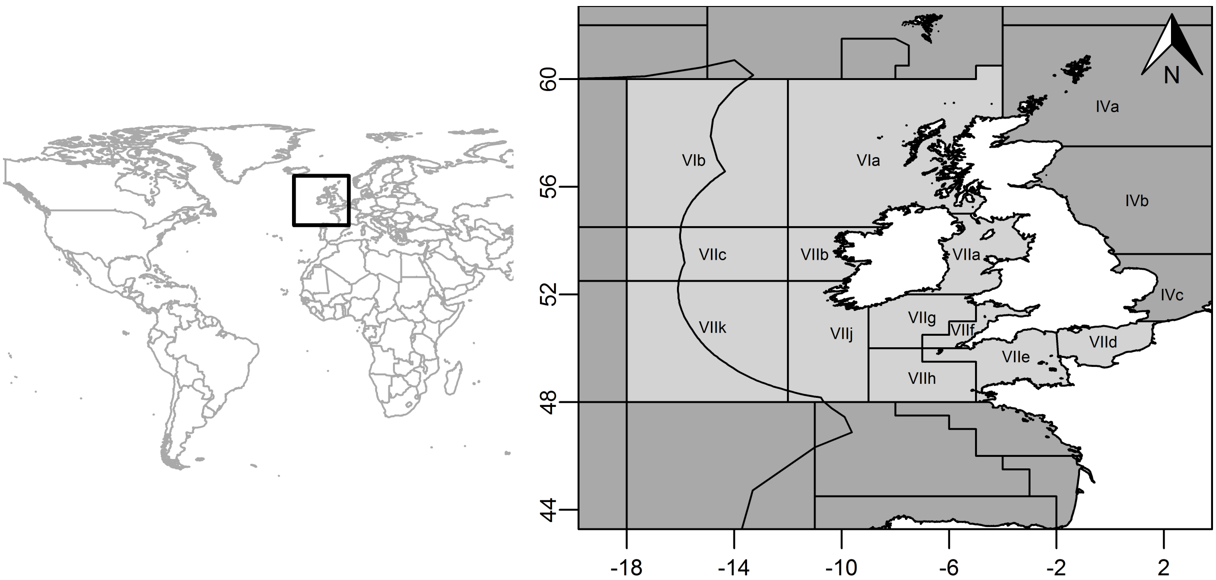


FIGURE 4.1 – Localization of the studied stock of pollack (shaded area in light grey). Names of the ICES divisions are indicated on the map.

The stock studied is located in ICES Subareas VI and VII (Fig. 4.1). The bulk of pollack catches occurs in Subarea VII. When processing commercial catch data, we first analyzed the data by Subarea to detect mistakes in the raw data. Then we looked for correlations among catch by country to correct the time series. We also devised alternative catch scenarios when information was missing. We calculated the ratio of catch by main fleets by country and applied these ratio to the reconstructed time series. Finally, we established possible catch scenarios for total recreational fishery. All of these duties are described in this section.

The main countries catching pollack from the stock studied were France, UK and Ireland. Catch data were available by country, with the longest time series given by UK from 1950 to 2015. For French landings, catch were missing in 1999. We used the mean of catch values of 1997, 1998, 2000 and 2001 to complete the time series.

In Subarea VI, only few years of data were available for Sweden and Spain with very high values compared to the other countries. Sweden has fished pollack in Subarea IV (outside the boundaries of the studied stock) since 1950, excluding years 1967 to 1972. During these 6 years, no catch was recorded in Subarea IV, whereas catch were suddenly recorded in Subarea VI. As the same phenomenon was observed for other species such as Atlantic salmon or northern shrimp, we assumed that there was a mistake in catch records and that these catches occurred in Subarea IV instead of Subarea VI. We therefore erased all data from Sweden for Subarea VI.

Spain recorded pollack catch from 1981 to 1988, and catches in the last 3 years were suspiciously high (between 850 and 2250 tons). A drop in the catch from 2200 tons in 1988 to 0 in 1989 was unrealistic. Spain happened to fish saithe (*Pollachius virens*) in Subarea VI and "pollock" is the name used in ICES data files for this species, which is very similar to the word "pollack". Between 1972 and 1976, catches of saithe ranged between 1000 tons and 2000 tons. From 1977 to 1980, no catches were recorded, and small catches were recorded after 1980. Spain does not have fishing quota for saithe in Subarea VI, but have 1.5% of pollack TAC in this Subarea. According to expert opinion, it was more likely that Spain caught saithe in Subarea VI, and that high catches recorded for pollack came from misspelling species names when entering the data in ICES files. We therefore erased all data from Spain for Subarea VI. Missing data for Spain in Subarea 7 were set to zero.

To build a Stock Synthesis model, we needed to specify a selectivity function. The problem of using aggregated catch is that it assumes the same selectivity for all aggregated fisheries, which is not believed to be accurate in this case. We therefore decided to make the assumption that the same fleets from different countries had the same selectivity and to split the catch into three main fleets: trawlers, nets and lines. We calculated the catch ratio for each main fleet for France, Ireland and UK based on available data, but the level of information needed was available for a limited number of years (Table 4.1).

UK catch data were positively correlated to Irish catch data in Subarea VI ($p - val = 4.185e^{-10\cdot}$; adjusted R-squared = 0.618) and in Subarea VII ($p - val = 3.498e^{-9\cdot}$; adjusted R-squared = 0.576). French data started in 1977 because no records were available for previous years. No correlation was found between the UK and French time series, so we established catch scenarios as follows. In a first step, three scenarios of total commercial catch by country were set:

Scenario C1 (base model): Ireland catch data had two gaps: the first between1950 and 1960; the second between 1973 and 1985. We used the correlation between UK and Irish time series to fill these gaps. For Subarea VI, French catch was set at the same level as UK catch in 1950, then decreased by subtracting to the catch from previous year the mean of the 4 first recorded years divided by the number of years between 1951 and 1977 (Eqn 4.1, with N_1=26). For Subarea VII, French catches were set at the same level as UK in 1950, and then increased by adding to the catch from previous year the mean of the first 4 recorded years divided by N_1 (Eqn 4.2).

$$C_i = C_{i-1} - \frac{\frac{\sum_{1977}^{1980} C_i}{4}}{N_1} \tag{4.1}$$

$$C_i = C_{i-1} + \frac{\frac{\sum_{1977}^{1980} C_i}{4}}{N_1} \tag{4.2}$$

Scenario C2: Catch data for Ireland in both Subareas and for France in Subarea VI were reconstructed the same way as in scenario 1. For VII, French catches were set low from 1950 to 1970 with random values from a normal distribution with a CV of 0.25. The normal function had a mean of 300 tons and a standard deviation of 75. Then a rapid increase was set from 1970 to 1976 (Eqn 4.3) as follows:

$$C_i = C_{i-1} + \frac{\frac{\sum_{1977}^{1980} C_i}{4} - C_{1970}}{N_2} \tag{4.3}$$

Where N_2=6 is the number of years between 1970 and 1976.

Scenario C3: No catch reconstruction was done. The gap in Irish catch data and the lack of French catch data before 1977 were interpreted as a result of no fishing effort.

Then, the mean catch ratio values calculated previously (Table 4.1) were applied to the catches by country and by main fleet of each commercial catch scenario for the available years. To complete the time series, the mean catch ratio values of the four first years of available data were applied to each main fleet from each country (Table 4.1). Finally, all catches were aggregated by main gear.

TABLE 4.1 – Mean catch ratio by main fleet for France, England and Ireland. Standard deviation between years is specified in brackets.

Fishing gear	Trawl	Line	Net	Other
France: 2000 to 2015	0.69 (0.07)	0.13 (0.05)	0.17 (0.05)	0.01 (0.01)
France: 2000 to 2003	0.79 (0.02)	0.07 (0.01)	0.13 (0.04)	0.01 (0.01)
England: 2009 to 2015	0.09 (0.01)	0.09 (0.02)	0.8 (0.02)	0.01 (0.01)
England: 2009 to 2012	0.09 (0.01)	0.1 (0.01)	0.8 (0.01)	0.01 (0.003)
Ireland: 2003 to 2015	0.38 (0.09)	-	0.47 (0.11)	0.15 (0.05)
Ireland: 2003 to 2006	0.48 (0.09)	-	0.35 (0.06)	0.17 (0.05)

When building the Stock Synthesis model, we considered that the commercial catch scenario 1 was the most likely and used it to construct the base model.

Recreational catch scenarios, five in total, were also develop as follows:

Scenario R1 (base model): Recreational catch increased from 1950 to 2015 to reach 2000 tons (Eqn 4.4).

$$R_{1950} = \frac{2000}{N_r};\ R_{i+1} = R_i + \frac{2000}{N_r} \tag{4.4}$$

Scenario R2: Recreational catch increased from 1950 to 2015 to reach 4000 tons (Eqn 4.5).

$$R_{1950} = \frac{4000}{N_r};\ R_{i+1} = R_i + \frac{4000}{N_r} \tag{4.5}$$

Where N_r is the length of the time series, in this case 66.

Scenario R3: Recreational catch are drawn from a normal distribution with a mean of 2000 tons and a standard deviation of 100.

Scenario R4: Recreational catch are drawn from a normal distribution with a mean of 4000 tons and a standard deviation of 100.

Scenario R5: Recreational catch are assumed to be low and are set to zero in the model.

4.1.2.2. Length data processing

Length data were available from French and Irish catch. French length data (Table 4.2) came from the Onboard Observer (ObsMer) program, and all main fleet were sampled. The Observer is an employee from Ifremer or from an external company who samples fish on random fishing boats. For the Irish length composition data (Table 4.3), only Trawl and Net were sampled.

TABLE 4.2 – Available length data from French Onboard Observer program (ObsMer).

year	Number of sampled fishing trip			Number of length measures		
	Trawl	Net	Line	Trawl	Net	Line
2003	14	3	-	38	29	-
2004	10	4	-	30	5	-
2005	55	3	-	141	5	-
2006	66	4	-	281	8	-
2007	26	24	-	65	92	-
2008	97	5	-	267	9	-
2009	137	52	39	659	398	191
2010	98	80	22	612	628	100
2011	72	66	8	253	293	16
2012	117	96	7	482	440	102
2013	140	48	-	797	172	-
2014	202	37	3	1303	98	25
2015	158	73	32	700	413	287

TABLE 4.3 – Available length data from Ireland.

year	Number of sampled fishing trip		Number of length measures	
	Trawl	Net	Trawl	Net
2002	1	-	50	-
2006	1	-	161	-
2007	8	-	67	-
2008	10	-	303	-
2009	45	2	506	75
2010	37	8	352	778
2011	31	9	418	352
2012	34	5	281	200
2013	4	3	76	151

In a preliminary study, some high residuals were observed when fitting a Stock Synthesis model with length data. The cause of the bad fit was identified to be the sampling of a high number of small individuals among ObsMer length data in 2005 and 2012. The small individuals sampled in 2005 came from discarded catches. In 2012, the small individuals came from samplings on small gillnets using mesh sizes under 80 mm in the Western English Channel. These small mesh sizes are used to fish species such as gurnard or red mullet inshore, on sandy or rocky sea-beds. Aggregation of pollack juveniles can be caught by these fisheries as by-catch species. These two occurrences of small individuals in the length data were not consistent with the selectivity calculated by the model among all years, which resulted in the bad fit. These samplings were therefore erased in the final model, which improved the model fit.

4.1.2.3. Calculation of Catch Per Unit Effort

Ireland provided a time series of Catch Per Unit Effort (CPUE) from 1995 to 2014. All fleets using otter trawls were selected, and landings were divided by effort without any standardization method. Ifremer provided revised French landings from a separate analysis of logbook and auction data and VMS which allocates landings correctly by fishing ground (SACROIS methodology used at present as Official Landings). Data were available from 2000 to 2015 and were used to calculate a French time series of abundance indices.

We selected hauls from Otter Bottom Trawls in Subareas VI and VII, with a mesh size between 70 and 119 mm. These trawlers fish the bulk of pollack catch in France. We did not include divisions VIb and VIIk, where total landing from all years were less than 1000 kg. The available factors were the month, the ICES division, the vessel power, the mesh size and the year. The mesh size factor was composed by two categories: mesh size between 70 and 99 mm, and mesh size between 100 and 119 mm. Model selection using Akaike's Information Criteria (AIC) was applied to choose the model best supported by the data (Burnham and Anderson, 2002). The deltaAIC values were calculated for each model family as the difference between each model and the model with the lowest AIC (Table 4). The full lognormal model had the smallest deltaAIC value (Table 4.4). The full binomial model did not have the smallest deltaAIC value but as the value was not above 10, the model was not considered very unlikely (Burnham and Anderson, 2002). A lognormal Delta-GLM was therefore applied (Aitchison, 1955 [4]; Stefánsson, 1996 [247]; Maunder and Punt, 2004 [176]) on the full model to obtain the CPUE time series. To calculate CVs for the CPUE, data were bootstrapped within each year.

TABLE 4.4 – DeltaAIC values for lognormal, binomial and gamma models applied to French data. The full model is composed of all factors.

Model	deltaAIC lognormal	deltaAIC binomial	deltaAIC gamma
full	0	7	0
year	19750	94	22834
year, month	14157	101	12582
year, division	15871	6	17536
year, power	12395	84	16485
year, mesh size	19731	81	22606
year, month,division	10081	12	7856
year, month, power	6199	90	5826
year, month, mesh size	14155	89	12414
year, month, power, mesh size	5243	85	4647
year, month, division, power	862	6	168
year, month, division, mesh size	9940	14	7856
year, division, gear	15628	7	17516
year, power, gear	11310	78	15255
year, division, power	7480	0	10983

4.1.2.4. Mortality and life history parameters

A natural mortality value of 0.2 year^{-1} is used for the assessment of pollack with the DCAC model (ICES, 2016a). This value is commonly applied for gadoids from European seas when the amount of data is limited but it has no real scientific basis. We used an application (The Natural Mortality tool; http://barefootecologist.com.au/shiny_m) to estimate natural mortality (M). We used methods based on maximum age (Then_Amax 1 to 3 and Hamel_Amax) and on the von Bertalanffy K parameter (AnC, Jensen_VBGF 1 and 2). The methods were used to construct an informative prior for natural mortality value (Fig. 4.2). Method references can be found in the application.

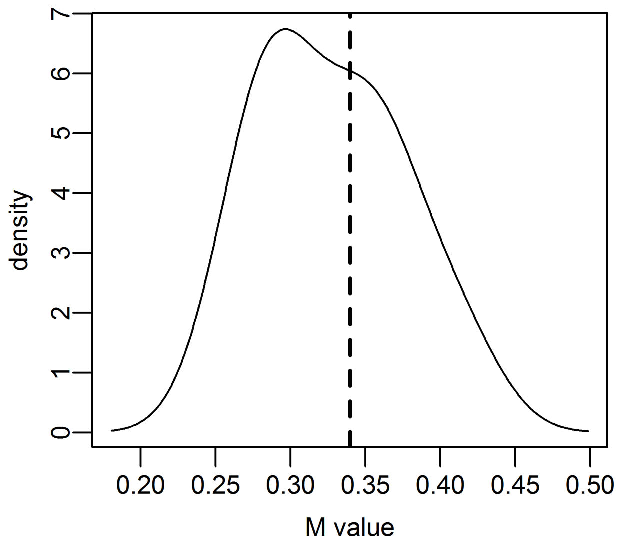


FIGURE 4.2 – Distribution of natural mortality value. The vertical dotted line is the median.

Additional life history parameters were provided by special studies carried out for pollack (pers. comm. Ifremer). Fish sampled were weighted, measured, and both macroscopic and microscopic determination of maturity was done. We used the updated parameters (Table 4.5) in the Stock Synthesis model. A median natural mortality value of 0.34 was estimated.

TABLE 4.5 – Life history parameters of the pollack stock of ICES Subareas VI and VII.

Lmat50	Lmat95	Linf	K	t0	Age max
43.71	55.31	98.2	0.182	-0.935	15

4.1.2.5. LB-SPR method

The spawning potential ratio (SPR) of a stock is the proportion of the unfished reproductive potential left at any given level of fishing pressure (Goodyear, 1993 [107]; Walters and Martell, 2004 [264]). SPR values are often used to set target and limit reference points for fisheries (Clark, 2002 [52]). While this is typically derived from data-rich stock assessments, data-limited methods have also been devised to calculate this value.

The Length-based Spawning Potential Ratio (LB-SPR) model (Hordyk et al., 2015c [132]) is equilibrium based, and relies on several assumptions. The length data must be representative of the exploited stock and the selectivity should be asymptotic to avoid over-estimates of fishing mortality and under-estimates of SPR. Individual growth should be adequately described by the von Bertalanffy equation. Given sexual differentiation in life history values is common in fishes, biological parameters and length composition are typically female fish only. It also assumes the distribution of lengths at age is normal and that natural mortality and growth rates are constant through time.

The LB-SPR method has been developed for data-limited fisheries, where a representative sample of the size structure of catch and some information on the life history of the stock are available. The method uses the ratio M/K of natural mortality (M) and the von Bertalanffy growth coefficient (K), which is believed to vary less across stocks and species than M (Prince et al., 2015 [208]). The method ultimately produces a stock status value relative to an unfished status. The application used can be freely found at: http://barefootecologist.com.au/lbspr.

In a first step, we used the LBSPR method on the trawl length data. The life history parameters used to apply the method can be found in Table 4.5. A value of 1.866 was used for M/K. In a second step, we aggregated pollack length data from Trawl, Net, and Line fishery. To preserve the selectivity associated to each fishery, we multiplied each length frequency by the effective sampling size of the corresponding year before summing the length data for each year. We selected years 2008 to 2015 where the total number of raw length measures was above 500 per year.

4.1.2.6. Stock Synthesis model

The base model is composed of the commercial catch data from scenario C1, the recreational catch data from scenario R1, and the CPUE and length data from French and Irish fleets. Length data were separated by main fishing gear (Trawl, Net and Line) with different selectivities for each gear.

The selectivity functions for commercial catch were set as double normal logistic functions with 6 parameters. Several trials were carried on to evaluate the capacity of the model to estimate these parameters from available length data. The model was able to evaluate four parameters, typical in the application of this function. The values of the last length bin selectivity and the width of the descending slope had to be fixed. For trawl fishery, we assumed that the selectivity did not change for big individuals, making it asymptotic in behavior. For both Net and Line fisheries, we assumed that the selectivity decreased for big individuals.

Two time series of CPUE were considered, both assuming the same selectivity as the trawl fishery. Final parameters values describing the selectivity functions can be found in Table 4.5. As no length data were available for recreational fishery, all the selectivity parameters had to be fixed. We set selectivity parameters close to the estimated parameters from Net and Line fishery, except for the peak start value which was set 9 cm lower than the value estimated for Net and Line fishery. The value of 9 cm was the difference between the mean value of the length data from Net and Line fishery and the mean length of recreational catch estimated by phone survey (Levrel et al., 2013 [165]).

The standard Beverton-Holt stock-recruitment function was used. Two parameters had to be specified: the log of virgin recruitment level ($\ln R_0$), and the steepness of the stock-recruitment relationship. A meta-analysis conducted by Punt et al. (2005) [216] gives a range of values for prior on steepness. For clupeiformes, gadiformes and pleuronectiformes, a steepness with a mean of 0.866 and 95% probability intervals of [0.606, 0.986] is recommended. We used this value in the base model. The natural mortality is estimated by the model. The informative prior follows a normal distribution with a mean of 0.34 and a standard deviation of 0.05. Length at 50% maturity is set to 43.7 cm.

Length composition were weighted following Francis (2011) [92] iterative reweighting. The underlying idea of the reweighting process is that three types of errors arise in a stock assessment: the observation error between the true and observed data, the process error between the true and expected data, and the total error between the observed and expected data. Before running the model, stage 1 weights were set. Once the model was run, weights were adjusted according to the information from the first run and the model was run again. Weights were adjusted several times until the weights reached stable values.

Sensitivity analysis were conducted and divided into two groups: likelihood components and model specification. We also did profiles on negative log-likelihood of natural mortality, recruitment and steepness (Appendix D).

4.1.2.7. Ensemble modeling

When picking one model as the base or reference model, one by definition is not including model misspecification error. In an attempt to include model misspecification directly into the final results, an ensemble modeling approach was used, called the bootstrap model averaging (Davidson, 2004 [62]; Davidson and Fan, 2006 [63]). The base model and 10 other models were assumed to be plausible with differing levels of plausibility.

We first chose models with a different prior on natural mortality (mean values of 0.3 and 0.4), with different values of steepness (0.8 and 0.97), and with different values of length at maturity (40 and 48). For these models as well as the base model, we used the weighted AIC.

We also chose the recreational catch scenarios 2 and 3 and the commercial catch scenario 2. As these three models did not have the same input data as the base model, the AIC could not be used. They were arbitrarily weighted at the same level as the base model, according to expert opinion.

Finally, all weights were converted into ratios to have the sum of all ratios equals to 1. We then weighted the estimated biomass level from each Stock Synthesis model. For each year, we drew a normal distribution using the mean and the standard deviation value from the report file, and the number of replicates was equal to 100 000 times the weight ratio.

4.1.3. Results

4.1.3.1. Stock synthesis models

4.1.3.1.1. Results of the base model The estimated spawning biomass decreases from 36 815t in 1950 to 9 749t in 1991. From 1991 to 2013, the estimated spawning biomass increases to 16 513t and seems to be stable for the last two years of the time series (Fig. 4.3.a). Following the same trend, the relative spawning biomass decreases from 1 in 1950 to 0.265 in 1991. An increase follows with a value of 0.449 achieved in 2013 and a stabilization for the last two years (Fig. 4.3.b).

TABLE 4.6 – Mean values of the final selectivity functions' parameters of the base model after applying the associated function. Fixed parameters are in bold.

Selectivity parameter	Function	Net	Line	Trawl	Recreational fishery
Length at Peak start	None	64.4	64.1	53.5	**55.2**
Length at the beginning of the descending slope	Logistic	66.5	66.1	62.6	**57.2**
Width of the ascending slope	Exponential	376	305	128	**293**
Width of the descending slope	Exponential	**148**	**148**	**148**	**148**
Selectivity of the initial size bin	Logistic	0	0	0	**0**
Selectivity of the final size bin	Logistic	**0.38**	**0.38**	**0.99**	**0.38**

4.1.3.1.2. Sensitivity analysis on model specification The model based on a natural mortality estimated with no informative prior resulted in smaller median estimates of spawning biomass and larger confidence interval than the base model. Using a prior centered on 0.3 year^{-1} or 0.4 year^{-1} slightly changed the median estimates of spawning biomass between 1950 and 1990. But results after 1990 were similar. The model with a prior centered on 0.2 year^{-1} resulted in higher estimates of spawning biomass than the base model between 1950 and 1994, and smaller estimates than the base model after 1994 (Fig. 4.3.a). The base model estimated a depletion of 0.44. The biggest difference between the base model and alternative models in terms of stock status was obtained for a prior of M centered on 0.2 year^{-1}, with an estimated depletion of 0.25 (Appendix E and Fig. 4.3.b).

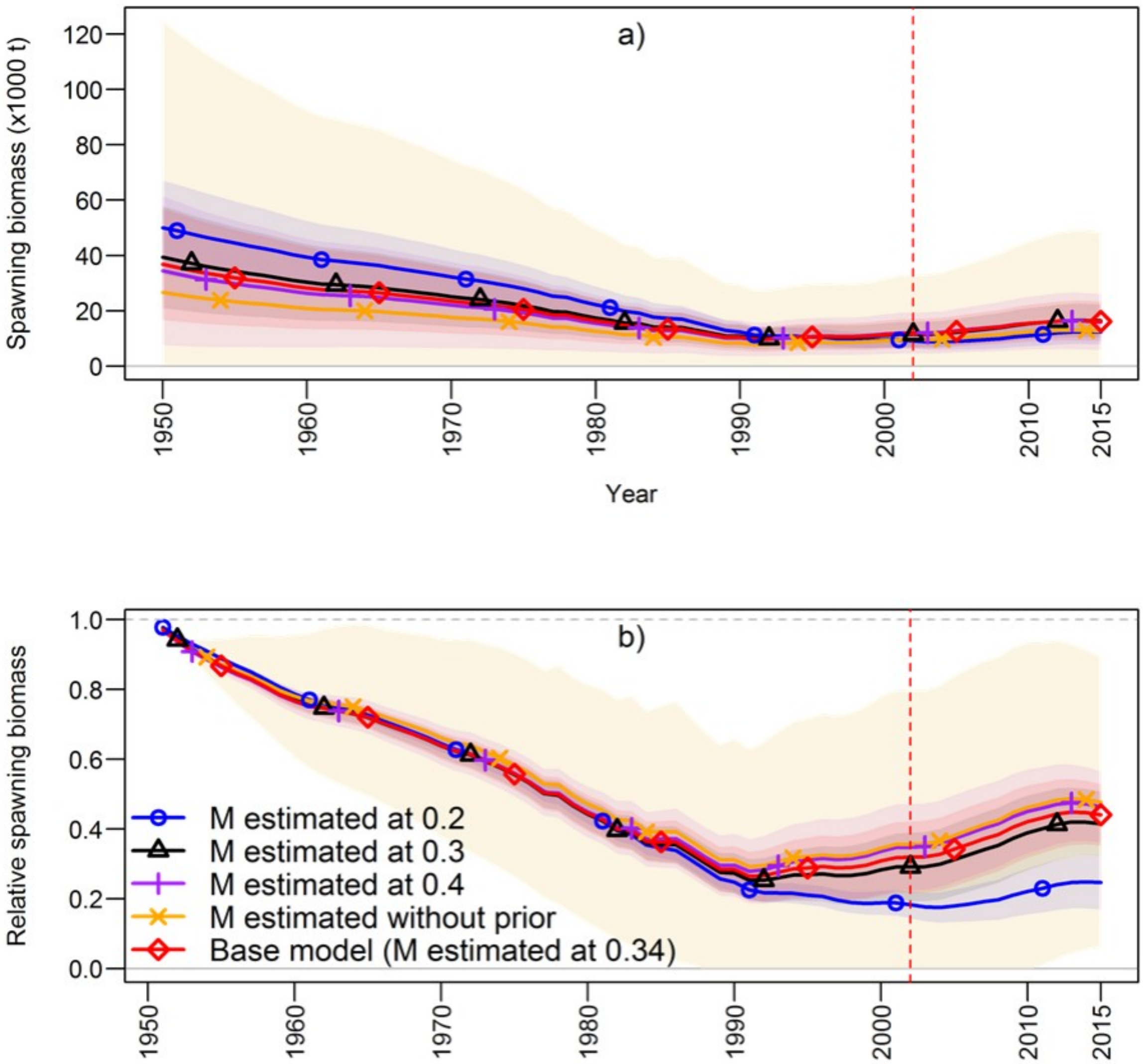


FIGURE 4.3 – Spawning biomass in metric tons (a) and relative spawning biomass (b) estimated by models with various specifications on natural mortality (M). Median estimates are represented in bold line and 95% confidence intervals are represented in shaded areas. The vertical dotted line indicates the first year of available length data.

Sensitivity in spawning biomass is less for the explored alternative values of steepness. Results of the spawning biomass are similar for the model based on a steepness fixed at 0.97 and for the model based on a steepness estimated with no informative prior. When no informative prior is used, the final steepness estimated by the model has a value of 0.99, which explains why results are similar. The model does not seem to be able to estimate the steepness. Between 1950 and 2002, the estimated spawning biomass is slightly different between the base model and the alternative models, but results are similar after 2002 (Fig. 4.4.a). Results of relative spawning biomass are similar between the base model and alternative models (Fig. 4.4.b).

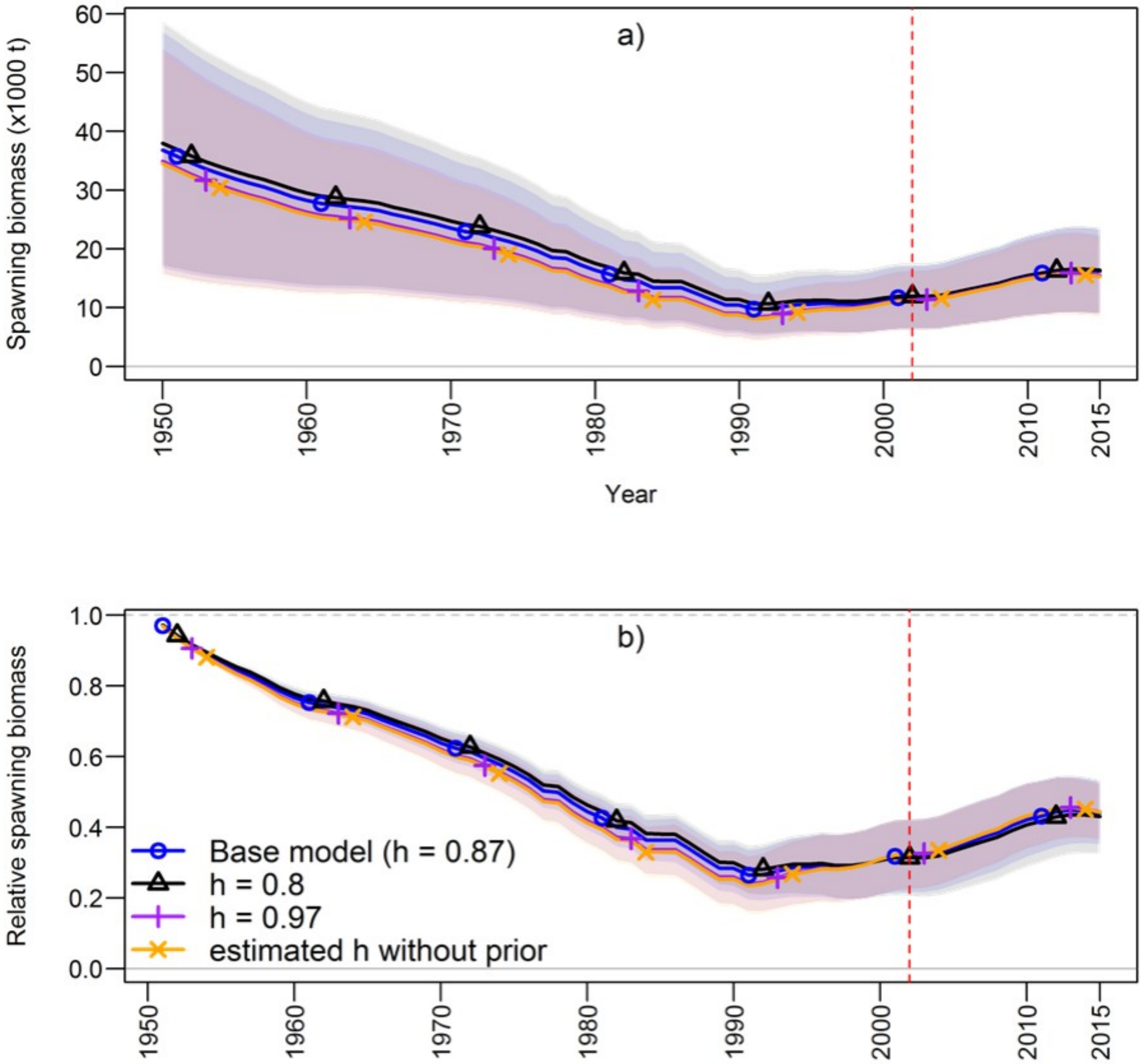


FIGURE 4.4 – Spawning biomass in metric tons (a) and relative spawning biomass (b) estimated by models with various specifications on steepness (h). Median estimates are represented in bold line and 95% confidence intervals are represented in shaded areas. The vertical dotted line indicates the first year of available length data.

Changing the value of the length at first maturity ($Lmat$) does not impact the trend of the estimated spawning biomass time series (Fig. 4.5.a) nor the trend of the relative spawning biomass (Fig. 4.5.b). But estimates are higher when *Lmat* is smaller, and estimates are smaller when *Lmat* is higher.

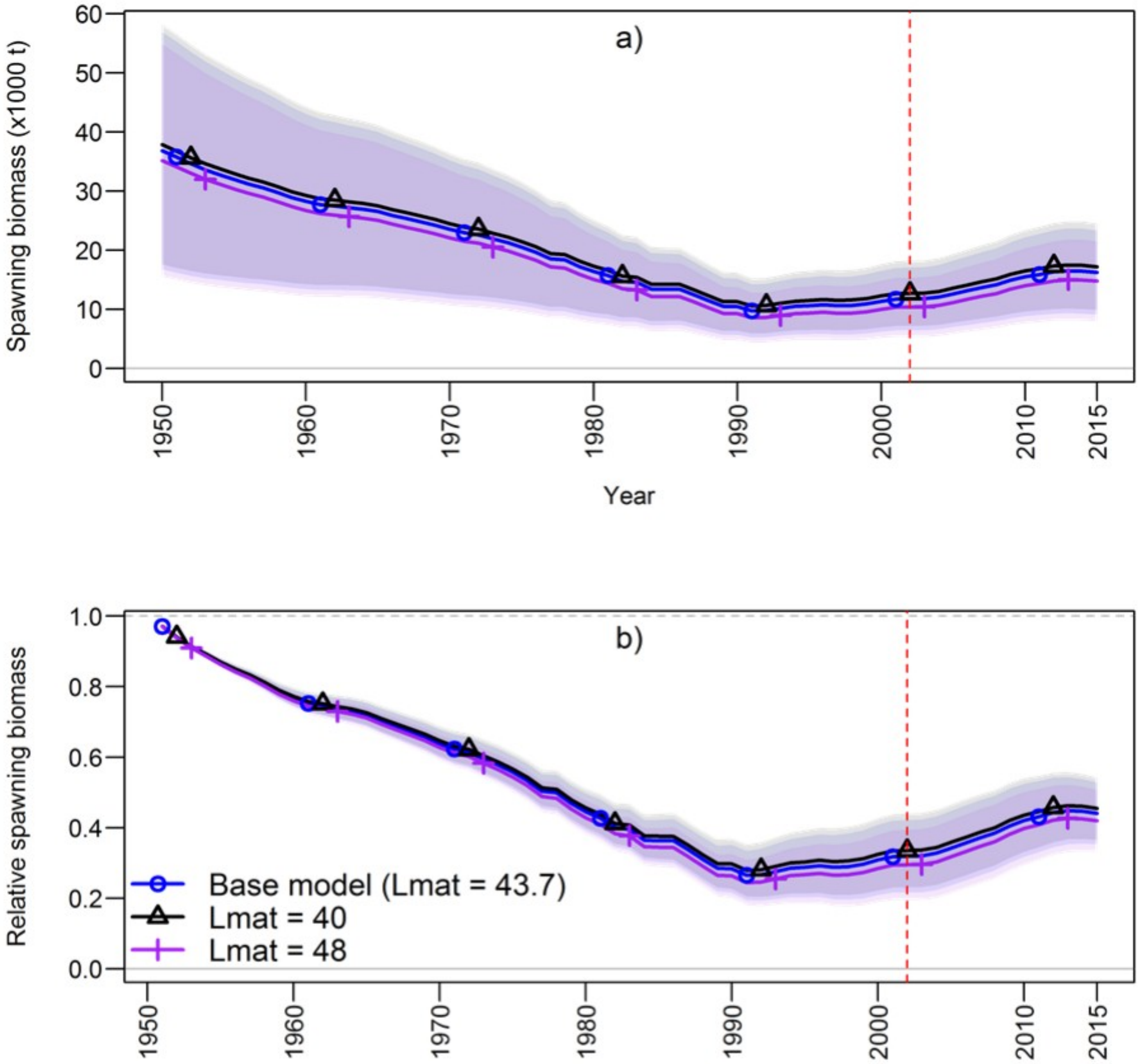


FIGURE 4.5 – Spawning biomass in metric tons (a) and relative spawning biomass (b) estimated by models with various specifications on length at 50% maturity (*Lmat*). Median estimates are represented in bold line and 95% confidence intervals are represented in shaded areas. The vertical dotted line indicates the first year of available length data.

4.1.3.1.3. Sensitivity analysis on likelihood components Compared to the base model, the scenario with no recreational catch gives smaller estimates of spawning biomass from 1950 to 1998, and slightly higher estimates after 1998. Estimates of spawning biomass are close for the base model and for the model with a fixed level of recreational catch of 2 000t. Between 1950 and 1992, results are close for the model with a fixed level of recreational catch of 4 000t and the model with an increasing level of recreational catch from 0 to 4 000t. Results differ after 1992, and the model based on the increasing level of recreational catch gives estimates of spawning biomass close to the base model (Fig. 4.6.a).

The most optimistic estimate of the final stock status is given by the model with no recreational catch. The less optimistic estimate of the final stock status is given by the model with an increasing level of recreational catch from 0 to 4 000t. The base model estimates a final relative spawning biomass slightly smaller than the model with a fixed level of recreational catch of 2 000t and similar to the model with a fixed level of recreational catch of 4 000t (Fig. 4.6.b).

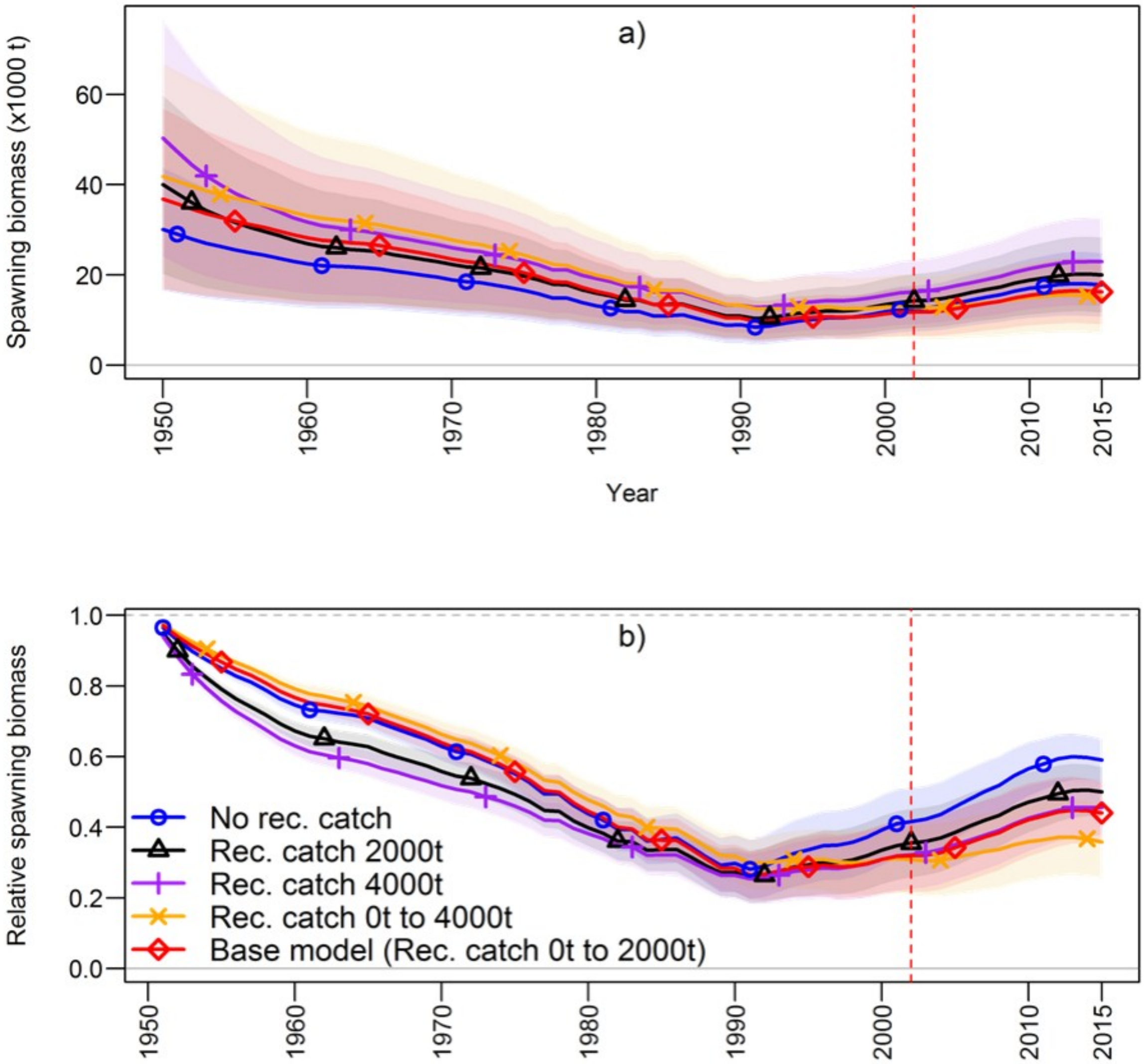


FIGURE 4.6 – Spawning biomass in metric tons (a) and relative spawning biomass (b) estimated by models based on various recreational catch (rec. catch) scenario. Median estimates are represented in bold line and 95% confidence intervals are represented in shaded areas. The vertical dotted line indicates the first year of available length data.

The estimates of spawning biomass and the estimates of relative spawning biomass from the base model and from the model following the catch scenario 2 differ between 1955 and 1988 but are close after 1988. The model with catch scenario 3 estimates a high level of spawning biomass and relative spawning biomass at the beginning of the time series of available catch data in 1986. Then a rapid decrease is estimated. From 2002 to 2015, results are close to the estimates obtained with the base model (Fig. 4.7.a and 4.7.b). The specific pattern observed for the catch scenario 3 is related to the lack of catch reconstruction. The lack of French catch data before 1977 is interpreted as a lack of fishing effort. Therefore the total catch increases suddenly in 1977, resulting in a strong biomass decrease.

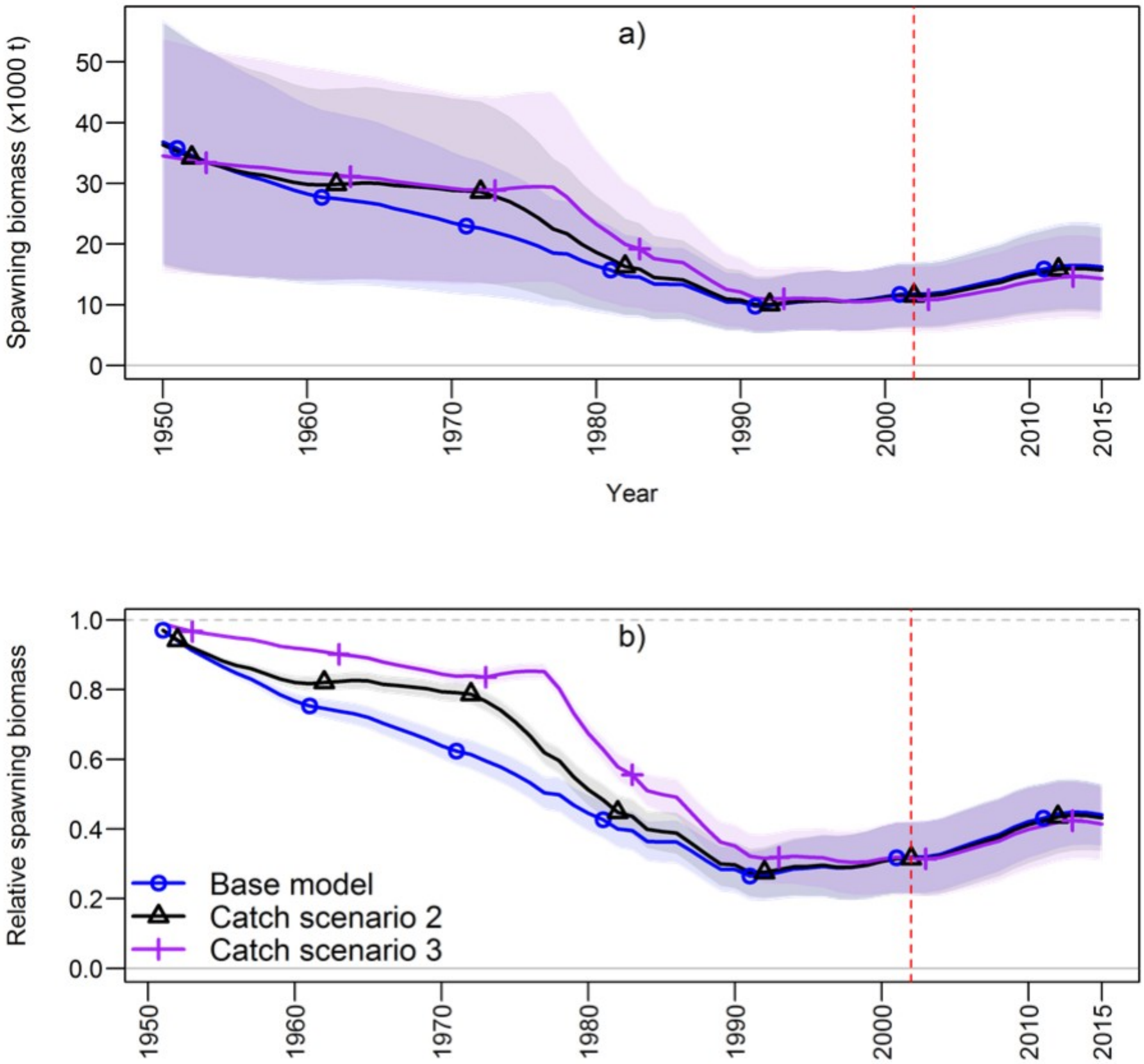


FIGURE 4.7 – Spawning biomass in metric tons (a) and relative spawning biomass (b) estimated by models based on various commercial catch scenario. Median estimates are represented in bold line and 95% confidence intervals are represented in shaded areas. The vertical dotted line indicates the first year of available length data.

The base model and the model without Irish CPUE give similar estimates of spawning biomass and relative spawning biomass. Compared to the base model, the model without French CPUE gives higher estimates of spawning biomass and relative spawning biomass. The model without length data gives the highest estimates of spawning biomass and relative spawning biomass, with the biggest confidence interval (Fig. 4.8.a and 4.8.b).

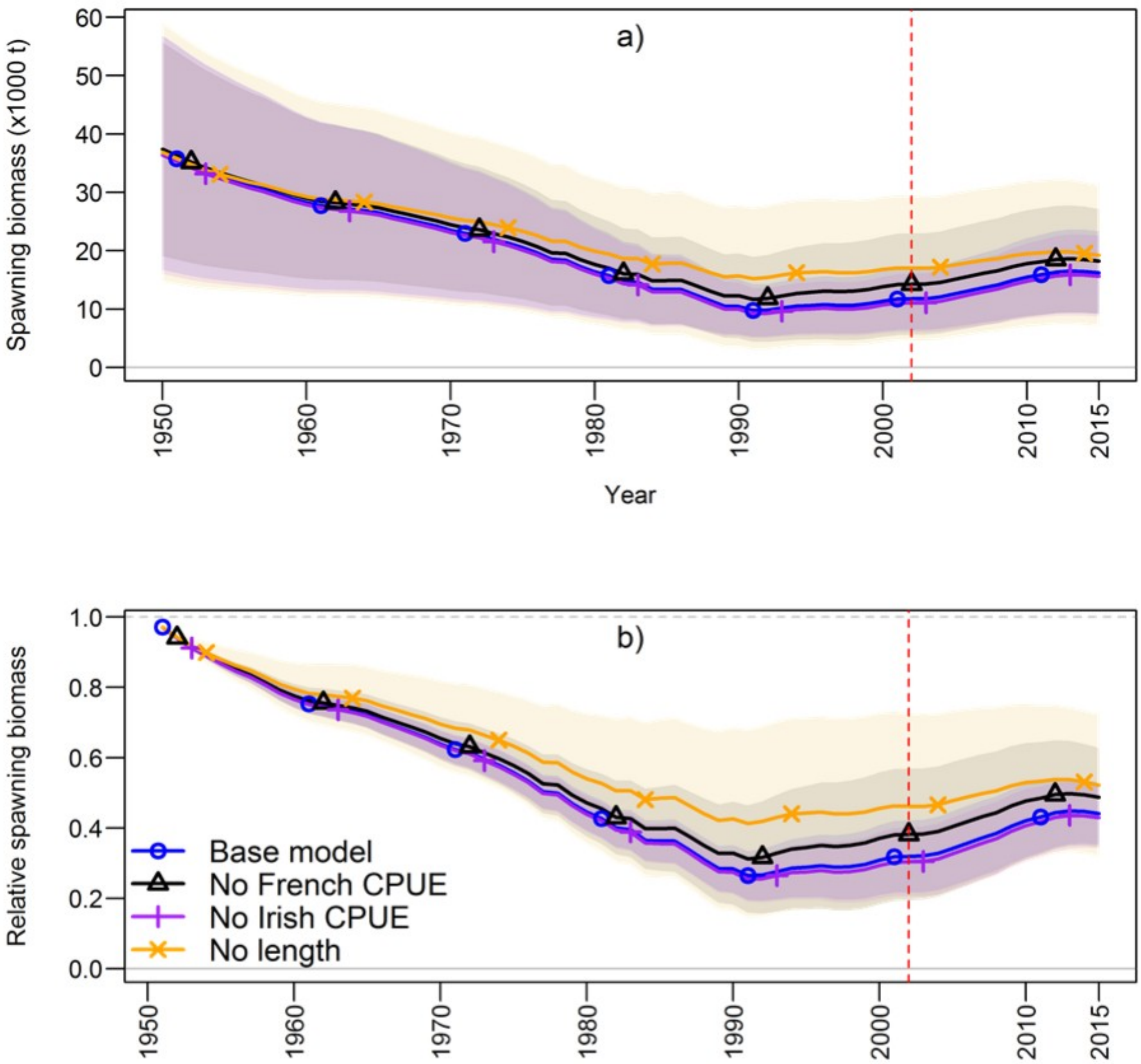


FIGURE 4.8 – Spawning biomass in metric tons (a) and relative spawning biomass (b) estimated by models based on various levels of data quantity. Median estimates are represented in bold line and 95% confidence intervals are represented in shaded areas. The vertical dotted line indicates the first year of available length data.

4.1.3.2. Comparison of the LBSPR results with the Stock Synthesis base model

In a first step, we compared the selectivity function obtained for trawlers. The mean value of the 50% selectivity (S_{L50}) and 95% selectivity (S_{L95}) were respectively 43.5 cm and 52.6 cm with the LBSPR method and respectively 44 cm and 50.35 cm with the Stock Synthesis base model (Fig. 4.9 and 4.10).

In a second step, we compared the results of the Stock Synthesis base model with the results of the LBSPR method applied on all length data. The mean spawning potential ratio calculated with the Stock Synthesis base model and with the LBSPR method were very close (Table 4.7).

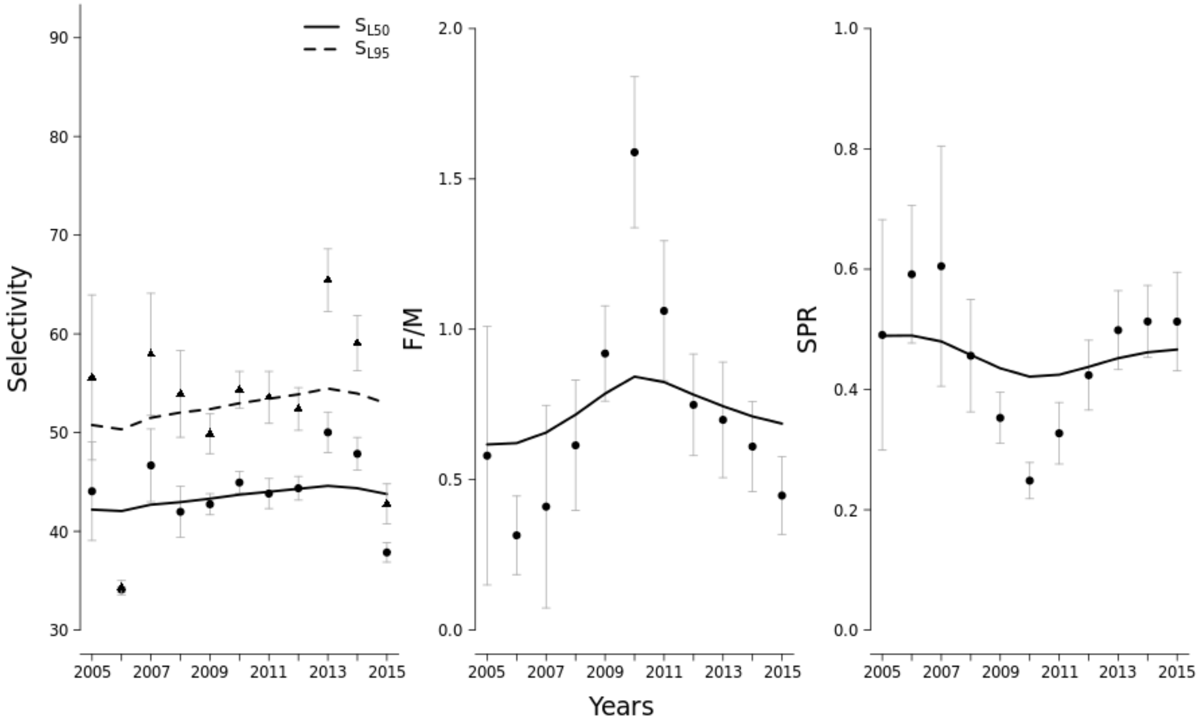


FIGURE 4.9 – Results of the LBSPR model applied on trawl length data for the selectivity, the ratio of fishing mortality on natural mortality and the spawning potential ratio from 2008 to 2015. A smoother was applied and is represented by the lines.

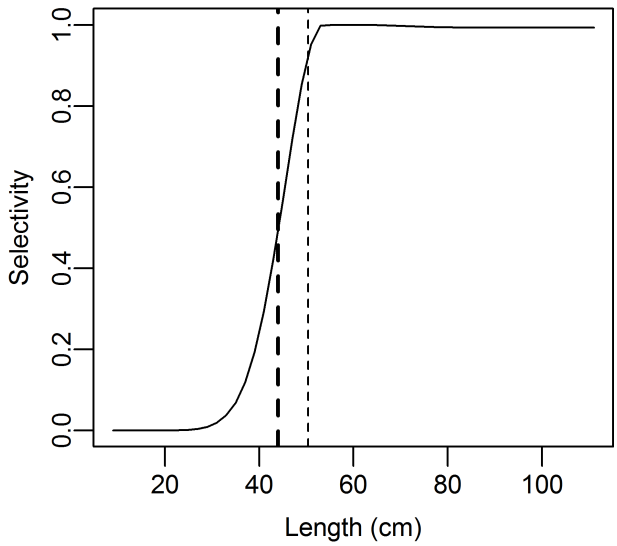


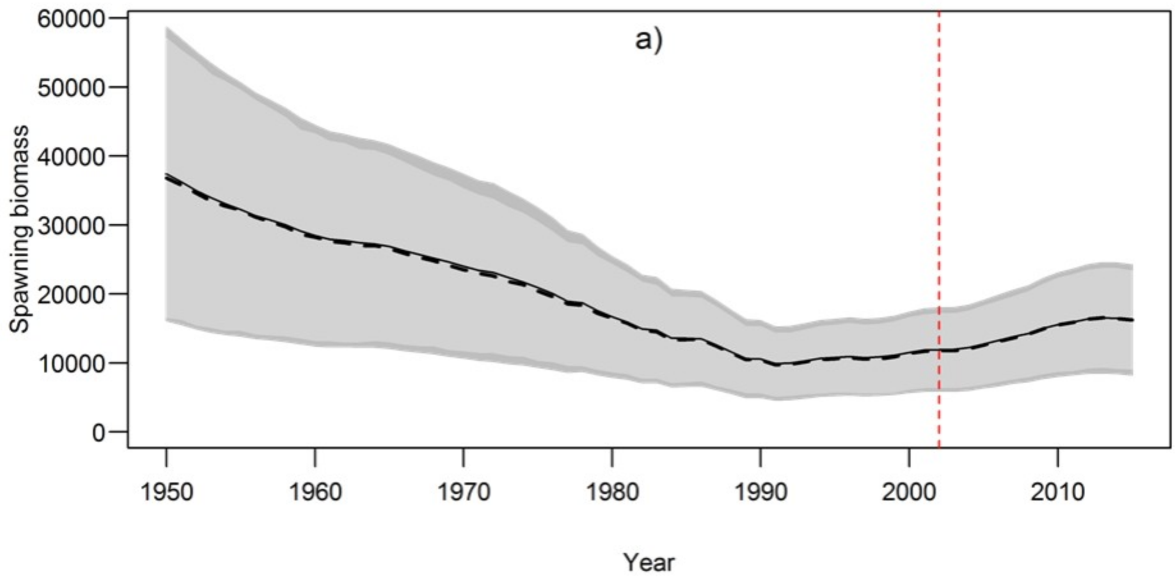
FIGURE 4.10 – Selectivity of the trawl fishery estimated from the available trawl length data by the Stock Synthesis model. The vertical bold dotted line indicates the length at 50% selectivity. The vertical dotted line indicates the length at 95% selectivity.

TABLE 4.7 – Results of the Spawning Potential Ratio (SPR) from the Stock Synthesis base model and the LBSPR model applied on all length data.

Year	**SPR**	
	SS3	**LBSPR**
2008	0.38	0.44
2009	0.41	0.33
2010	0.42	0.33
2011	0.43	0.32
2012	0.44	0.42
2013	0.45	0.47
2014	0.45	0.5
2015	0.44	0.46
Mean	**0.43**	**0.41**

4.1.3.3. Ensemble modeling

The median spawning biomass estimated by the ensemble modeling and the associated uncertainties are similar to the results obtained with the base model (Figure 4.11.a). While the median estimates of relative spawning biomass are similar between the ensemble modeling and the base model, the associated uncertainties are smaller for the base model before 1980 (Figure 4.11.b).



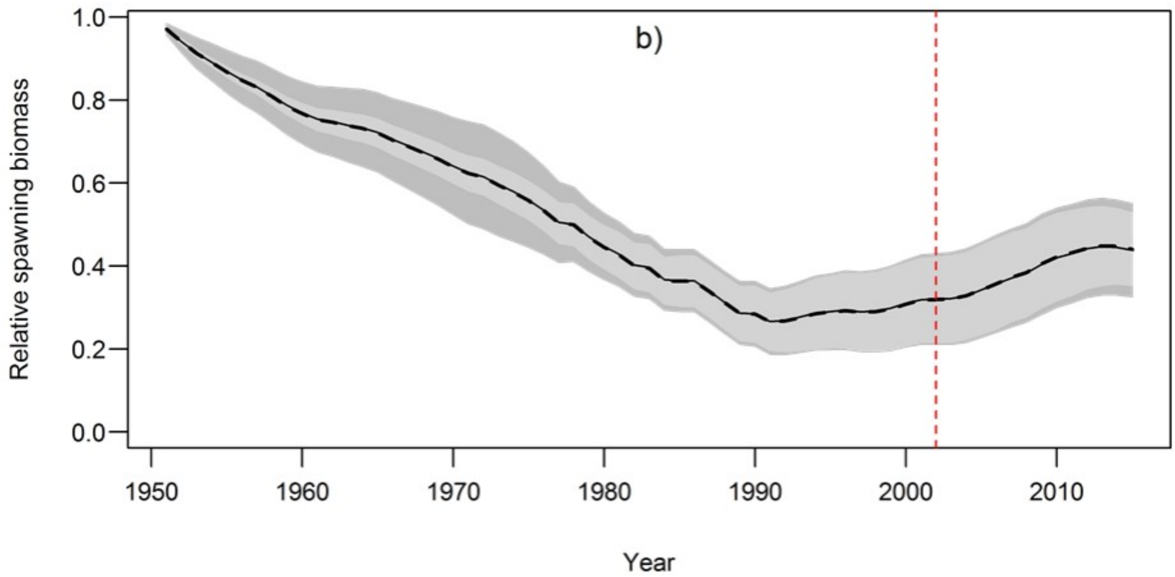


FIGURE 4.11 – Spawning biomass (a) and relative spawning biomass (b) estimated by the base model and by the ensemble modeling. Median estimates of the base model are represented by a bold dotted line and median estimates of the ensemble modeling are represented by a solid line. 95% confidence intervals are represented by a light-grey shaded area for the base model and by a grey shaded area for the ensemble modeling. The vertical dotted line indicates the first year of available length data.

4.1.4. Discussion

In this work, we constructed a Stock Synthesis model for the data-limited stock of pollack in the Celtic Seas Ecoregion. We used all available data and set some catch scenarios when no data were available. The MSY Btrigger is the stock size below which more conservative catch advice is needed to avoid impaired productivity. An usual value of MSY Btrigger set by the ICES is $0.35 \times B_0$, with B_0 the virgin biomass. According to the final stock status estimated by the base model and by the model averaging method (>0.4), the stock studied is within safe biological limits.

In a study based on simulated data, Wetzel and Punt (2011b) [268] evaluated the performance of Stock Synthesis in data-limited situations. Their results show that the inclusion of even small amounts of length-composition data can dramatically improve estimation performance. Our results lead to the same conclusion. The model without length composition data estimated higher values of spawning biomass than the base model, and with bigger uncertainties. In many cases, the assessment of data-limited stocks is done without integrating all available data. Exploring the use of integrated models such as Stock Synthesis could help improve the stock assessment. It could also be a first step to identify which data would be needed to improve the assessment.

Natural mortality (M) is related to the productivity of a fish stock and is known to be a very influential parameter in evaluating a stock's status (Mertz and Myers, 1997 [184]; Williams and Shertzer, 2003 [271]). The constant value of 0.2 year^{-1} has been commonly used for M in stock assessment of long-lived fish stocks from northern European seas (Beverton, 1964 [21]; Vetter, 1998 [261]). This approach is still used for some stocks, including our case study (ICES, 2016a [147]). It is recommended to evaluate several hypothesis about M and eliminate poorly supported hypothesis (Brodziak et al., 2011 [29]), and model-averaging methods can be useful to estimate uncertainty in stock assessment (Patterson et al., 2001 [197]). We compared models based on different specifications of natural mortality. A model with a prior of M centered on 0.2 was also tested. This value was not supported by the profile likelihood, nor by the method used to estimate M from life history parameters. We considered this value unrealistic and did not use it in the ensemble modeling. Our results show that the value of M acts as an important scaling factor. Higher values of M resulted in higher estimates of biomass ratio.

In data-limited situations, comparing different stock assessment methods is an important step to have more confidence in the results. It is interesting to notice that estimates of Spawning Potential Ratio (SPR) obtained from the Stock Synthesis base model and from the LBSPR method were close. A sensitivity analysis conducted on the type of data included in the Stock Synthesis model showed that information added by the length data came mostly from trawlers (Appendix E). The selectivity estimated by the Stock Synthesis model was close to the selectivity calculated with the LBSPR method. LBSPR proved a useful tool, though the age-structured nature of the Stock Synthesis model allowed for more derived quantities (such as spawning output and catch levels) to be calculated in addition to just stock status.

In the settings of the selectivity functions used in the Stock Synthesis base model, some choices had to be made on the values of the two fixed parameters. We assumed that the selectivity did not decrease for big individuals for trawl fishery, but decreased for net and line fishery. These assumptions were made based on a study on selectivity for cod and haddock (Huse et al., 2000 [133]) and for saithe (Pol et al., 2016 [205]), and based on expert opinion. We conducted a sensitivity analysis to evaluate the impact of changing the assumption on trawl fishery. Results of stock status were close between the base model and the alternative models (Appendix E).

Conclusion

This study brings considerable improvement in pollack stock assessment. Data which were available but not included in the former stock assessment are now being used. In a more general perspective, we showed that Stock Synthesis models can be applied to a data-limited stocks of mixed data availability and quality, while also proving a useful tool to compare and even assimilate different model specifications. Length composition data can change the results of stock status, showing the benefits of length data collection. A next step will be to investigate how to set appropriate management rules in a data-limited scenario.

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We thank Colm Lordan for providing the data of Irish CPUE and length composition data. We also thank Rick Methot for all the work on the development of Stock Synthesis that we used for this study. We thank Adrian Hordyk for the development of the LB-SPR method that we also used in this work. French data come from DPMA, declarative data managed by Ifremer – SIH – Système d'Informations Halieutiques. Financial support for this work comes from Ifremer and from the "Conseil Régional de Normandie".

4.2. Setting catch limit in a data-limited situation, case study of the stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion

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Abstract

During the last decade, several methods adapted to data-limited stock assessments have been developed thanks to a generalized request to provide stock assessment for all stocks, including data-limited stocks. Some simple methods, like the Depletion Corrected Average Catch (DCAC), are based on a limited amount of data type. Other methods, usually more complex, include all available data and require a certain number of assumptions on the data and parameters (e.g. Stock Synthesis models). As a high uncertainty is associated with the results of data-limited stock assessments, it is recommended to compare several methods. In this work, we concentrate on the objective of setting catch limits in a data limited scenario. The stock of pollack in the Celtic Seas Ecoregion is used as a case-study to compare results of various stock assessment methods. In a former study, a Stock Synthesis (SS) model was developed for this stock, based on all available data. Only the results of stock status were interpreted. In this study, we compare the results in terms of management reference points of this complete model with the results of a Simple Stock Synthesis model (SSS) and an extended Simple Stock Synthesis model (XSSS). The DLMtool is also used to compare results of MSY advice of simple methods based on few data. The MSY advice estimated by the SS model and the XSSS model were higher than the average median estimate of the simple methods and lower than the median estimate of the SSS model. Uncertainties associated with the MSY estimate were lower for the SS model and the XSSS model than for the other methods. The MSY estimated by the SS model was sensitive to the natural mortality value, and the MSY estimated by the SSS model was sensitive to the prior on the final stock status.

Keywords: data-limited, catch limit, MSY advice, pollack, *Pollachius pollachius*, Stock Synthesis, DLM

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Résumé

Au cours de la dernière décennie, de nombreuses méthodes ont été adaptées pour l'évaluation des stocks à données limitées suite à une demande globale d'évaluation de tous les stocks, y compris ceux à données limitées. Certaines méthodes simples, telle la méthode DCAC (≪ Depletion Corrected Average Catch ≫), sont basées sur un nombre limité de type de données. D'autres méthodes, habituellement plus complexes, intègrent toutes les données disponibles et requièrent un certain nombre d'hypothèses sur les données et les paramètres (par exemple les modèles Stock Synthesis). Puisqu'une forte incertitude est associée aux résultats des évaluations de stocks à données limitées, il est recommandé de comparer plusieurs méthodes. Ce travail a pour objectif de déterminer une valeur de captures maximales dans un scénario de données limitées. Le stock de lieu jaune de Manche-Mer Celtique est utilisé comme cas d'étude pour comparer les résultats de plusieurs méthodes d'évaluation de stock. Dans une étude préalable, un modèle Stock Synthesis (SS) avait été développé pour ce stock à partir de toutes les données disponibles. Seuls les résultats de statut du stock avaient été interprétés. Dans cette étude, les résultats de ce modèle complet sont comparés en termes de points de référence de gestion avec les résultats d'un modèle SSS (≪ Simple Stock Synthesis ≫) et d'un modèle XSSS (≪ extended Simple Stock Synthesis ≫). Le DLMtool est également utilisé pour comparer les résultats d'avis de MSY de méthodes simples basées sur peu de données. Les valeurs de MSY estimées par les modèles SS et XSSS étaient plus élevées que la moyenne des estimations médianes des méthodes simples et plus faibles que l'estimation médiane du modèle SSS. Les incertitudes associées à l'estimation de MSY étaient plus faibles pour les modèles SS et XSSS que pour les autres méthodes. La valeur de MSY estimée par le modèle SS était sensible à la valeur de mortalité naturelle, tandis que la valeur de MSY estimée par le modèle SSS était avant tout sensible au prior sur le statut final du stock.

Mots clés: données limitées, limitation de captures, avis au MSY, lieu jaune, *Pollachius pollachius*, Stock Synthesis, DLM

4.2.1. Introduction

Historically, the field of fish stock assessment has prioritized the data-rich stocks, usually the one with high commercial value (Bentley and Stokes, 2009 [18]). As a consequence, the effort to collect additional data was stalling. The poverty in data is usually associated with time-poverty. To increase efficiency, automating data processing can be useful. However, a thorough analysis of the data is needed to fully understand the bias in the data. This step is even more time-consuming for data-limited stocks because of the lower quality of the data (Bentley, 2014 [17]). Despite the historical backlog in the stock assessment of data-limited stocks, several methods adapted to these stocks have been developed in the last decade, demonstrating an increased interest for this new challenge. Changes of priorities in the research field are usually driven by political orientation. In the United States, the Magnuson-Stevens Reauthorization Act (DOC et al., 2007 [71]) specified the need to set an annual catch limit for the vast majority of fish stocks. In Europe, the European Commission asked the International Council for the Exploration of the Sea (ICES) to develop a methodology to provide assessments and advice on data-limited stocks. The workshop WKLIFE (ICES, 2012d [140]) was created for this purpose.

Stocks are considered data-limited when the type and (or) quality of available data is insufficient to conduct a quantitative stock assessment (Dowling et al., 2015 [76]). Simple methods, which require few data and strong assumptions, are useful to calculate first estimates of management reference points or stock status. Various studies based on simulation testing have been useful to analyse the ability of these methods to correctly describe a stock status and to set harvest control rules which would prevent the stock of being overfished (Wetzel and Punt, 2011a [267]; Carruthers et al., 2014 [40]). According to the amount of data available, it is also possible to apply more complex models. Stock Synthesis models (Methot and Wetzel, 2013 [185]) are integrated statistical age-structured stock assessment models which can adapt to various situations, from data-poor to data-rich stocks. It is therefore possible to compare models based on different levels of data-richness within the same framework.

The studied stock of pollack (*Pollachius pollachius*) is located in ICES Subareas VI and VII which are composed of the English Channel and the area around Ireland. The stock is subject to a minimum landing size of 30 cm, and the minimum mesh size for static gears is 90 mm. Total Allowable Catch (TAC) recommendations are based on a precautionary approach because of the uncertainty related to the results of the DCAC model currently applied with a natural mortality value of 0.2 by the European working group WGCSE (ICES, 2016a). The natural mortality of pollack has been estimated to be higher (Alemany et al., *in prep.* [5]), and the use of DCAC is not recommended if

M is greater than 0.2 (MacCall, 2009 [170]). While the DCAC uses only catch data and priors on some parameters, length data were available for the studied stock and were not yet used in the assessment. The time series of abundance indices from scientific surveys can't be used for this stock because of an inappropriate catchability. However, two time series of Catch Per Unit Effort (CPUE) were constructed, based on French and Irish trawl (Alemany et al., *in prep.* [5]), which were used to bring information on the depletion of the stock.

This study aims at comparing methods to set catch limits in a data-limited situation, using real data from the stock of pollack in the Celtic Seas Ecoregion. We implement a simple Stock Synthesis model (Cope, 2013 [57]) for pollack, using only catch data and a prior on the depletion level (SSS model). An extended Simple Stock Synthesis model (Cope et al., 2013 [58]; Wetzel and Punt, 2015 [269]) is then implemented by adding two abundance indices time series (XSSS model). In a previous work, a Stock Synthesis model was built by adding the available length composition data. Sensitivity analysis were conducted, and an ensemble modeling technique was applied to synthetize the results (SS model, Alemany et al., *in prep.* [5]). In this work, we compare results of these Stock Synthesis models based on various levels of data richness. We also use the DLMtool (Carruthers et al., 2014 [40]) to test simple methods and compare the results in terms of MSY advice. We analyse the sensitivity of the results to various specifications on the natural mortality and on the prior belief on the status of the stock.

4.2.2. Materials and methods

4.2.2.1. Assumptions shared by all models

The main countries catching pollack from the stock studied were France, UK and Ireland. Catch data were available by country, with the longest time series given by UK from 1950 to 2015. French data started in 1977 because no records were available for previous years. The first assumptions required for the studied stock were on the catch history of the stock. Several catch scenarios were tested for both commercial and recreational removals in a previous study (Alemany et al., *in prep.* [5]). The assumptions of the base model were chosen for the present work.

Ireland catch data had two gaps: the first between1950 and 1960; the second between 1973 and 1985. We used the correlation between UK and Irish time series to fill these gaps. For Subarea VI, French catch was set at the same level as UK catch in 1950, then decreased by subtracting to the catch from previous year the mean of the 4 first recorded years divided by N_1 (Eqn 4.6). For Subarea VII, French catches were set at the same level as UK in 1950, and then increased by adding to the catch from previous year the mean of the first 4 recorded years divided by N_1 (Eqn 4.7). A scenario was constructed for the recreational catch which increased from 1950 to 2015 to reach 2000 tons (Eqn 4.8).

$$C_i = C_{i-1} - \frac{\frac{\sum_{1977}^{1980} C_i}{4}}{N_1} \tag{4.6}$$

$$C_i = C_{i-1} + \frac{\frac{\sum_{1977}^{1980} C_i}{4}}{N_1} \tag{4.7}$$

$$R_{1950} = \frac{2000}{N_r};\ R_{i+1} = R_i + \frac{2000}{N_r} \tag{4.8}$$

Where N_1=26 is the number of years between 1950 and 1977 and N_r=66 is the length of the recreational catch time series.

Assumptions were also required for the model parameters. The mean value of the natural mortality, which used to be set at 0.2 (ICES, 2016a [147]), was set to 0.34 in this work, following the results of the previous study (Alemany et al., *in prep.* [5]).

4.2.2.2. Methods from the DLM tool

The user-friendly application of the DLMtool used for this work can be found at https://shcaba.shinyapps.io/Shiny_DLMtool/. A time series of Catch Per Unit Effort was calculated with the data from French trawlers (Alemany et al., *in prep.* [5]) and was used as an abundance indices time series. In a first step, all available methods were implemented. Six methods were then suppressed because of unrealistic MSY estimates (eg. MSY > 15 000 t). The description of the 27 remaining methods can be found online on the application website. To evaluate the long term effects of the various methods, a management strategy evaluation (MSE) was conducted with a projection of 20 years. The 27 methods tested to calculate MSY estimates were used, as well as four additional methods. These four input controls consisted in maintaining the current effort or 75% of the current effort, and setting a fishing selectivity according to the maturity curve or slightly higher than the maturity curve. The performance of each method was measured as the probability of the biomass to be lower than B_{MSY} and the probability of F to be higher than F_{MSY}. 1 000 simulations were run to calculate the MSY estimates and 500 simulations were run for the MSE. Details on the parametrization of the MSE are given in Table 4.8. The results of the MSE were calculated from the 200 last runs to avoid taking into account results of the model before convergence was achieved.

TABLE 4.8 – Parameters specifications for the MSE run with the DLMtool.

Parameter	**Mean value**	**SD**
Natural mortality *M*	[0.31, 0.37]	[0, 0.1]
Asymptotic length *Linf*	[87, 113]	[0, 0.025]
Von Bertalanffy parameter *K*	[0.145, 0.22]	[0, 0.025]
Von Bertalanffy parameter t_0	[-1.33, -0.61]	
Length-weight parameter *a*	1.37e-5	
Length-weight parameter *b*	2.88	
Steepness *h*	[0.85, 0.89]	
Length at 50% maturity *Lmat*	[41, 47]	
Estimate of current biomass divided by virgin biomass	[0.45, 0.55]	

4.2.2.3. Application of the Stock Synthesis models

Three models were built with the Stock Synthesis framework (Methot and Wetzel, 2013 [185]), based on different levels of data-richness. The data used for each model are summarized in Table 4.9. The SS model included all available data. The steepness parameter was fixed at 0.87. The selectivity functions for commercial catch were set as double normal logistic functions with 6 parameters. The values of the last length bin selectivity and the width of the descending slope were fixed, while the other parameters were inferred from the length data. Two time series of CPUE were considered, both assuming the same selectivity as the trawl fishery. As no length data were available for recreational fishery, all the selectivity parameters were fixed close to the estimated parameters from Net and Line fishery, except for the peak start value which was set 9 cm lower than the value estimated for Net and Line fishery. The value of 9 cm was the difference between the mean value of the length data from Net and Line fishery and the mean length of recreational catch estimated by phone survey (Levrel et al., 2013 [165]).

The XSSS model (Cope et al., 2013 [58]; Wetzel and Punt, 2015 [269]) is a simplified implementation of Stock Synthesis based on the same population model. The length data were not used, and the selectivity parameters were all fixed (Table 4.10). A prior was required on the prior belief on the status of the stock (D). This information was treated in the model as two observed survey values, with the first value (= 1) observed the first year, and the second value (= D) observed at the end of the catch time series. An adaptive importance sampling was applied to XSSS. It was based on 1000 population trajectories created from draws for each of the prior distributions and 400 draws at each step, except the last draw which was 1000.

The SSS model (Cope, 2013 [57]) is a greater simplification of Stock Synthesis than the XSSS model. The CPUE time series were not used in the model, only a prior on D

was required to mimic the Depletion-Based Stock Reduction Analysis (DB-SRA) method. A Monte Carlo approach was used, and the results were inferred from 1000 draws.

TABLE 4.9 – Data requirements of the Stock Synthesis models.

Model	Catch	Stock status	Abundance indices	Length composition
SS	X		X	X
XSSS	X	X	X	
SSS	X	X		

TABLE 4.10 – Mean values of the selectivity functions' parameters of the XSSS and SSS models after applying the associated function. All parameters are fixed.

Selectivity parameter	Function	Net and Line	Trawl	Recreational fishery
Length at Peak start	None	50	50	55.2
Length at the beginning of the descending slope	Logistic	80.9	80.9	57.5
Width of the ascending slope	Exponential	403	403	293
Width of the descending slope	Exponential	148	148	148
Selectivity of the initial size bin	Logistic	0.018	0.018	0
Selectivity of the final size bin	Logistic	0.38	0.99	0.38

4.2.2.4. Sensitivity analysis

The sensitivity of the results to the specifications on M and D were analysed for the DLMtool methods, the SS model and the SSS model. The values of 0.2 and 0.4 were tested for M, and the values of 0.4 and 0.6 were tested for D. The sensitivity of the MSY estimates were compared for all models. For the SS model and the SSS model, the sensitivity of the relative spawning biomass estimates was also analysed. Additional sensitivity analysis on the catch scenarios and the steepness were run for the SSS model. The values of 0.8 and 0.97 were tested for the steepness. The alternative catch scenario are described in the following.

Scenario C2: Catch data for Ireland in both Subareas and for France in Subarea VI were reconstructed the same way as in scenario 1. For VII, French catches were set low from 1950 to 1970 with random values from a normal distribution with a CV of 0.25. The normal function had a mean of 300 tons and a standard deviation of 75. Then a rapid increase was set from 1970 to 1976 (Eqn 4.9). Scenario C3: No catch reconstruction was done. The gap in Irish catch data and the lack of French catch data before 1977 were interpreted as a result of no fishing effort.

Scenario R2: Recreational catch increased from 1950 to 2015 to reach 4000 tons (Eqn 4.10). Scenario R3: Recreational catch were drawn from a normal distribution with a mean of 2000 tons and a standard deviation of 100. Scenario R4: Recreational catch were drawn from a normal distribution with a mean of 4000 tons and a standard deviation of 100. Scenario R5: Recreational catch were assumed to be low and were set to zero in the model.

$$C_i = C_{i-1} + \frac{\frac{\sum_{1977}^{1980} C_i}{4} - C_{1970}}{N_2} \tag{4.9}$$

$$R_{1950} = \frac{4000}{N_r};\ R_{i+1} = R_i + \frac{4000}{N_r} \tag{4.10}$$

Where N_2=6 is the number of years between 1970 and 1976.

4.2.3. Results

4.2.3.1. Results of the models built with a Stock Synthesis framework

The estimates of relative spawning biomass are similar for the SS and XSSS models, although larger uncertainties are associated with the results of the SS model. The relative spawning biomass estimated by the SSS model is higher and gives a more optimistic final stock status. A substantial range of uncertainty is associated with the result of the SSS model (Fig. 4.12.a). The estimates of fishing mortality at MSY (F_{MSY}) obtained with the SSS and the XSSS models are close (0.33 and 0.31 respectively). A higher value (F_{MSY} = 0.46) is estimated by the SS model (Fig. 4.12.b).

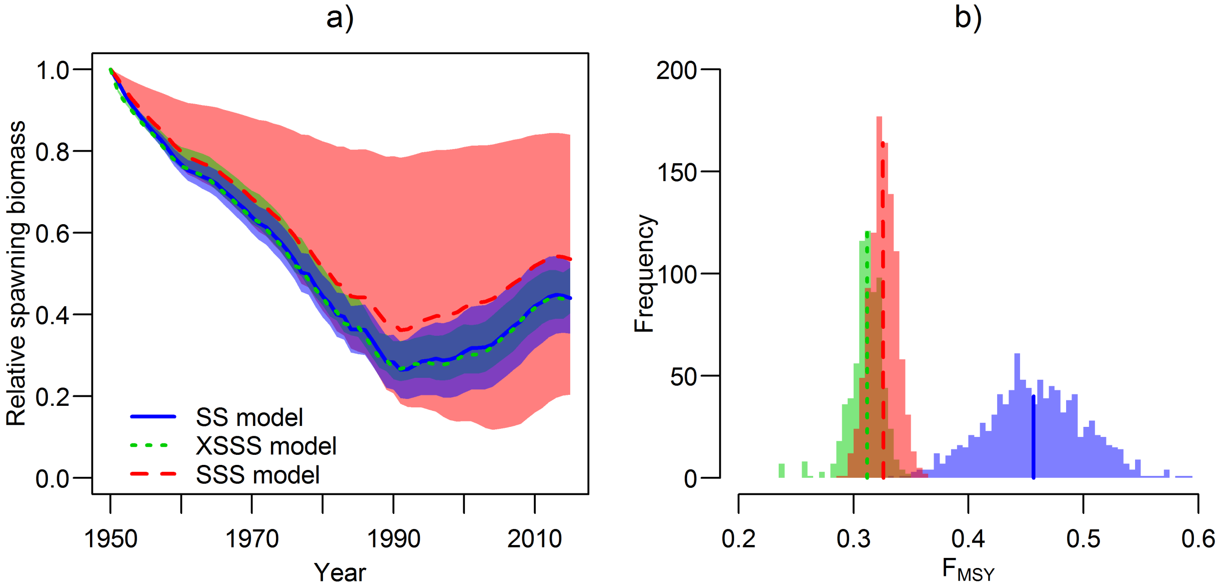

FIGURE 4.12 – (a) Relative spawning biomass and (b) F_{MSY} value estimated by the SS model (solid line), the XSSS model (dotted line) and the SSS model (dashed line). The 95% confidence intervals on (a) are represented by the shaded areas. The vertical lines on (b) indicate the median values.

4.2.3.2. Results from the DLMtool

The use of the DLMtool resulted in a wide range of MSY estimates (Figure 4.13). The YPR and the BK methods resulted in estimates of MSY higher than 10 000 t. The SPmod, the Itarget1, the HDAAC, the Gcontrol and the CC4 methods resulted in estimates of MSY smaller than 5 000 t. The results of the MSE (Table 4.11) show that after 20 years of management none of the methods tested with the DLMtool had a probability of the biomass being under $0.2 \times B_{MSY}$ higher than 50%. Therefore, none of the methods had a probability of resulting in a stock collapse higher than 50%.

The methods CC1, DBSRA, DBSRA_40, GB_slope, Gcontrol, SBT1, SPmod and SPslope resulted in $P(B < 0.5 \times B_{MSY})$ higher than 50% after 20 years of management. The most promising methods were Itarget1, curE75 and matlenlim which resulted in $P(B < B$ MSY $)$ and $P(F > F_{MSY})$ lower than 10% after 20 years of management. The method Itarget1 consists in reducing incrementally the fishing effort to reach a target relative abundance index. The method curE75 also results in a decreasing fishing effort. The effort is maintained at a level equals to 75% of the current effort. Finally, the method matlenlim consists in adjusting the fishing selectivity according to the maturity curve.

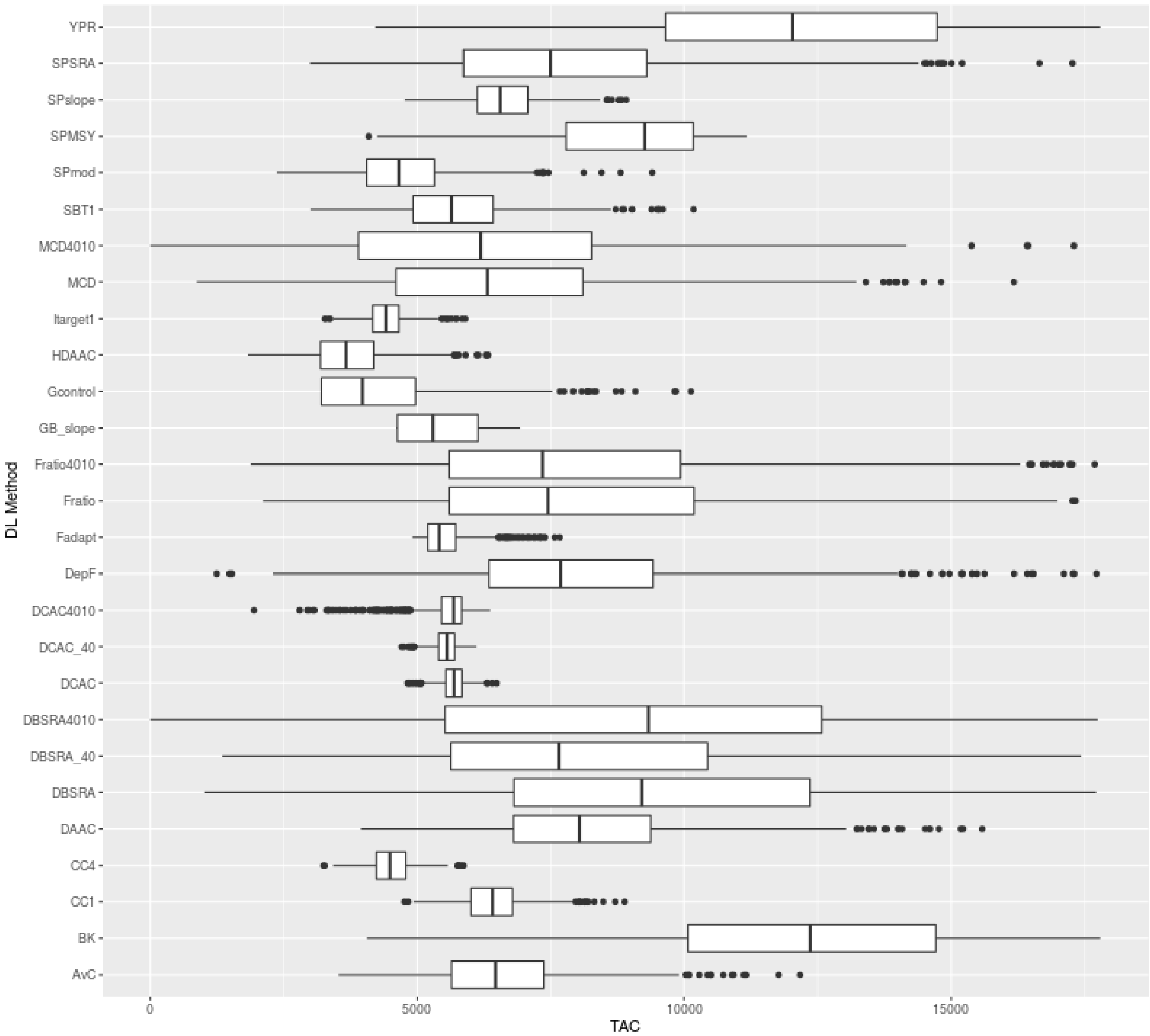

FIGURE 4.13 – TAC estimated by the DLMtool for various methods.

TABLE 4.11 – Results of the MSE after 10 years and 20 years in percentages.

Method	$P(B<B_{MSY})$		$P(B<0.5*B_{MSY})$		$P(B<0.2*B_{MSY})$		$P(F>F_{MSY})$	
	10 years	20 years	10 years	20 years	10 years	20 years	10 years	20 years
AvC	33	55.5	6.5	31	0.5	10	24.5	50.5
BK	64	66.5	28	27	2	2.5	43.5	43.5
CC1	43	90.5	14	79.5	1.5	32.5	45.5	90.5
CC4	6	16.5	0.5	9	0	2	3	15.5
DAAC	42	49	16	27	3	6	36	43
DBSRA	69.5	80	42	53.5	12.5	16.5	56.5	67.5
DBSRA_40	79.5	94.5	51.5	89.5	8	47	79.5	94.5
DBSRA4010	47	52	6.5	15.5	1	2.5	14	20.5
DCAC	12.5	22.5	0	6	0	0	4	14
DCAC_40	9	15	0	3.5	0	0	1.5	7.5
DCAC4010	10.5	17.5	0	2	0	0	2.5	9
DepF	35.5	34.5	6.5	7	0	0.5	21.5	18.5
Fadapt	61	76	36	35	3.5	6.5	57	48.5
Fratio	50.5	43.5	15.5	14.5	0.5	1.5	29	25.5
Fratio4010	22.5	29.5	3	4	0	0	16	18.5
GB_slope	35.5	80	18.5	67.5	2.5	29	37	81.5
Gcontrol	41	73	22	65	3.5	27.5	41.5	73
HDAAC	9	13	1	2	0	0	5	6
Itarget1	4.5	7.5	0	0	0	0	0.5	1.5
MCD	32.5	39.5	9.5	13	0.5	1.5	21	29.5
MCD4010	32	36.5	7.5	9.5	0.5	0.5	22	20
SBT1	34	79	20	66	2	27	36	80
SPmod	61	89.5	50.5	87	11.5	40.5	60.5	89
SPMSY	17.5	32	8	22.5	1	9.5	19	31
SPslope	32	59.5	13	52	2	22.5	33	58
SPSRA	51	59	28.5	40	9	16	40.5	50
YPR	63	62	26	25.5	1.5	3	38	36
curE	12.5	13.5	0.5	0	0	0	5	7.5
curE75	7	7.5	0	0	0	0	2	4
matlenlim	8.5	8.5	0	0	0	0	5	7.5
matlenlim2	29	30.5	2.5	1	0	0	5	8

4.2.3.3. Comparison of the results from the DLMtool and from the Stock Synthesis models

The values of MSY estimated by the XSSS and the SS models are similar, with a median value around 7 900 t. The peaks are higher and the distribution curves are narrower than the two other models. The SSS model gives a higher MSY value and the averaged simple methods tested with the DLMtool result in the most precautionary advice. The SSS model and the averaged results of the DLMtool probability distributions are positively skewed (Table 4.12; Fig. 4.14).

TABLE 4.12 – MSY estimated by the DLMtool and the Stock Synthesis models.

Model	DLM	SS3_ma	SS3	XSSS	SSS
MSY	6009	8007.025	7895.82	7904.07	8848.52

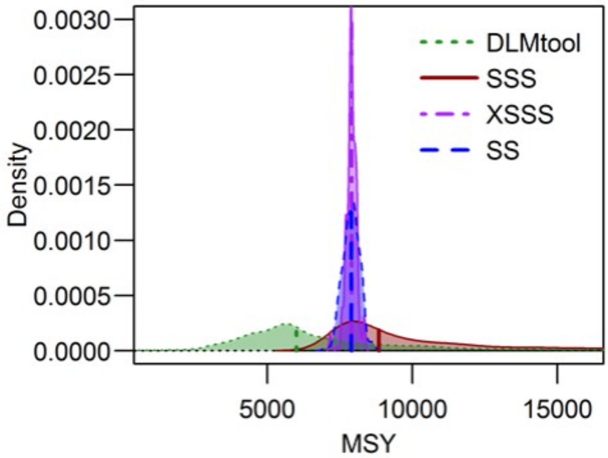

FIGURE 4.14 – Distributions of MSY estimates from the DLMtool results (dotted line), the SSS model (solid line) and the SS ensemble modeling (dashed line). The vertical lines indicate the median values.

4.2.3.4. Sensitivity of the results

The sensitivity of the estimate of MSY to the specifications on natural mortality (M) and depletion (D) is plotted on Fig. 4.15 for the various models tested with the DLMtool. It is interesting to note that a different value of M or D do not have the same impact for the various models tested. A smaller value of M results in a substantially smaller estimate of MSY for the YPR, Fratio, Fratio4010 and DepF methods. However, a slightly higher estimate of MSY is obtained for the SPSRA, Fadapt and BK methods. A higher value of D results in a slightly higher estimate of MSY for the SPSRA, HDAAC and Fratio methods, and results in a substantially higher estimate of MSY for the DAAC method.

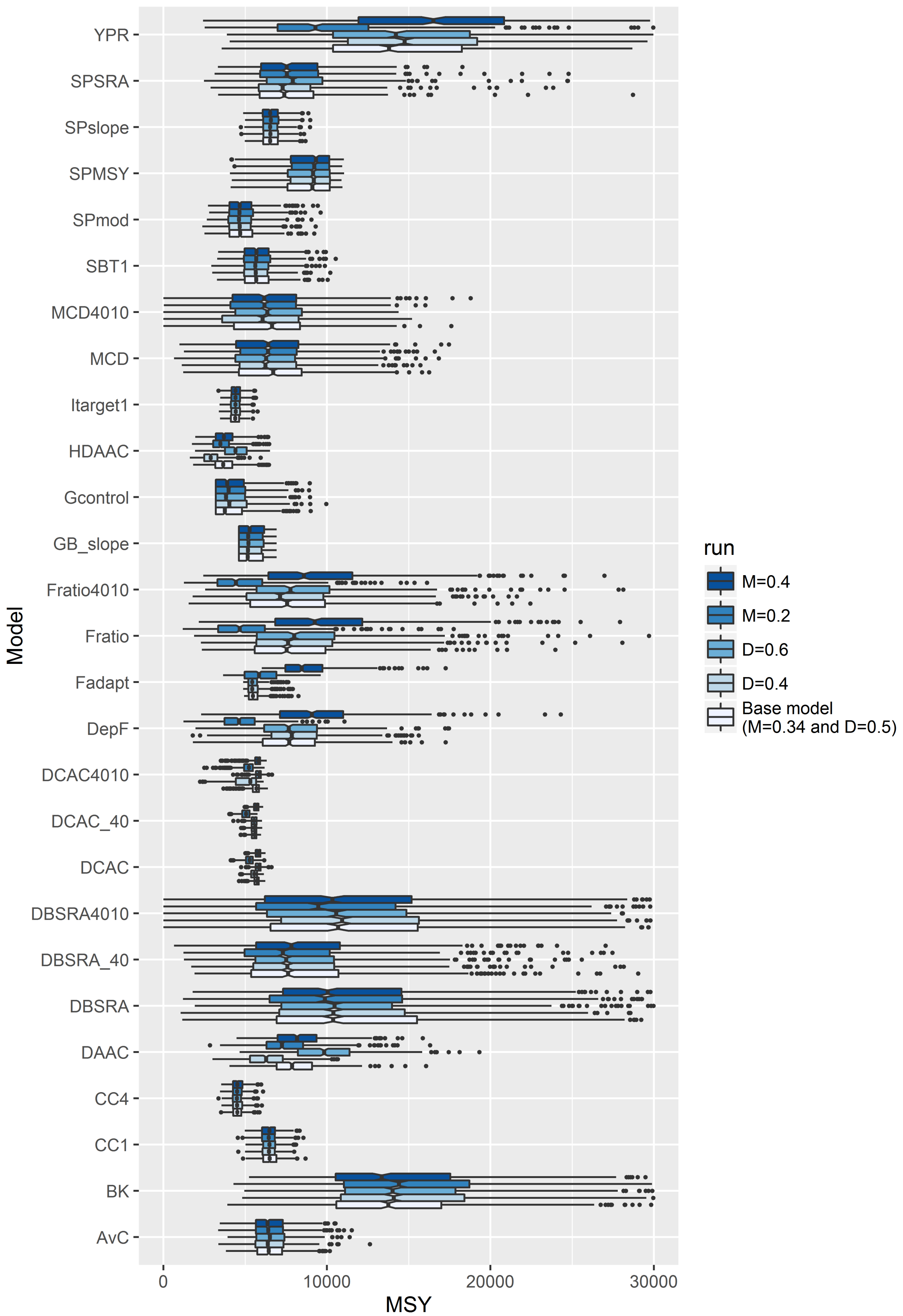

FIGURE 4.15 – Boxplots of the MSY estimates from the various models tested with the DLMtool.

However, when the estimate of MSY is based on the whole range of methods, the sensitivity of the result to M and D is less substantial. A smaller value of M results in a MSY estimate 366 t smaller and a higher value of M results in a MSY estimate 318 t higher (Fig. 4.16.a). A smaller value of D results in a MSY estimate 100 t smaller and a higher value of D results in a MSY estimate 82 t higher (Fig. 4.16.b).

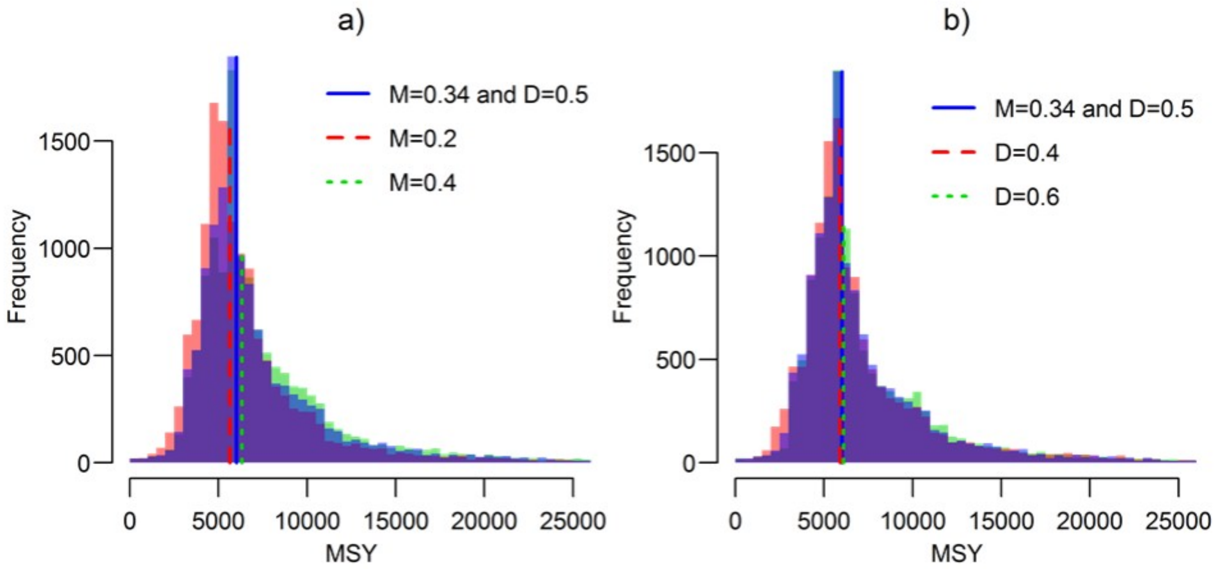

FIGURE 4.16 – Distribution of the MSY estimates from the DLMtool for various specifications on (a) natural mortality and (b) depletion. The vertical lines indicate the median values.

The sensitivity of the results to the specification on M is higher for the SS model than for the SSS model. The final stock status estimated by the SSS model are similar for the various specifications on M, whereas the final stock status estimated by the SS model is substantially more optimistic for the base model and the model with M=0.4 than for the model with M=0.2 (Fig. 4.17.a; Fig. 4.18.a).

However, the results of the SSS model are highly sensitive to the specification on D. A higher value of D results in a more optimistic final stock status and in a 1 587 t higher MSY estimate, whereas a smaller value of D results in a smaller relative spawning biomass and in a 787 t lower MSY estimate (Fig. 4.18.b; Fig. 4.19).

For the SS model, a smaller value of M results in an 879 t lower MSY estimate and a higher value of M results in a 203 t higher MSY estimate (Fig. 4.17.b). For the SSS model, a smaller value of M results in a 265 t lower MSY estimate and a higher value of M results in a 65 t higher MSY estimate (Fig. 4.19).

The assumptions on recreational catch have a substantial impact on the MSY value estimated by the SSS model. The run with no recreational catch results in a 1 919 t lower

MSY estimate and the run with a constant recreational removal of 4 000t results in a 3 140 t higher MSY estimate (Fig. 4.19). The assumptions on the steepness parameter have a low impact on the MSY value estimated by the SSS model. The run with a lower steepness results in a 221 t lower MSY estimate and the run with a higher steepness results in a 401 t higher MSY estimate (Fig. 4.19).

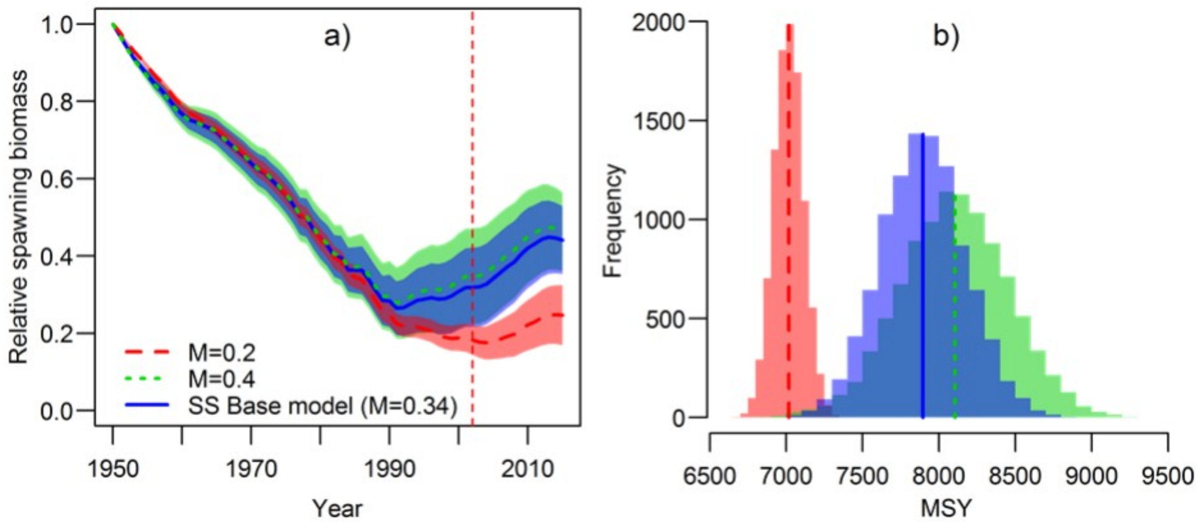

FIGURE 4.17 – Distribution of the relative spawning biomass estimates (a) and distribution of the MSY estimates (b) for various specifications on natural mortality of the SS model. The vertical dotted line on (a) indicates the first year of available length data. The vertical lines on (b) indicate the median values.

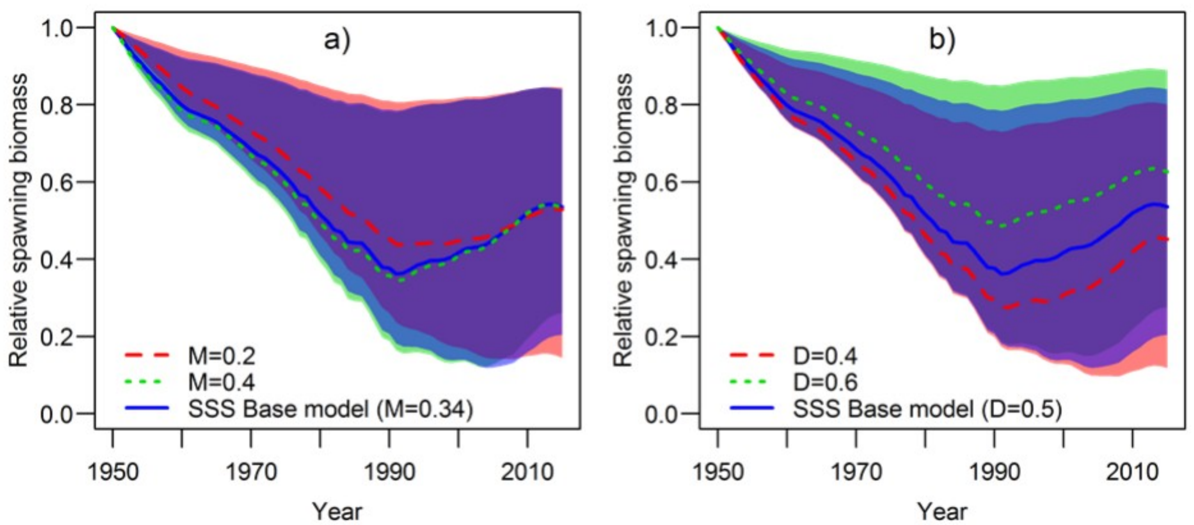

FIGURE 4.18 – Distribution of the relative spawning biomass estimates from the SSS model for various specifications on (a) the natural mortality and (b) the depletion.

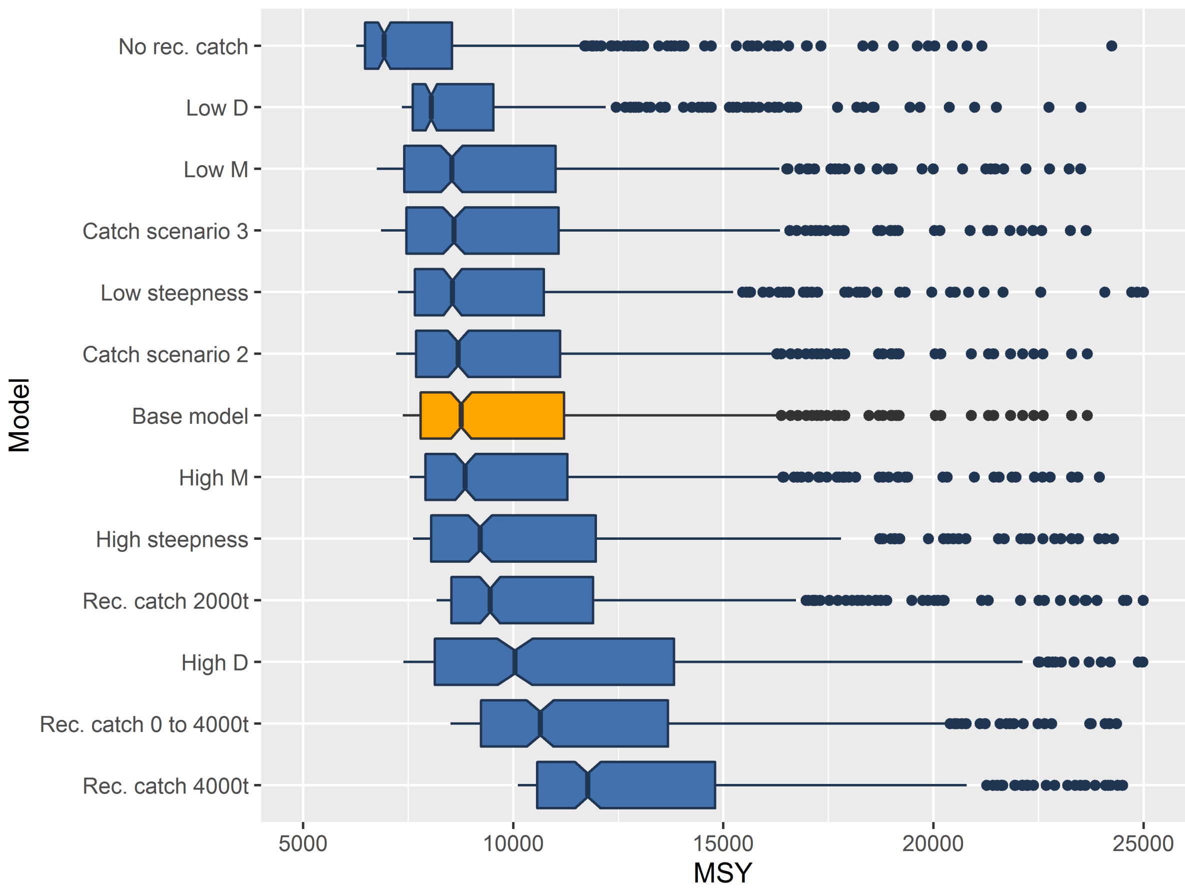

FIGURE 4.19 – Boxplots of the MSY estimates from the SSS model for various specifications on model parameters and likelihood composition. The boxplots are ordered in ascending order.

4.2.4. Discussion

4.2.4.1. Sensitivity of the results

In Wetzel and Punt (2015) [269], the DCAC method is compared to the DB-SRA method with a MSE. The DCAC appears to be more conservative, which is also the conclusion of our study. A common issue with simple stock assessment models is that they are dependent on the depletion level set by the user. The results of the sensitivity of MSY estimates for the SSS model show that the MSY is estimated higher when a higher prior is specified on D. In simulation studies, Wetzel and Punt (2011a) [267] also found that the overfishing limit can be overestimated when the prior distribution for relative biomass is specified higher than the true value. While the MSY estimated by some DLMtool methods is impacted by the specification on D, the impact is lower when the result is calculated as an average of all methods. This result shows the benefit of testing several simple methods to manage data-limited stocks.

The assumptions on recreational catch impact substantially the value of MSY estimated by the SSS model. When no recreational removals are added, the model interpretation is that the stock is less productive than in the scenario of the base model. Therefore, this assumption acts as scaling factor in the estimation of the spawning biomass. Although the final stock status is not substantially impacted by the assumptions, the level of spawning biomass estimated in the various runs differs (Appendix F). This results in great differences of MSY estimates.

The more complex SS model does not require D value, but is more sensitive to M than the SSS model. A lower value of M results in a lower estimate of MSY. This result can be explained by a lower productivity of the stock interpreted by the model. In data-limited situations, the value of M can be inferred from life history parameters, which was done for this stock (Alemany et al., *in prep.* [5]). Even the calculation of life history parameters might be problematic for data-limited stocks when no funding is available. Using the Robin Hood story, Punt et al. (2011) [217] recommended to "borrow from the data-rich to give to the data-poor". The Bayesian framework is useful to implement models based on data from various stocks and transfer information when possible.

4.2.4.2. Limitations and recommendations

According to our results, the biomass of pollack stock has decreased from 1950 to 1990 and has increased during the 25 following years, although the fishing quotas have not limited the fishery. We identify two main hypothesis to explain this self-regulation. The first cause might be the behavior of the stock. The bulk of the catches occur during a specific period of the year, when mature individuals aggregate to spawn between April and June. Outside of this time interval, big individuals might be hard to fish when the biomass is low. For example in the English Channel, pollack hides in wrecks which might have contributed to its protection. The second explanation is the fishing market demand which can be lower than the potential catches (Thomas et al., 2014 [250]).

When a stock assessment is conducted, the uncertainty in stock status and in the level of removals required to achieve sustainability results in a higher probability of a stock to become overfished (Rosenberg et al., 2007 [232]; ICES, 2012d [140]). In data-limited stocks, the uncertainty can arise at various levels: the biology of the species, the selectivity, the misreporting in commercial catch and the unrecorded recreational catch are the most common examples. In some cases, the level of recreational removals can reach up to almost 50% of the total removals (Coll et al., 2014 [55]). In this work, we based the analysis on the assumption that the recreational catch increased from 1950 to 2015 and reached 2000 tons in 2015. But this scenario is subjective and incorrect assumptions on the recreational removals can have a substantial impact on the results. Indeed, higher removals from recreational fishery would be interpreted by the model as a higher productivity of the stock, resulting in a higher MSY estimate. A survey investigating the historical removals of recreational fishery could greatly improve the precision of the results.

Another assumption made for this work was that pollack in Subareas VI and VII consisted in a single stock unit. Although a genetic analysis has been carried out by Charrier et al. (2006) [46] to explore the population genetic structure, there is still a lack of information on the precise geographic delimitation of the stock. Even though individuals from the Bay of Biscay had a significantly different genetic than individuals from the western English Channel, additional genetic structure differences might have not been detected because of the small sample sizes and the limited number of loci. As highlighted by Charrier et al. (2006) [46], knowledge of the genetic structure and dispersal patterns of a fish population is essential to set proper management boundaries. Further research on the genetic structure of the stock could therefore benefit its management.

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CHAPITRE 5

CHAPITRE 5 : Utilisation d'une démarche hiérarchique Bayésienne pour estimer les paramètres de croissance et de maturité du lieu jaune

"*L'accès à l'information n'est pas un luxe, mais une nécessité.*"

Anne-Marie Bertrand (1998), dans **Les bibliothèques.**

Présentation de l'article "Update of the life-history parameters of pollack (*Pollachius pollachius*) using a Bayesian hierarchical model"

Au cours du chapitre 4, nous avons vu qu'il est primordial d'utiliser une valeur correcte de mortalité naturelle (M) dans une évaluation de stock car les résultats peuvent grandement différer selon cette valeur. Dans un cadre de données limitées, le calcul de M se fait généralement à partir des paramètres biologiques du stock, d'où l'importance du calcul et/ou de la mise à jour de ces paramètres. Les informations disponibles sur les paramètres de croissance et les paramètres de la relation taille-poids du lieu jaune datent respectivement de 1964 et 1986 (Moreau, 1964 [189]; Dorel, 1986 [74]). Les paramètres de maturité du stock IX ont récemment été estimés (Alonso-Fernández et al., 2013 [8]), en revanche pour les stocks VII et VIII cette information est manquante. Ce cinquième chapitre propose d'employer un cadre hiérarchique Bayésien pour estimer les paramètres biologiques du lieu jaune afin de tirer profit au mieux des connaissances et données disponibles.

Trois stocks de lieu jaune situés dans les eaux Européennes sont étudiés : le stock VII situé dans la Manche et la Mer Celtique, le stock VIII situé dans le Golfe de Gascogne, et le stock IX localisé au niveau de la côte Ibérique. Dans un premier temps, les données collectées dans le cadre de cette étude sont analysées avec des méthodes d'inférence fréquentiste. Les paramètres de la relation taille-poids et de l'équation de Von Bertalanffy sont estimés par une méthode de régression des moindres carrés non linéaire. Les paramètres de la relation de Von Bertalanffy ne sont estimés que pour les stocks VII et VIII, car le stock IX ne dispose pas de données d'âge. L'ogive de maturité en fonction de la taille (d'où l'on déduit la taille pour laquelle 50% des individus sont matures) est estimée par un modèle linéaire généralisé avec une distribution binomiale et une fonction de lien logit. Seul le stock VII dispose de données de maturité collectées dans le cadre de cette étude.

Dans un deuxième temps, outre les données collectées, les données disponibles dans la littérature sont mises à profit pour la construction d'un modèle hiérarchique Bayésien. Les résultats de Moreau (1964) [189] permettent de construire des priors faiblement informatifs pour les paramètres de l'équation de Von Bertalanffy, et les résultats de Dorel (1986) [74] permettent de construire des priors légèrement informatifs pour les paramètres de la relation taille-poids. Deux matrices de variance-covariance sont construites, de dimension 2 pour les paramètres de la relation taille-poids, et de dimension 3 pour les paramètres de l'équation de Von Bertalanffy. L'information relative aux corrélations entre les différents paramètres est utilisée pour estimer les paramètres de croissance du stock IX. La taille à 50% de maturité est également estimée dans le modèle Bayésien par un sous-modèle de régression logistique. Une relation liant la taille à 50% de maturité et la taille asymptotique a été développée par Froese et Binohlan (2003) [93]. Cette relation est utilisée pour fournir une estimation de taille à 50% de maturité pour le stock VIII, qui pourrait servir à la construction d'un prior informatif si des données venaient à être collectées sur la maturité du lieu jaune dans le Golfe de Gascogne.

Les courbes de Von Bertalanffy et de la relation taille-poids calculées avec l'inférence fréquentiste à partir des données collectées sont comparées aux courbes obtenues avec les données de Moreau (1964) [189] et de Dorel (1986) [74], pour les stocks VII et VIII. Bien que les courbes de Von Bertalanffy soient relativement similaires, une taille plus grande est atteinte par les individus des données récentes que par les individus de l'échantillonnage de Moreau (1964) [189] pour un même âge, et ce pour les deux stocks de lieu jaune. Les courbes de la relation taille-poids sont similaires pour le stock VII, mais diffèrent pour le stock VIII au-delà de 60 cm.

Le modèle hiérarchique Bayésien donne des estimations des paramètres de la relation taille-poids proches pour les stocks VII et IX et des estimations des paramètres de l'équation de Von Bertalanffy proches pour les stocks VII et VIII. La taille à 50% de maturité est estimée à 51.8 cm pour les femelles et à 41.5 cm pour les mâles. Cette différence entre les mâles et les femelles confirme les résultats de Alonso-Fernández et al. (2013) [8] qui estiment la taille à 50% de maturité à 47.1 cm pour les femelles et à 36.1 cm pour les mâles.

La taille minimale de capture pour le lieu jaune est de 30 cm pour les Etats membres de l'Union Européenne. Cette valeur est, d'après les résultats de notre étude et les résultats de Alonso-Fernández et al. (2013) [8], bien en deçà de la taille à 50% de maturité des femelles. Une mesure consistant à augmenter la taille minimale de capture semblerait donc judicieuse pour cette espèce. Les mesures de gestion portant sur la sélectivité peuvent permettre d'améliorer l'état d'un stock tout en conservant les mêmes niveaux d'exploitation (Vasilakopoulos et al., 2011 [259], 2016 [260]).

Au cours de ce travail, nous avons mis à jour plusieurs paramètres biologiques pour trois stocks de lieu jaune en utilisant à la fois des méthodes fréquentistes basées uniquement sur les données collectées et des méthodes Bayésiennes pour lesquelles les informations provenaient à la fois des priors construits à partir de travaux antérieurs et des données collectées. Dans le cas des paramètres de maturité, les résultats obtenus avec les deux approches sont très similaires. Pour les paramètres de la relation taille-poids et les paramètres de croissance, l'apport du modèle hiérarchique Bayésien réside dans les matrices de variance-covariance. Elles permettent d'inclure l'information contenue dans les relations entre les paramètres afin de réduire le biais qui pourrait survenir en cas d'échantillonnage biaisé. En outre, la méthode Bayésienne nous a permis d'estimer des paramètres de croissance pour le lieu jaune du stock IX, ainsi qu'une taille à 50% de maturité pour le lieu jaune du stock VIII malgré l'absence de données collectées. Nous recommandons donc l'utilisation des valeurs obtenues avec les méthodes Bayésiennes. La collecte de données supplémentaires reste cependant un objectif à atteindre, et lorsque les ressources sont insuffisantes, la science participative devient une approche prometteuse. Nous développerons cette idée au cours du dernier chapitre.

Update of the life-history parameters of pollack (*Pollachius pollachius*) using a Bayesian hierarchical model

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Abstract

The available data on the biology of pollack are sparse and the data richness vary from one stock to another. We focus on three stocks of pollack located in the English Channel, the Bay of Biscay, and the Iberian Coast. These stocks are considered data-limited and further research is required to assess the stocks. Updated biological parameters are needed to conduct a reliable stock assessment, not only to incorporate the parameters in the model, but also to calculate a value of natural mortality. This study aims at updating the growth, the length-weight relationship and the maturity parameters of this species, using data and empirical equations from the literature as well as data collected for the purpose of this work. The maturity data collected are analysed with a macroscopic and a microscopic method. A hierarchical Bayesian model is constructed to include all available information in a single model. Embedding the covariance between parameters within the model, in addition to the data available in the literature and the collected data, allows us to estimate the Von Bertalanffy growth parameters of the Iberian Coast stock despite the lack of age data for this stock. The estimates of the Von Bertalanffy growth equation parameters were close for the stocks from the English Channel and the Bay of Biscay. In the English Channel, the length at 50% maturity calculated with the Bayesian inference was higher for the females (51.8 cm) than for the males (41.5 cm).

Keywords: biological parameter, Bayesian, hierarchical model, pollack, *Pollachius pollachius*

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Résumé

Les données disponibles sur la biologie du lieu jaune sont rares, et la richesse en données varie d'un stock à l'autre. Notre étude se concentre sur trois stocks de lieu jaune localisés dans la Manche, le Golfe de Gascogne et la côte Ibérique. Ces stocks sont considérés comme étant à données limitées et des recherches plus approfondies sont nécessaires afin de réaliser l'évaluation de ces stocks. Des paramètres biologiques mis à jour sont également nécessaires pour mener une évaluation de stock fiable, non seulement afin d'incorporer ces paramètres dans le modèle, mais aussi pour calculer une valeur de mortalité naturelle. Cette étude a pour objectif de mettre à jour les paramètres de croissance, de maturité, et de la relation taille-poids de cette espèce en utilisant des données et des équations tirées de la littérature, ainsi que des données collectées dans le cadre de ce travail. Les données de maturité collectées ont été analysées avec une méthode macroscopique et microscopique. Un modèle hiérarchique Bayésien est construit pour inclure toute l'information disponible dans un unique modèle. Grâce à l'utilisation conjointe de matrices de covariances, de données de la littérature et de données collectées pour les stocks de Manche et du Golfe de Gascogne, les paramètres de la relation de croissance de Von Bertalanffy du stock de la côte Ibérique peuvent être estimés malgré l'absence de données collectées pour ce stock. Les estimations des paramètres de l'équation de Von Bertalanffy étaient proches pour les stocks de la Manche et du Golfe de Gascogne. Dans la Manche, la taille à 50% de maturité calculées avec l'inférence Bayésienne était plus élevée pour les femelles (51.8 cm) que pour les mâles (41.5 cm).

Mots clés: paramètre biologique, Bayésien, modèle hiérarchique, lieu jaune, *Pollachius pollachius*

5.1. Introduction

Most stock assessment models require information on the life history parameters of the stock studied, hence the importance of collecting data required to update these parameters. Stocks from the same species can have various life history parameters (Begg and Waldman, 1999 [16]). However, the existence of life-history correlates has been demonstrated by several authors (Charnov, 1993 [45]; Jensen, 1996 [156], 1997 [157]; Froese and Pauly, 2000 [94]; Froese and Binohlan, 2003 [93]) and can be useful when a limited amount of data is available to calculate the life-history parameters of a stock. The use of a hierarchical Bayesian framework is also useful in data-limited situations to transfer information between stocks (Helser and Lai, 2004 [122]; Pulkkinen et al., 2011 [211]; Doll and Lauer, 2013 [72]; Froese et al., 2014 [95]).

In the present study, some life-history parameters of three stocks of pollack located within European waters are calculated. The stock located in the English Channel and the Celtic Sea is studied by the European working group WGCSE and is named "pol.27.67" (formerly named "pol-celt") by the International Council for the Exploration of the Sea (ICES). The stocks located in the Bay of Biscay and in the Iberian Coast are both part of the same management unit named "pol.27.89a" (formerly named "pol-89a") which is studied by the European working group WGBIE. The stocks "pol.27.67" and "pol.27.89a" are both data-limited stocks: the amount of data is not sufficient to conduct a classical stock assessment. There is no consensus on stock identity. Although Charrier et al. (2006) [46] found a significant genetic differentiation between individuals originating from the western English Channel and the Bay of Biscay, the differentiation was weak and further investigations are required.

Moreau (1964) [189] compares several characteristics of pollack sampled from different areas to try to distinguish various populations. Individuals are sampled in the Iberian Coast, the Bay of Biscay, the entrance of the English Channel, and in the North, West, South and East of Ireland.

The results show that the population from the Iberian Coast can be clearly separated from the others. The individuals sampled in this area have a longer head, a first anal fin which is located in a more backward position, a smaller number of vertebrae, and their growth is significantly different from the growth observed in the other areas. No clear differences could be identified between the other areas and Moreau (1964) [189] assumes that individuals sampled from Ireland to the Bay of Biscay belong to the same population but have a specific geographic distribution according to their age. Younger individuals are more likely to be found in the Irish Sea and in the entrance of the English Channel, while adults stay in deeper waters near the edge of the continental shelf.

The spawning ground of pollack is wide, expanding from Portugal to Norway, between February and May. The spawning begins later in northern areas than in the southern part of the species' range of distribution (Moreau, 1964 [189]). Recent studies of maturity stages on pollack in Iberian waters (Alonso-Fernández et al., 2013 [8]) show that length at which 50% of the fish are mature is significantly different between females (47.5 cm) and males (36.1 cm). The lack of information on the life history parameters of pollack specific to each stock was underlined by the European working group WGNEW (ICES, 2014a [143]). The aim of the present study is to update the biological parameters of pollack in order to obtain the most updated and accurate parameter values according to the available data. For practical purposes, the three stocks studied are named according to the main ICES Area of the geographic location: stock VII for the English Channel and Ireland, stock VIII for the Bay of Biscay and stock IX for the Iberian Coast. Following the recommendation of Roa et al. (1998) [224] and Doll and Lauer (2013) [72], a Monte Carlo approach is used to update the maturity ogive, the length-weight relationship and the growth of the three stocks of pollack and to estimate the associated confidence intervals.

5.2. Materials and methods

5.2.1. Description of the data

The data used in this study can be separated in two groups: the information available from the literature, and the data collected recently from 2014 to 2016. The data were collected opportunistically from survey and with the help of commercial and recreational fishermen so as to cover the presumed size and weight range. The sampling on gonads was carried out only on the stock VII in 2016, between March and July to cover the spawning season.

Mean values of length at age were available from a study carried out by Moreau (1964) [189] for pollack in various area from the North of Ireland to the Iberian Coast. The corresponding Von Bertalanffy growth parameters could be calculated by adjusting a Von Bertalanffy growth equation to these mean values. Data on the length-weight relationship parameters were available for pollack in the areas of the English Channel and the Bay of Biscay (Dorel, 1986 [74]). These data were used to construct informative prior distributions in the hierarchical Bayesian model (Table 5.2).

An empirical relationship between the length at maturity ($Lmat$) and the asymptotic length ($Linf$) was developed by Froese and Binohlan (2003) [93] based on a meta-analysis on several species:

$$Lmat \sim 10^{0.8979 \times log(Linf) - 0.0782} \tag{5.1}$$

Length and weight collected data were available for the three stocks of pollack. Age data were collected for the stocks VII and VIII. Additional data on maturity were collected for the stock VII. While length and weight data can easily be collected without buying the fish, this is not possible for maturity data and difficult for age data. To overpass this difficulty, we used a particular extraction method to collect the otoliths. By passing through the fish gills, we were able to collect age data without damaging the fish. To collect gonad samples, we went onboard with commercial and recreational fishermen. All the data used for this study are summarized in Table 5.1.

The maturity stage could be identified with a macroscopic method for 310 individuals, among which 222 (79 females and 143 males) were also identified with a histological method. Gonad samples were kept in a Davidson preparation for 36 hours to fix the tissues, and were then transferred to a vial filled with 70% ethanol until processing. The first step of the process was the dehydratation done by an automaton Leica TP 1020. The samples were then embedded in paraffin, sectioned and colored. We scanned the glass slides with an Aperio slide scanner using the ScanScope®CS System and we analysed the digital slides with the software ImageScope.

Table 5.1 – Summary of all the available data from the literature and from additional data collection. The number of data collected is specified in brackets.

Stock	Available information from the literature	Collected data
VII	- Mean length at age (Moreau, 1964 [189])	Length (649)
	- Parameters a and b from the length-weight relationship (Dorel, 1986 [74])	Weight (649)
		Age (578)
		Maturity stage (222)
VIII	- Mean length at age (Moreau, 1964 [189])	Length (115)
	- Parameters a and b from the length-weight relationship (Dorel, 1986 [74])	Weight (115)
		Age (115)
IX	- Mean length at age (Moreau, 1964 [189])	Length (622)
	- Length at maturity (Alonso-Fernández et al., 2013 [8])	Weight (622)

5.2.2. Preliminary analysis of the data with frequentist inference

The length-weight relationship and the Von Bertalanffy growth relationship were calculated for pollack stocks VII and VIII with non-linear least squares regressions. The results obtained with the collected data were compared to the results of Moreau (1964) [189] and Dorel (1986) [74].

We classified each fish in a maturity stage following the microscopic classification described in Brown-Peterson et al. (2011) [32] as well as the macroscopic classification used by the International Council for the Exploration for the Sea (ICES). Seven maturity stages were considered: immature (1), early developing (2A), developing (2B), spawning capable (3A), actively spawning (3B), regressing (4A) and regenerating (4B). These stages were then grouped into four simplified stages: immature (1), developing (2), spawning (3) and regressing (4) to compare the classification of the macroscopic analysis with the classification of the histological analysis. Finally, the stages are grouped into two stages to calculate the length at 50% maturity: immature (stage 1) and mature (all the other stages).

The microscopic analysis allows to identify the first signs of vitellogenesis in stage 2A and therefore correctly classify the fish as mature. However, the macroscopic analysis can be misleading if no microscopic analysis is carried out to verify the classification. Some fish might be classified as stage 2A although no vitellogenesis has yet begun. Therefore we compare the results of length at 50% maturity ($Lmat$) based on the macroscopic analysis with three different classification methods. All fish classified as stage 2A are assumed to be immature for the first method and mature for the second method. The third method consists in ordering the fish classified as stage 2A in ascending order of length, and assuming that the fish belonging to the first half are mature. The calculation of Lmat is based on the generalized linear models with a binomial family distribution. The function glm() and the logit link of the R software (version 3.1.3) are used.

During the microscopic analysis, the largest width and the smallest width of the ovarian wall was also recorded for each female gonad.

5.2.3. Construction of the hierarchical Bayesian model

5.2.3.1. Observation equations

The length-weight relationship is formulated as follows:

$$log(W_{i,j}) \sim N\left(log\left(a_j \times L_{i,j}^{b_j}\right), \sigma_{lw,j}^2\right) \tag{5.2}$$

where $W_{i,j}$ and $L_{i,j}$ are respectively the observed weight (in g) and the observed length (in cm) of the individual i from the pollack stock j, a_j and b_j are the parameters of the length-weight relationship and $\sigma_{lw,j}^2$ is the variance of individual observations about the average length-weight relationship, drawn from a non-informative distribution for each pollack stock j. The Von Bertalanffy growth equation is formulated as follows:

$$log(L_{i,j}) \sim N\left(log\left[L_{\infty j} \times \left(1 - e^{-K_j(t_{i,j}-t_{0j})}\right)\right], \sigma^2_{vb,j}\right) \tag{5.3}$$

where $t_{i,j}$ is the observed age in years of the individual i from the stock j, $L_{\infty j}$ is the asymptotic length at which growth is zero, K_j is the growth parameter, t_{0j} is the theoretical age at which the fish would have had zero size and $\sigma^2_{vb,j}$ is the variance of individual observations about the average growth curve, drawn from a non-informative distribution for each pollack stock j.

TABLE 5.2 – Specification on the prior distributions.

Parameter	Description	Distribution
${\sigma_{lw,j}}^2$	Variance of the observation errors in the length-weight relationship	InverseGamma(0.01, 0.01)
${\sigma_{vb,j}}^2$	Variance of the observation errors in the Von Bertalanffy growth equation	InverseGamma(0.01, 0.01)
μ_a	Grand mean of a_j	Lognormal(μ = 0.00613, CV = 0.8)
μ_b	Grand mean of b_j	Lognormal(μ = 3.115, CV = 0.8)
$\mu_{L\infty}$	Grand mean of $L_{\infty j}$	Lognormal(μ = 93.04, CV = 0.8)
μ_K	Grand mean of K_j	Lognormal(μ = 0.2311, CV = 0.8)
μ_{t0}	Grand mean of t_{0_j}	Normal(μ = 0.006119, CV = 10)
α_1	Grand mean of $\beta_{1,k}$	Normal(μ = 0.1, CV = 100)
α_2	Grand mean of $\beta_{2,k}$	Normal(μ = 0.1, CV = 100)
${\sigma_1}^2$	Variance of $\beta_{1,k}$	InverseGamma(0.01, 0.01)
${\sigma_2}^2$	Variance of $\beta_{2,k}$	InverseGamma(0.01, 0.01)

5.2.3.2. Covariance matrices

A hierarchical structure is set to model the between stocks variability of parameters, whereby capturing the covariance between those parameters. The vectors of parameters $\theta_{lw,j}$ composed of a_j and b_j and $\theta_{vb,j}$, composed of $L_{\infty j}$, K_j and t_{0j}. $\theta_{lw,j}$ and $\theta_{vb,j}$ are drawn respectively in a 2-dimensional multinormal distribution with the grand mean $\mu_{lw} = (\mu_a, \mu_b)$ and in a 3-dimensional multinormal distribution with the grand mean $\mu_{vb} = (\mu_{L\infty}, \mu_K, \mu_{t0})$.

$$\theta_{lw,j} \sim MVN(\mu_{lw}, \Delta_{lw}) \; ; \; \theta_{vb,j} \sim MVN(\mu_{vb}, \Delta_{vb}) \tag{5.4}$$

The grand means μ_a, μ_b, $\mu_{L\infty}$, μ_K and μ_{t0} are assumed to be exchangeable among the three pollack stocks considered. Each component follows a normal distribution with an informative hyperprior and a coefficient of variation of 0.8. Details on the construction of the grand means are given in Table 2. The multinormal distributions have covariance matrices Δ_{lw} and Δ_{vb}:

$$\Delta_{lw} = \begin{bmatrix} var(a_j) & covar(a_j, b_j) \\ covar(b_j, a_j) & var(b_j) \end{bmatrix} \tag{5.5}$$

$$\Delta_{vb} = \begin{bmatrix} var(L_{\infty j}) & covar(L_{\infty j}, K_j) & covar(L_{\infty j}, t_{0j}) \\ covar(K_j, L_{\infty j}) & var(K_{\infty j}) & covar(K_j, t_{0j}) \\ covar(t_{0j}, L_{\infty j}) & covar(t_{0j}, K_j) & var(t_{0j}) \end{bmatrix} \tag{5.6}$$

and are drawn in non informative Wishart distributions

$$\Delta_{lw}^{-1} \sim Wishart(\varphi_{lw}, 2) \ ; \ \Delta_{vb}^{-1} \sim Wishart(\varphi_{vb}, 3) \tag{5.7}$$

where φ_{lw} and φ_{vb} are non-informative matrices of dimensions 2 and 3 respectively, with 1 as diagonal elements and 0 otherwise. The covariance matrices are then used in the following equations:

5.2.3.3. Analysis of the maturity data

The analysis of the microscopic maturity data from stock VII was integrated in the hierarchical Bayesian model, although this part was not hierarchical. The calculation of the length at 50% maturity was based on equations 8, 9 and 10 where $mat_{i,k}$ is the observed maturity stage of each fish i from the data subset k (F for females, M for males, or FM for both sexes). $mat_{i,k}$ is expressed as a binary value of either 1 (mature) or 0 (immature). $\beta_{1,k}$ and $\beta_{2,k}$ are the parameters of the logistic regression model which are assumed to follow a normal distribution with respectively mean α_1 and α_2 and variances σ_1^2 and σ_2^2. Details on the prior distribution of α_1, α_2, σ_1^2 and σ_2^2 are given in Table 2.

$$\beta_{1,k} \sim N(\alpha_1, \sigma_1^2) \ ; \ \beta_{2,k} \sim N(\alpha_2, \sigma_2^2) \tag{5.8}$$

$$mat_{i,k} \sim Bernoulli\left(logit(\beta_{1,k} + \beta_{2,k} \times L_{i,k})\right) \tag{5.9}$$

$$L_{mat,k} = -\beta_{1,k}/\beta_{2,k} \tag{5.10}$$

The relationship between the length at maturity and the asymptotic length (Eqn 5.1) developed by Froese and Binohlan (2003) [93] was also included in the hierarchical Bayesian model. The aim was to estimate a value of length at 50% maturity for the stock IX, using the value of asymptotic length calculated in the model.

5.2.3.4. P-values

Posterior predictive p-values (Gelman et al., 2014 [102]; Archambault et al., 2016 [10]) were calculated to evaluate how the model a posteriori fitted to the data. The same method was used to calculate the p-values plw_val_j for the length-weight relationship (Eqn 5.11) and pvb_val_j for the Von Bertalanffy growth equation (Eqn 5.12), whereas a specific method was used to calculate $pmat\_val_k$ for the maturity data (Eqn 5.13).

$$plw_{i,j} = \begin{cases} 1 & \text{if } Ws_{i,j} - W_{i,j} \geq 0 \\ 0 & \text{if } Ws_{i,j} - W_{i,j} < 0 \end{cases} \; ; \; plw\_val_j = \frac{\sum plw_{i,j}}{Nlw_j} \tag{5.11}$$

$$pvb_{i,j} = \begin{cases} 1 & \text{if } Ls_{i,j} - L_{i,j} \geq 0 \\ 0 & \text{if } Ls_{i,j} - L_{i,j} < 0 \end{cases} \; ; \; pvb\_val_j = \frac{\sum pvb_{i,j}}{Nvb_j} \tag{5.12}$$

$$pmat_{i,k} = |mats_{i,k} - mat_{i,k}| \; ; \; pmat\_val_k = \frac{\sum pmat_{i,k}}{Nmat_k} \tag{5.13}$$

The posterior predictive p-values plw_val_j and pvb_val_j can take values ranging from 0 to 1, while $pmat\_val_k$ can take values above 0. For the length and weight data, p-values concentrating near 0 or 1 indicate that the observed pattern would be unlikely to be seen in replications of the data if the model were true, and thus indicate lack of model fit. For the maturity data, p-values concentrating near 0 indicate a good model fit.

5.2.3.5. Computational details

Three chains of 100,000 Markov Chain Monte Carlo (MCMC) samples were simulated using OpenBUGS (OpenBUGS V3.2.3 ; Lunn et al., 2009 [169]). A burn-in period of 10,000 samples was used to avoid dependence of the MCMC samples on the initial conditions, and each chain was thinned by 50 to reduce autocorrelation. Convergence of the MCMC simulations to the posterior distribution was checked using the Brooks-Gelman-Rubin (BGR) convergence diagnostic (Brooks and Gelman, 1998 [31]).

5.3. Results

5.3.1. Update of the Von Bertalanffy and length-weight relationships with frequentist inference

The Von Bertalanffy growth curves calculated with the frequentist inference and based on the recent sampling slightly differ from the growth curves based on the data from

Moreau (1964) [189] for both stocks VII and VIII (Fig. 5.1). The plot of the length-weight relationship shows a similar curve for the recent sampling and the data from Dorel (1986) [74] for the pollack stock VII, whereas the curve differs between the two data sources for the stock VIII after 60 cm.

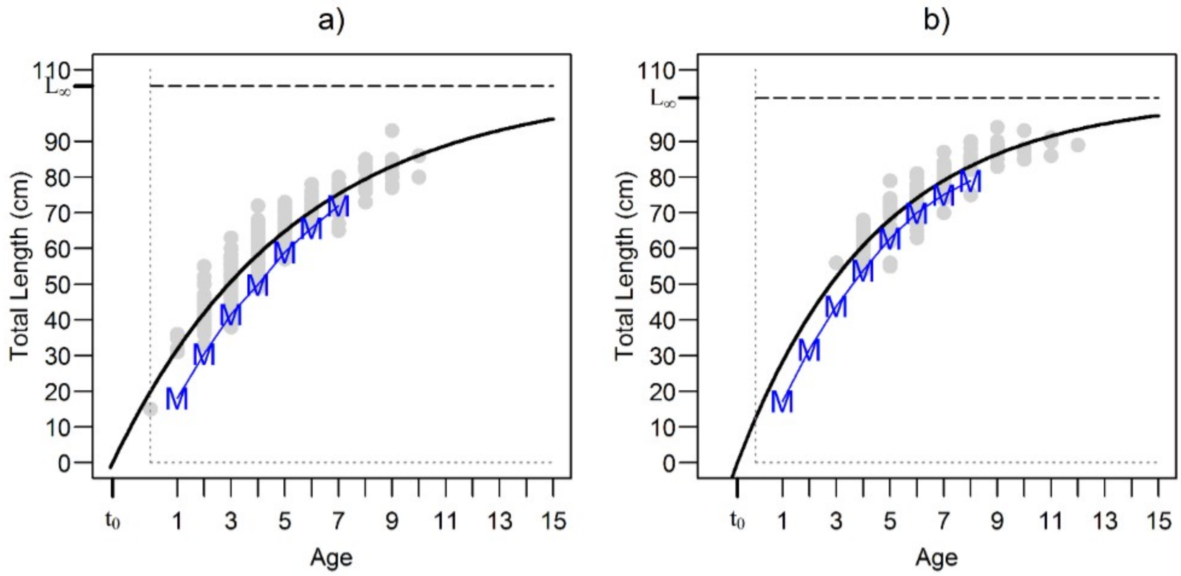

FIGURE 5.1 – Comparison of the Von Bertalanffy growth curve based on the recent sampling (solid bold line) with the curve based on the data from Moreau (1964) [189] (solid line with "M") for a) the stock VII and b) the stock VIII.

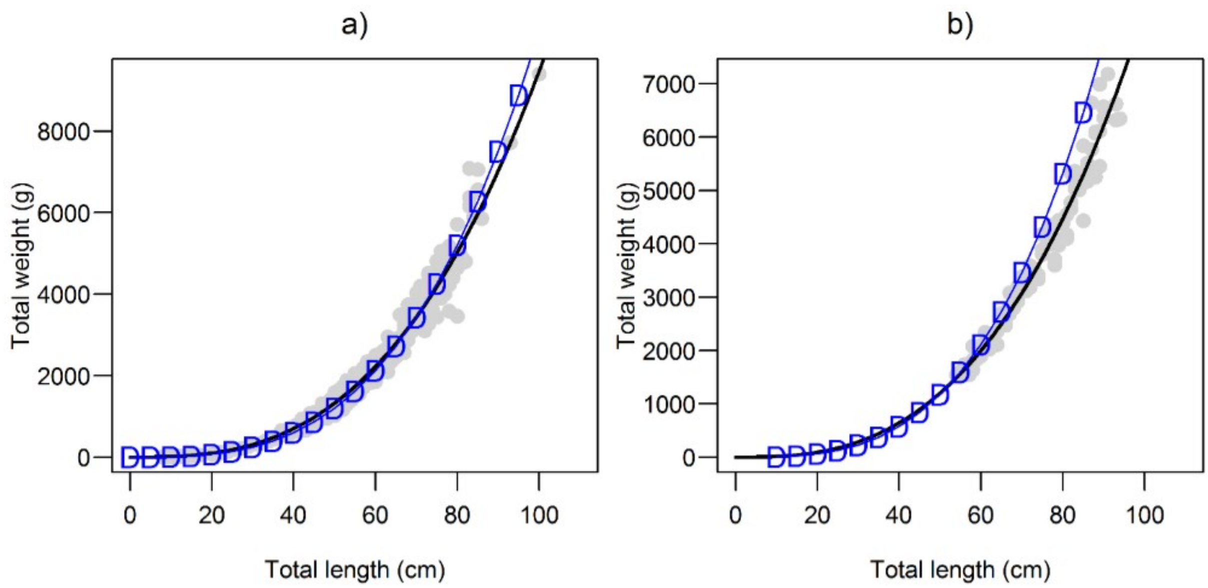

FIGURE 5.2 – Comparison of the length-weight relationship based on the recent sampling (solid bold line) with the curve based on the data from Dorel (1986) [74] (solid line with "D") for a) the stock VII and b) the stock VIII.

The estimates of the length-weight relationship parameters a and b are close for the pollack stocks VII and VIII (Table 5.3). The asymptotic length estimated for the stock VII is greater than the estimate of L_∞ for the stock VIII, while the estimate of K is greater for the stock VIII (Table 5.3). This would indicate a slower growth of the individuals from the stock VII, with higher maximum lengths achieved.

TABLE 5.3 – Estimates of the parameters from the length-weight relationship and from the Von Bertalanffy growth equation calculated with frequentist inference. The standard errors are specified in brackets.

Parameter	Stock			Number of data		
	VII	VIII	IX	VII	VIII	IX
a	1.99e-2. (1.8e-3.)	2.13e-2 (5.2e-3.)	1.18e-2 (1.2e-3.)	649	115	622
b	2.84 (2.1e-2.)	2.8 (5.6e-2)	2.97 (2.4e-2.)			
L_∞	105.491 (4.6)	102.143 (6.14)	-			
K	0.149 (0.02)	0.193 (0.05)	-	578	115	-
t_0	-1.414 (0.19)	-0.682 (0.71)	-			

5.3.2. Analysis of the maturity data from stock VII with frequentist inference

The table 5.4 presents the comparison between the microscopic and macroscopic classification of the gonads sampled for the stock VII. The main misspecification for males were gonads in stage 4 which were classified as stage 2 by the macroscopic evaluation. For females, the two main misspecifications were gonads in stage 1 classified in stage 2 or 4 by the macroscopic evaluation. The maximum width of the ovary wall measured during the microscopic analysis was significantly higher for the gonads classified as maturity stages 3 and 4 than for the gonads classified as maturity stage 1 (Fig. 5.3).

TABLE 5.4 – Comparison of the maturity stages from the microscopic and macroscopic analysis. Data from the English Channel sampling. The maturity stages are immature (1), developing (2), spawning (3) and regressing (4).

Sex	Macroscopic	Microscopic			
		1	2	3	4
M	1	16	0	0	0
	2	2	3	3	10
	3	0	3	46	3
	4	0	0	5	52
F	1	26	0	0	1
	2	15	0	2	0
	3	0	0	4	0
	4	7	0	2	22

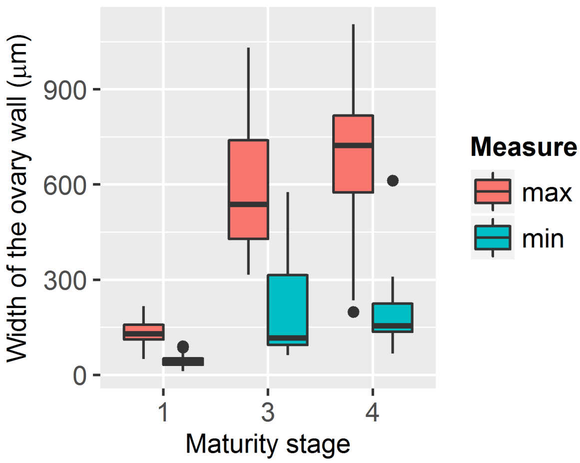

FIGURE 5.3 – Maximum and minimum width of the ovary wall for each maturity stage, based on microscopic analysis.

The table 5.5 presents the estimates of length at 50% maturity based on various datasets. For the dataset of females and the dataset of both sexes, the median estimates of Lmat based on the microscopic analysis were close to the results based on the macroscopic analysis when all individuals classified as stage 2A were assumed to be immature (Table 5.5 and Fig. 5.4). For the dataset of males, these median estimates were close when all individuals classified as stage 2A were assumed to be mature (Table 5.5).

TABLE 5.5 – Length at 50% maturity (in cm) calculated with a binomial model in frequentist statistics, based on various datasets (F for females, M for males and F+M for both sexes). Standard errors are specified in brackets.

Sex	Proportion	Microscopic	Macroscopic (100% of stage 2A mature)	Macroscopic (50% of stage 2A mature)	Macroscopic (0% of stage 2A mature)
F	0.05	47.42 (1.34)	31.62 (3.34)	41.06 (1.37)	35.13 (3.13)
	0.25	49.98 (0.83)	39.21 (1.79)	44.76 (0.79)	45.15 (1.63)
	0.5	**51.51 (0.78)**	**43.73 (1.16)**	**46.97 (0.69)**	**51.12 (1.38)**
	0.75	53.03 (0.98)	48.24 (1.3)	49.17 (0.88)	57.09 (1.95)
	0.95	55.59 (1.59)	55.84 (2.68)	52.87 (1.51)	67.11 (3.6)
M	0.05	27.55 (4.71)	26.8 (4.62)	30.33 (3.52)	30.41 (3.55)
	0.25	35.82 (2.82)	35.05 (2.81)	37.46 (2.11)	38.08 (2.09)
	0.5	**40.75 (1.84)**	**39.96 (1.86)**	**41.7 (1.41)**	**42.64 (1.38)**
	0.75	45.68 (1.32)	44.87 (1.31)	45.95 (1.11)	47.2 (1.12)
	0.95	53.95 (2.37)	53.13 (2.2)	53.07 (1.94)	54.87 (2.06)
F+M	0.05	35.6 (1.91)	29.84 (2.6)	36.26 (1.53)	31.71 (2.42)
	0.25	42.3 (1.05)	37.52 (1.49)	41.67 (0.87)	40.77 (1.31)
	0.5	**46.28 (0.75)**	**42.09 (0.97)**	**44.89 (0.62)**	**46.16 (0.86)**
	0.75	50.27 (0.85)	46.66 (0.83)	48.11 (0.66)	51.55 (0.96)
	0.95	56.97 (1.62)	54.35 (1.63)	53.51 (1.22)	60.6 (1.93)

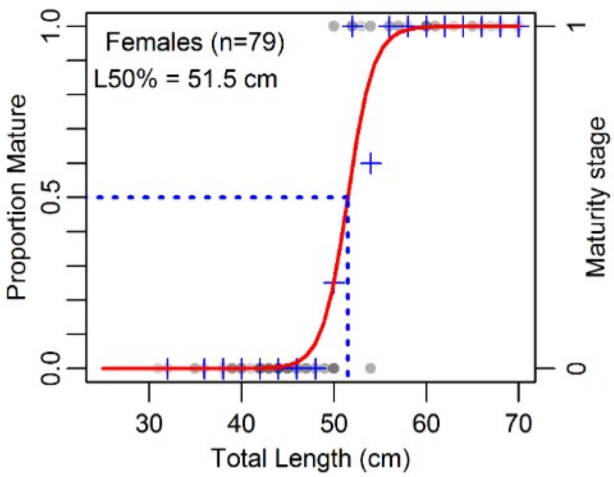

FIGURE 5.4 – Length at 50% maturity calculated with the binomial model in frequentist statistics from histological data for females of pollack stock VII.

5.3.3. Hierarchical Bayesian model

The estimated covariance matrices are the following:

$$\Delta_{lw} = \begin{bmatrix} 0.48 & 0.009 \\ 0.009 & 0.75 \end{bmatrix} \text{ and } \Delta_{vb} = \begin{bmatrix} 301.4 & -1.5 & -16.8 \\ -1.5 & 0.52 & 0.085 \\ -16.8 & 0.085 & 1.77 \end{bmatrix} \tag{5.14}$$

Parameters from the Von Bertalanffy growth equation and from the length-weight relationship are estimated with precision (Fig. 5.5). The median estimates of a and b are close for the stocks VII and IX, while the stock VIII has a higher a value and a lower b value (Table 5.6). The median estimates of the Von Bertalanffy equation parameters are close for the stocks VII and VIII, while the stock IX has a lower value of L_∞ and higher values of K and t_0 (Fig. 5.5 and Table 5.6).

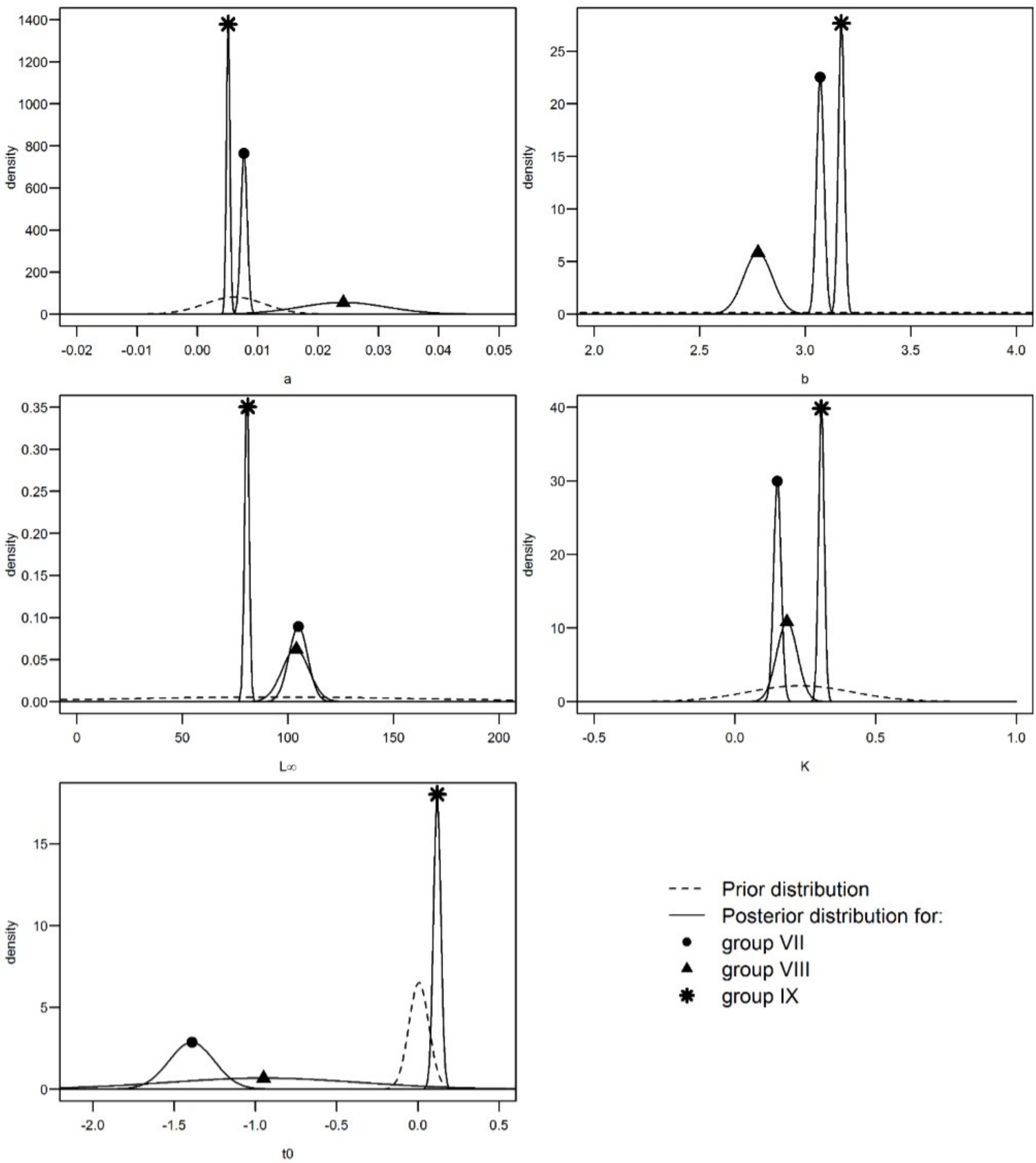

FIGURE 5.5 – Prior and posterior distributions of the parameters from the length-weight relationship and from the Von Bertalanffy growth equation.

The posterior distributions of the maturity ogive curve parameters are wider for the females than for the males and for both sexes (Fig. 5.6). This can be explained by the smaller number of data collected for the females. The resulting median estimate of length at 50% maturity is higher for females than for males (Table 5.6), which is consistent with the results of Alonso-Fernández et al. (2013) [8]. The estimates of length at 50%

maturity obtained with the hierarchical Bayesian model are close to the results obtained with the frequentist inference (Table 5.5). This was an expected result because the prior distribution of the maturity ogive parameters β_1 and β_2 (see Eqns 5.8, 5.9, 5.10 and Table 5.2) were weakly informative and the analysis of the maturity data were not affected by the correlation matrices.

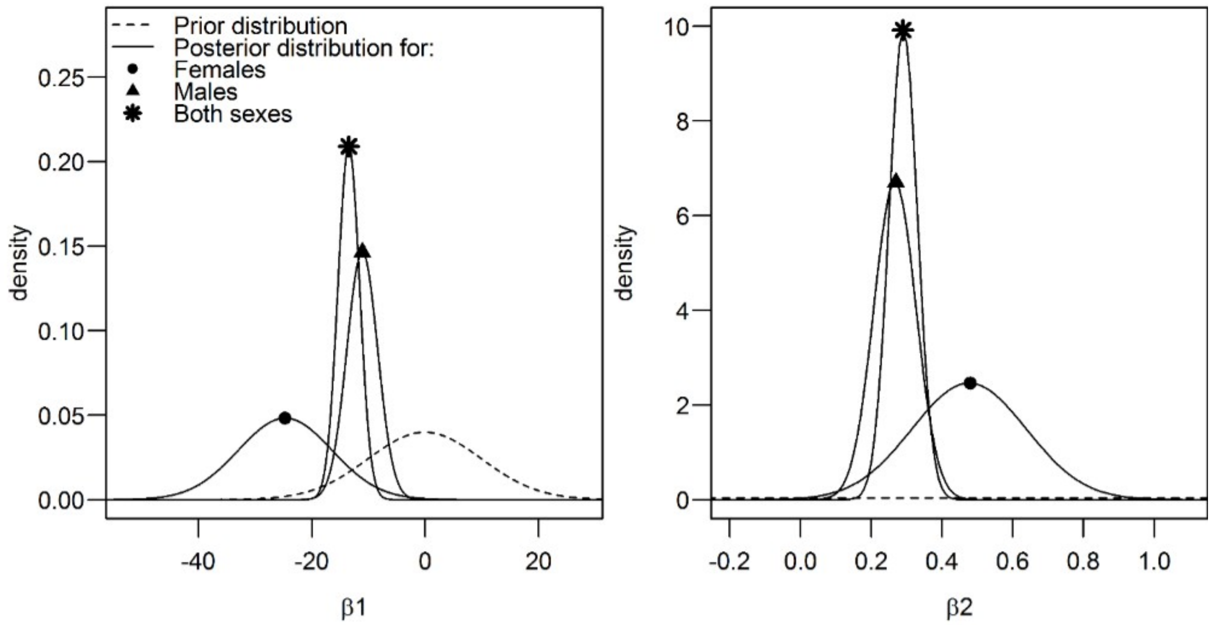

FIGURE 5.6 – Prior and posterior distributions of the parameters β_1 and β_2 from the maturity ogive curve of pollack stock VII.

TABLE 5.6 – Median estimates of the parameters from the length-weight relationship and from the Von Bertalanffy growth equation, and median estimates of length at 50% maturity (in cm) calculated with the hierarchical Bayesian model. The standard deviations are specified in brackets. The values of length at 50% maturity in bold are data from the literature (Alonso-Fernández et al., 2013 [8]).

Parameter	Stock VII	Stock VIII	Stock IX	Number of data VII	Number of data VIII	Number of data IX
a	7.7e^{-3} (5.2e^{-4})	2.31e^{-2} (7.2e^{-3})	5.09e^{-3} (2.9e^{-4})	649	115	622
b	3.07 (1.8e^{-2})	2.78 (6.8e^{-2})	3.17 (1.4e^{-2})			
L∞	104.5 (4.5)	102.7 (6.4)	80.5 (1)	578	115	80
K	0.15 (1.3e^{-2})	0.18 (3.7e^{-2})	0.31 (1e^{-2})			
t_0	-1.38 (1.4e^{-1})	-0.91 (6e^{-1})	0.12 (2.2e^{-2})			
$Lmat_F$	51.8 (1.1)	54 (19.4)	**47.1**	79	-	**304**
$Lmat_M$	41.5 (1.7)	-	**36.1**	143	-	**194**
$Lmat_{FM}$	46.3 (7.4e^{-1})	-	**42.3**	222	-	**498**

The posterior predictive p-values of length and weight data are close to 0.5 for the three stocks of pollack studied, indicating that the model is well able to reproduce these data. The calculation of the p-values are different for the maturity data (see Eqn 5.12), therefore the small values obtained indicate a good fit to the data (Table 5.7).

TABLE 5.7 – The posterior predictive p-values of the hierarchical Bayesian model.

p-value	Stock		
	VII	VIII	IX
pvb_val	0.49	0.49	0.5
plw_val	0.48	0.5	0.5
$pmat\_val_F$	0.22	-	-
$pmat\_val_M$	0.12	-	-
$pmat\_val_{FM}$	0.15	-	-

5.4. Discussion

In this work, we have updated several life history parameters of pollack, using both frequentist and Bayesian methods. The results obtained with both methods are close for the maturity parameters and for the Von Bertalanffy growth parameters but differ for the length-weight parameters of stocks VII and IX. For these stocks, few big individuals are sampled, while the sampling from the stock VIII lacks small individuals. While the parameters estimated with the frequentist method are based only on the collected data, the parameters estimated with the Bayesian model are based on the collected data and on the variance-covariance matrix. Therefore the information of the relationship between the parameters is included, which should help reduce the bias in the results in case of skewed sampling. Furthermore, the hierarchical Bayesian model enables to estimate Von Bertalanffy growth parameters for the stock IX despite the lack of age data. We recommend that the parameters estimated with the hierarchical Bayesian model be used until further data become available.

The maturity ogives used for stock assessment purposes are often calculated through macroscopic evaluation of the maturity stages, which might lead to biased and imprecise results. In our sampling from the English Channel, we compared the macroscopic and microscopic maturity stage determination. Our results show that without the microscopic confirmation, misspecifications occurred and lead to different results of the length at first maturity. The maturity scale used for macroscopic determination is the one used in the ICES scientific surveys. The stage 2A is particularly problematic. It is assumed to be the beginning of the maturing phase, but there is no certainty that the fish will spawn during the year. With the microscopic analysis, it is possible to detect corticoid alveoli which mean that the spawning should occur during the year of observation.

A comparison of macroscopic and microscopic maturity stage determination was done by Ferreri et al. (2009) [87] on the European anchovy and by Vitale et al. (2006) on the Kattegat cod. Both studies conclude to a misspecification of maturity stages when no microscopic analysis are used and underline the need for standardized protocols. Vitale et al. (2006) [262] recommend to use the gonadosomatic and hepatosomatic indices which may serve as robust proxies for discriminating the maturity stages. The Workshop WKMATHIS (ICES, *in prep.* [151]) aims at comparing the existing methods for maturity determination, and at establishing a standardized protocol. A promising work has been proposed on the use of various criteria (fish length, gonadosomatic index, month, ratio of the gonad length on total fish length. . .) in a decision tree. The tree could be built based on microscopic analysis and could then be used to update the maturity parameters with data from macroscopic analysis.

It is a common issue for data-limited stocks to lack the sufficient funds required to update its life-history parameters. For our study, we collected otoliths and gonads without buying the fish thanks to the help of professional and recreational fishermen. We advocate the use of participative science and the involvement of all actors of the fishing industry to improve data collection. However, when no fish can be bought, the sampling might be biased because of a strong dependence on the weather and on fishermen's availability. The weak point in our sampling on fish gonads was the lack of stage 2 females because of the short duration of this stage and the impossibility to go onboard at the crucial moment.

The lack of resources also leads to poor knowledge on the genetic structure of the stock, hence the uncertainty around the delineation of the fish stock. The analysis of life-history parameters and their evolution can bring information on stock identity (Begg et al., 1999 [15]). However, life-history parameters are sensitive to the environmental conditions and to the fishing pressure. It might therefore be misleading to infer the result of stock identity based on life-history parameters from a short temporal scale. Begg and Waldman (1999) [16] underline the importance of using various methods to define stock identity. The case of pollack in the Skagerrak and Kattegat shows the danger of a high fishing pressure on a stock with uncertain delineation. This population has experienced a high fishing pressure between the 1950s and the 1970s. A rapid decline has been observed after the 1970s and the spawning aggregation of adults has disappeared since the 1990s. It is not clear yet whether the loss of spawning aggregations was the result of range contraction or loss of distinct populations (Cardinale et al., 2012 [38]).

The minimum landing size for pollack in the European Member States is 30 cm

(European Council Regulation 850/1998). According to the results of our work, the size at first maturity is way above 30 cm for pollack. We therefore recommend that the minimum landing size be increased. Indeed, the stock might currently be impacted by too small catches and working on selectivity can help improve stock status with a same exploitation rate level (Vasilakopoulos et al., 2011 [259], 2016 [260]).

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CHAPITRE 6

CHAPITRE 6 : Discussion générale et perspectives

"*I do not know what I may appear to the world; but to myself I seem to have been only like a boy playing on the seashore, and diverting myself in now and then finding a smoother pebble or a prettier shell than ordinary, whilst the great ocean of truth lay all undiscovered before me.*"

Isaac Newton (1855), from **Memoirs of the life, writings, and discoveries of Sir Isaac Newton** written by Sir David Brewster.

6.1. Conclusion sur les résultats obtenus

Nous allons à présent revenir sur les principales conclusions qui découlent de cette étude. Le deuxième chapitre aborde l'étendue des méthodes disponibles pour l'évaluation des stocks à données limitées. Tandis que certains modèles s'ajustent uniquement sur des données de taille ou des données de captures, d'autres méthodes plus complexes permettent l'intégration de données de différentes natures et d'ainsi utiliser toutes les données disponibles. Une conclusion importante est la nécessité de comparer les résultats de plusieurs modèles pour évaluer un stock à données limitées, et l'importance des analyses de sensibilité permettant de tester l'effet des différentes hypothèses sur les résultats des modèles.

Le chapitre suivant reprend un modèle de biomasse à deux stades appliqué au stock de seiche de Manche. Ce modèle est adapté en statistiques Bayésiennes et des résultats similaires sont obtenus. Un modèle multi-annuel de déplétion généralisée est également appliqué sur le stock de seiche, ne prenant cependant pas en compte les captures anglaises. Bien que les estimations diffèrent en termes de valeur absolue, les valeurs relatives de biomasse et d'effort de pêche suivent les mêmes tendances. Par la suite, le modèle Bayésien de biomasse à deux stades est amélioré par un travail spécifique sur le paramètre de croissance de biomasse. Un prior informatif est construit, et une variabilité inter-annuelle est ajoutée sur le paramètre de croissance afin d'aboutir à un nouveau modèle écologiquement plus réaliste. Ce modèle permet de suivre l'évolution du taux d'exploitation et donne des proxys pour le recrutement et la biomasse de géniteurs qui laissent penser que la biomasse adulte n'est pas limitante pour le recrutement.

Au cours du quatrième chapitre, un modèle Stock Synthesis est construit pour le stock de lieu jaune de Mer Celtique. Dans un premier temps, l'évaluation du stock est menée dans le but de conclure sur l'état du stock. L'estimation du statut du stock indique une diminution de la biomasse relative entre 1950 et 1991, puis une remontée lente jusqu'à la fin de la série chronologique. La valeur de MSY Btrigger habituellement employée par le CIEM est de $0.35 \times B_0$. L'estimation du statut final du stock étant supérieure à ce point de référence, nous avons conclu que le stock ne semblait pas en danger au vu des résultats du modèle. Les analyses de sensibilité montrent que l'estimation de l'état final du stock est sensible à la valeur de mortalité naturelle employée dans le modèle, d'où l'importance de la fiabilité de cette valeur. Dans un deuxième temps, notre travail se concentre sur l'estimation d'une valeur de MSY dans une optique de gestion du stock. Les résultats d'un modèle complet Stock Synthesis sont comparés aux résultats de modèles SSS et XSSS. Ces modèles alternatifs sont construits avec la même plateforme de modélisation mais sont moins gourmands en données. Les modèles SSS et XSSS estiment une valeur de mortalité par pêche au MSY (FMSY) assez proche (0.33 et 0.31 respectivement), tandis que le modèle SS estime une valeur plus élevée (0.46). En revanche pour la valeur de MSY, les modèles SS et XSSS estiment une valeur similaire (7896 t et 7904 t respectivement) tandis que la valeur estimée par le modèle SSS est supérieure (8849 t). L'outil DLMtools est également employé, et les estimations de MSY des différents modèles testés avec cet outil sont synthétisées en une unique distribution dont la valeur médiane est de 6009 t. Pour le stock étudié, les méthodes simples résultent donc en une recommandation de gestion plus conservative que les méthodes de type Stock Synthesis.

Le cinquième chapitre propose une mise à jour des paramètres biologiques du lieu jaune. Une première analyse s'appuie sur l'inférence fréquentiste pour estimer les paramètres de croissance de la relation taille-poids et de la taille à 50% de maturité à partir des données collectées. Une légère différence a été observée entre les courbes de croissance basées sur la récente collecte de données et les courbes basées sur les données de Moreau (1964) [189]. Une première hypothèse pouvant être avancée pour expliquer cette observation est la différence au niveau des données d'échantillonnage. En effet, l'âge des individus échantillonnés dans l'étude de Moreau (1964) [189] s'étendait de 1 à 7 ans pour le groupe VII et de 1 à 8 ans pour le groupe VIII. En revanche pour les données collectées récemment, l'échantillonnage du groupe VII s'étendait de 0 à 10 ans, avec un unique individu de 15 ans, et l'échantillonnage du groupe VIII s'étendait de 4 à 12 ans. D'autres hypothèses possibles seraient une influence de la pêche sur les paramètres de croissance (Conover and Munch, 2002 [56]; Heino et al., 2013 [120]), une influence de variations des conditions environnementales, ou encore un effet d'une technique différente de lecture d'âge à partir des otolithes. Dans un deuxième temps, un modèle hiérarchique Bayésien est construit, intégrant à la fois les données de la littérature et les données récoltées dans le cadre de cette étude. Des matrices de variance-covariance sont utilisées afin de tirer profit des corrélations existant entre les différents paramètres. Des valeurs proches sont obtenues pour les paramètres de croissance des groupes VII et VIII, avec des tailles asymptotiques supérieures aux résultats de Moreau (1964) [189]. L'estimation de la taille à 50% de maturité des femelles est supérieure à celle des mâles, ce qui rejoint les résultats d'Alonso-Fernández et al. (2013) [8].

Au cours de l'ensemble de cette étude, nous avons testé différentes méthodes d'évaluation de stocks pouvant s'adapter à des cycles de vie particuliers, et à des données variables en nature et en quantité. Les deux cas d'étude que sont le stock de lieu jaune de Mer Celtique et le stock de seiche de Manche, bien que tous deux à données limitées, se différencient par des cycles de vie différents. A travers ces deux stocks, nous avons pu explorer aussi bien des méthodes adaptées à des cycles de vie longs que des méthodes spécifiques aux espèces à cycle de vie court. Nous avons cherché à intégrer l'ensemble des informations disponibles et à quantifier les incertitudes associées aux résultats à l'aide d'un cadre Bayésien, qui s'est avéré utile pour les deux cas d'étude. Des analyses de sensibilité ont permis d'identifier les effets de différentes hypothèses et l'impact de variations dans les données utilisées. Nous avons souligné l'importance de tester différents modèles et de tester différentes hypothèses dans un cadre de données limitées. Notre étude a apporté des avancées concrètes dans l'évaluation de stocks pour les deux cas d'études. Il reste cependant quelques points problématiques et plusieurs pistes d'amélioration dont nous allons discuter par la suite.

6.2. Discussion sur les limites des résultats et perspectives de recherche

Les statistiques Bayésiennes ont été employées pour construire les modèles présentés dans les chapitres 3 et 5. Ce cadre particulier d'analyse mérite une discussion plus approfondie. Plusieurs critiques sont adressées aux statistiques Bayésiennes, la plus fréquente étant sans doute la présence de subjectivité dans cette approche. Gelman (2008) [101] tente de reprendre le point de vue d'un chercheur sceptique vis-à-vis des statistiques Bayésiennes. Le risque d'une méthode reposant sur des priors informatifs serait d'avoir un choix de prior orienté par l'utilisateur, mettant en danger l'objectivité de l'analyse. Cette critique, justifiée, peut être atténuée par des analyses de sensibilité rigoureuses permettant d'évaluer les effets des différentes hypothèses du modèle. L'éternel débat opposant les statistiques fréquentistes aux statistiques Bayésiennes prend source dans les visions différentes qui les caractérisent. En statistiques Bayésiennes, l'objectif est d'employer toute l'information disponible et de faire des progrès rapides. Les données subjectives ne sont pas écartées car elles représentent une source d'information non négligeable, particulièrement dans un cadre de données limitées. A l'inverse, l'approche fréquentiste cherche à faire parler uniquement les données observées (Blum et al., 2006 [23]).

Au cours du troisième chapitre, les modèles développés visaient à estimer l'évolution du stock de seiche de Manche en termes de biomasse et de pression de pêche. Un travail particulier a été mené sur le paramètre de croissance de biomasse g, qui reste cependant dépendant du prior informatif. Par ailleurs, la variabilité interannuelle du paramètre g n'est pour l'instant pas liée aux variations des conditions environnementales. Cette piste pourrait être intéressante mais nécessiterait une étude approfondie des relations entre des variables environnementales et des données de croissance ou de mortalité naturelle de la seiche. Il serait idéal de pouvoir procéder à des expériences de marquage-recapture qui permettraient de mieux caractériser la variabilité inter- et intra-annuelle de la croissance de la seiche et d'analyser à une échelle fine le lien entre les variations de croissance et les variables environnementales. Toujours dans l'idée d'améliorer la précision du prior informatif sur g, il serait intéressant de s'appuyer sur un cadre hiérarchique Bayésien pour développer une méta-analyse regroupant l'ensemble des informations disponibles sur la croissance et la mortalité naturelle des différents stocks de seiche.

Un deuxième point problématique concerne les incertitudes relatives aux migrations de la seiche de Manche. La présence au cours de certaines années de deux micro-cohortes aux dates de migration différentes (octobre et avril) a en effet été mise en évidence par Royer et al. (2006) [236]. Cette observation constitue un frein à l'utilisation d'un modèle à deux cohortes, car le calcul de la croissance de biomasse de la cohorte 0+ pourrait être biaisé. En effet, ce calcul utilise les indices d'abondance issus de la campagne scientifique CGFS d'octobre. Le risque est donc de ne prendre en compte qu'une seule micro-cohorte. Une piste intéressante serait de modifier la structure du modèle de biomasse à deux stades en scindant la cohorte 0+ en deux micro-cohortes. Il serait alors nécessaire de pouvoir déterminer quelle fraction de la cohorte 0+ compose la première vague de migration. Pour cela, il faudrait analyser de manière plus fine les distributions de taille des seiches, en utilisant à la fois les données issues du programme Obsmer et les données d'échantillonnage des débarquements. Il n'est cependant pas certain que les données disponibles soient suffisantes pour correctement extraire les informations requises.

Un troisième point de discussion sur nos travaux autour de la seiche concerne l'hypothèse du cycle de vie exclusif de deux ans pour la seiche de Manche. Le modèle de biomasse à deux stades est pour l'instant construit selon cette hypothèse et devrait donc être modifié pour une application par exemple au stock du Golfe de Gascogne, composé d'un mélange de seiches aux cycles de vie d'un et deux ans. De nouveau, des données de marquage-recapture seraient nécessaires pour vérifier que la majorité des seiches de

Manche effectue un cycle de vie de deux ans. Avec le phénomène de réchauffement des eaux, il est possible que la proportion de seiches effectuant un cycle de vie d'un an en Manche augmente, auquel cas la structure du modèle devrait être modifiée.

Au cours du premier chapitre, nous avons souligné l'absence de gestion communautaire pour le stock de seiche de Manche. Bien que le modèle de biomasse à deux stades permette un suivi des tendances d'évolution de la biomasse de l'ensemble du stock, il ne fournit pas de points de références. La traduction opérationnelle en termes de gestion reste donc une étape à franchir. Dans un contexte de recrutement très variable, un optimum d'exploitation sur du moyen à long terme semble peu utile (Caddy, 1983 [35]; Beddington et al., 1990 [14]). Une gestion au cours de la saison semble davantage adaptée, mais suppose un accès rapide aux données et vraisemblablement la mise en place d'une gestion participative. Nous avons évoqué dans les conclusions des travaux sur la seiche qu'il était possible d'estimer avec le modèle un niveau de biomasse au milieu de la saison de pêche, et qu'une mesure de gestion possible du côté français serait de ne pas lever l'interdiction de chalutage dans la bande des 3 milles. Afin de pouvoir justifier la mise en place de mesures à plus grande échelle, une évolution spatialisée du modèle est à privilégier.

Concernant les travaux sur le stock de lieu jaune de Mer Celtique, la première partie du chapitre 4 concluait qu'il n'était pas en situation de danger. Cette conclusion mérite cependant d'être discutée car elle est dépendante de plusieurs hypothèses. Une première hypothèse concerne la valeur de mortalité naturelle qui influence de manière non négligeable l'estimation du statut final du stock. Cette valeur a été calculée de manière indirecte par des équations de la littérature reliant M à des paramètres biologiques de l'espèce. Elle est donc à considérer avec précaution, et l'incertitude associée à cette estimation provient principalement de deux sources : le calcul des paramètres biologiques, et les équations utilisées qui sont issues de méta-analyses et ne sont donc pas spécifiques de l'espèce. De plus, cette mortalité naturelle peut être influencée par des conditions environnementales particulières, et peut présenter une variabilité interannuelle pour l'instant non prise en compte dans le modèle. La piste des modèles trophiques pourrait être explorée pour estimer la valeur de M à travers l'utilisation de modèles comme Ecopath (Christensen et Pauly, 1992 [50]) et EcoTroph (Gascuel, 2005 [97]; Galscuel et al., 2009 [100], 2011 [99]).

Une deuxième hypothèse concerne les niveaux de prélèvement par pêche récréative. Contrairement au groupe de travail WGCSE, notre étude intègre une série de captures par pêche récréative qui résulte en des estimations de MSY prenant en compte l'ensemble des captures commerciales et récréatives. Une analyse de sensibilité est réalisée sur la série de captures commerciales et selon le scénario utilisé, les résultats peuvent différer de manière importante. Le problème du manque de données concernant la pêche récréative, qui n'est pas spécifique aux stocks à données limitées, est donc une composante majeure de l'incertitude autour des résultats. En France, le lieu jaune est la troisième espèce la plus pêchée par la pêche récréative en termes de tonnage derrière le bar et le maquereau (Levrel et al., 2013 [165]). Une enquête téléphonique conduite en 2011-2013 a permis d'estimer le niveau de prélèvement de lieu jaune par la pêche récréative à 2274 t par an. Cette valeur concerne l'ensemble des pêcheurs récréatifs français, et une analyse des données brutes serait nécessaire afin de séparer les prélèvements des zones CIEM VII et VIII. Des informations issues d'une enquête conduite en 2009-2011 sont également disponibles. Actuellement, les informations sur la pêche récréative au Royaume-Uni et en Irlande sont manquantes. Pour y parer, une enquête rigoureuse auprès des pêcheurs récréatifs serait nécessaire. La plus grande difficulté réside dans la collecte d'information sur les niveaux de prélèvement des années les plus anciennes. En effet, s'il semble plausible que les pêcheurs puissent donner des estimations de leurs captures sur les années récentes, il est moins probable qu'ils se souviennent avec précision des quantités pêchées plusieurs années auparavant.

Au cours de la deuxième partie du quatrième chapitre, l'axe de recherche portait davantage sur l'estimation de points de référence permettant de donner des avis de gestion pour le stock étudié. Puisque les données de capture intègrent un scénario de captures récréatives, l'estimation de captures au MSY obtenue tient compte de l'ensemble des captures à la fois commerciales et récréatives. Un résultat intéressant de la MSE est que la mesure curE qui consiste à maintenir l'effort de pêche actuel résulte en une probabilité $P(B < 0.5 \times B_{MSY})$ nulle et en une probabilité $P(B < B_{MSY})$ de 13.5%. Théoriquement, ceci implique que si l'effort de pêche reste aux niveaux actuels, le stock devrait rester dans des limites biologiques favorables malgré l'absence de mesures de gestion. En revanche, dans la pratique, en cas d'avancées technologiques ou d'amélioration des techniques de pêche, cette conclusion ne sera plus valide. Bien que le stock de lieu jaune de Mer Celtique soit soumis à des mesures de gestion, les captures globales, qui avoisinent les 4 000 t depuis une dizaine d'années, sont largement en deçà du TAC annuel de 12 543 t (ICES, 2017a [149]). Dans le détail, les quotas alloués à l'Irlande et au Royaume-Uni sont parfois limitant, tandis que la France n'atteint jamais son quota de lieu jaune pour ce stock.

Lors du calcul de CPUE pour les données françaises, la standardisation tenait compte de la puissance des navires et permettait donc de corriger la série au regard de l'augmentation de la puissance des navires de pêche. Cependant, l'amélioration technique des flottilles et un possible effet patron n'ont pas été pris en compte et pourraient être un facteur de biais (Squires and Vestergaard, 2015 [246]). Or ce genre d'information est difficile à obtenir de manière objective et quantifiée. En revanche, il est possible d'artificiellement augmenter l'effort et de tester le nouveau scénario. Nous avons réalisé un test avec une augmentation de 2% par an à titre purement exploratoire. Cependant, les séries de CPUE d'Irlande et de France ne débutent qu'en 1995 et 2000 respectivement, tandis que les premières données de captures sont disponibles en 1950. L'augmentation artificielle chaque année de l'effort a ainsi pour effet de diminuer le contraste des deux séries de données. Le modèle interprète cela comme une moindre diminution d'abondance et donne une estimation plus optimiste du statut final du stock et une estimation des captures au MSY plus élevée. Un travail plus approfondi sur le paramètre de capturabilité serait nécessaire, cependant le temps manquait pour compléter nos recherches.

Au cours du chapitre 5, certaines valeurs de paramètres biologiques sont estimées malgré l'absence de données collectées et sont donc à utiliser avec précaution. D'une part, les équations développées par Froese and Binohlan (2003) [93] sont une généralisation sur plusieurs espèces de poissons. D'autre part, les matrices de variance-covariance du modèle s'appuient uniquement sur les paramètres de trois stocks. Il est donc important de noter que l'objectif était non pas de prédire des valeurs précises, mais plutôt de proposer des valeurs pouvant servir de prior pour une étude ultérieure. La collecte de données supplémentaires permettra de réduire l'incertitude autour des paramètres.

Nous avons abordé au cours de ce même chapitre la problématique de délimitation des stocks, qui est souvent incertaine malgré son importance en évaluation de stocks (Begg and Waldman, 1999 [16]). On peut notamment évoquer le stock de lieu jaune de Skagerrak et Kattegat qui a vu son taux de captures diminuer de 80% au cours des 30 dernières années. Les agrégations d'adultes ont aujourd'hui disparu, et il semble que l'absence d'informations sur la structure du stock et la constante pression de pêche élevée aient eu raison de ce stock. Cependant, l'identité du stock reste très floue, et le stade des hypothèses ne peut pas être dépassé du fait de l'absence de données de génétique ou de marquage-recapture (Cardinale et al., 2012 [38]). Concernant le stock de lieu jaune de Mer Celtique, il existe une grande incertitude quant aux limites géographiques du stock (Charrier et al., 2006 [46]; ICES, 2014a [143], 2016a [147]). A l'heure actuelle, les stocks VII et VIII sont considérés par le CIEM comme étant des stocks distincts. S'il s'avérait qu'ils constituent en réalité un unique stock, les conclusions du quatrième chapitre pourraient ne plus être valides et il serait alors nécessaire de mettre à jour les modèles.

Les études génétiques de grande ampleur permettent de mieux définir les limites géographiques des stocks mais sont très coûteuses. Il est également possible d'examiner les traits d'histoire de vie et leur évolution au cours du temps. L'évolution de ces paramètres peut en effet apporter des informations sur la structure du stock (Begg et al., 1999 [15]). Cependant, du fait de la plasticité des paramètres d'histoire de vie aux modifications environnementales et à la pression de pêche, il est risqué de tirer des conclusions quant à la structure du stock en se basant uniquement sur une courte fenêtre temporelle. Il est donc nécessaire de collecter des données sur plusieurs années. Cette manière de différencier les stocks reste à utiliser avec précaution. En effet, il est également possible que les différences observées entre les traits d'histoire de vie de deux stocks soient des différences non pas génotypiques mais phénotypiques, dues à des conditions environnementales locales différentes. Begg and Waldman (1999) [16] soulignent l'importance d'employer plusieurs méthodes pour récolter le maximum d'indices quant à l'identification des stocks. Selon eux, le processus d'identification du stock devrait être considéré comme un travail continu en constante évolution, qui doit être mis à jour lorsque de nouvelles avancées technologiques émergent.

Des données de marquage-recapture seraient d'une grande utilité pour évaluer la dispersion géographique du lieu jaune. Il serait ainsi possible de définir de manière plus précise les limites géographiques du stock et d'améliorer les connaissances sur ses déplacements. L'étude réalisée par Echave (2017) [79] sur le stock de sébastolobe à courtes épines (*Sebastolobus alascanus*) d'Alaska a permis de confirmer que l'échelle de gestion du stock était cohérente avec la structure du stock. Une gestion à une échelle non appropriée peut avoir pour conséquence une diminution locale d'abondance si l'effort de pêche n'est pas réparti en fonction de l'abondance, surtout sur un stock présentant de faibles mouvements (Echave, 2017 [79]).

Une étude récente réalisée par Halpern et al. (2017) [116] examine l'évolution d'indicateurs de l'état global des océans. Si les indicateurs ne montrent pas de changement important à l'échelle mondiale, l'examen des résultats à l'échelle des pays permet une analyse plus fine de leur évolution. Afin d'évaluer le statut des stocks exploités, les valeurs de B/B_{MSY} sont employées. Les conclusions relatives au secteur de la pêche montrent une amélioration de l'état des stocks dans les pays développés. Halpern et al. (2017) [116] et Worm and Branch (2012) [273] soulignent l'importance d'une bonne gouvernance pour l'amélioration de l'état des océans. Les efforts fournis par les pêcheurs, les organismes rendant des avis de gestion, les organismes décisionnels et les scientifiques portent peu à peu leurs fruits. Cependant, un long chemin reste encore à parcourir afin de gérer de manière adéquate l'ensemble des stocks, y compris ceux à données limitées. La gestion des stocks de poisson est un domaine en constante évolution, avec de nouvelles données régulièrement disponibles, et de nouvelles méthodes et avancées scientifiques qui émergent. Si les modèles d'évaluation de stocks mono-spécifiques restent indispensables, l'intégration de données de plusieurs stocks dans des modèles pluri spécifiques, prenant en compte des interactions avec l'environnement, des interactions entre espèces, et intégrant des données économiques et sociales, est un axe de recherche parallèle d'une importance cruciale.

La prise en compte des données environnementales est d'autant plus importante dans le contexte actuel de changement climatique qui peut entraîner des effets directs ou indirects sur les populations et les écosystèmes marins (Harley et al., 2006 [119]; Brander, 2010 [28]; Pörtner and Peck, 2010 [209]). Le réchauffement des eaux a déjà provoqué des déplacements des limites géographiques de plusieurs espèces, et il est attendu que cette tendance se poursuive (Perry et al., 2005 [201]). Des projections de pertes et gains de captures entre 2005 et 2055 ont été réalisées par Cheung et al. (2010) [49] sous différents scénarios de changement climatique. Les résultats montrent qu'une importante redistribution des potentiels de captures est à attendre, avec une augmentation moyenne de 30 à 70% dans les régions de haute latitude et une perte pouvant aller jusqu'à 40% dans les régions tropicales.

Pour conclure sur l'ensemble de ce travail, nous avons exploré plusieurs axes de recherche sur les méthodes adaptées à l'évaluation des stocks à données limitées, que l'espèce présente un cycle de vie long ou court. Pour le lieu jaune, nous avons récolté des données supplémentaires en collaborant avec les pêcheurs. Cependant, nous avons été confronté aux limites de ces méthodes participatives puisque pour les données de maturité, notre échantillonnage ne comprenait aucun individu femelle au stade 2. L'écart en termes de données récoltées est important entre certains stocks à données limitées et les stocks riches en données, pour lesquels les protocoles d'échantillonnage incluent la collecte des otolithes et la détermination du stade de maturité (ICES, 2015a [145]). Le stock de lieu jaune de Mer Celtique fait partie des espèces pour lesquelles les otolithes doivent être échantillonnées, cependant très peu d'individus sont pêchés au cours de la campagnes scientifique IBTS, d'où le manque de données pour ce stock. Il pourrait être intéressant de mettre à contribution les programmes d'échantillonnage par des observateurs embarqués tels que le programme Obsmer afin d'inclure la collecte d'otolithes par les ouïes dans le protocole (voir http://sih.ifremer.fr/content/download/5587/40495/file/Manuel_OBSMER_V2_2_2012.pdf pour une description du protocole d'échantillonnage actuel d'Obsmer).

6.3. Ouverture sur l'utilité des méthodes participatives

Revenons sur l'exemple que nous avions utilisé dans le chapitre introductif sur l'effondrement des stocks de morue de Terre-Neuve. Durant plusieurs années précédant l'effondrement du stock, les pêcheurs côtiers s'étaient plaints d'une diminution de leurs prises due aux grandes quantités prélevées par la pêche hauturière. Bien que relayée par les médias, cette information était restée vaine aux yeux des organismes de gestion (Mason, 2002 [175]). Par la suite, face à des signes plus clairs de mauvais état du stock, des mesures de gestion ont été mises en place dans une tentative d'enrayer la chute d'abondance.

Cependant, les quotas imposés étaient toujours supérieurs aux recommandations des scientifiques, et force est de constater que la gestion n'a pour ce cas pas permis d'empêcher l'effondrement du stock. Cet exemple illustre bien la complexité que représente la gestion des stocks, et la nécessité d'une meilleure collaboration et communication entre les différents acteurs de la pêche. De tels échecs de gestion entraînent une défiance des pêcheurs envers le système de gouvernance, et c'est en incluant les pêcheurs dans le processus de gestion que la confiance pourrait être rétablie. Les pêcheurs étant au contact direct de l'écosystème marin, ils possèdent une connaissance de terrain pouvant apporter de précieuses informations. De plus, les pêcheurs sont davantage enclins à respecter les règles de gestion lorsqu'ils ont été inclus dans le processus de gestion, ayant un rôle actif plutôt que de subir les mesures (Daw and Gray, 2005 [64]).

Nous avons réalisé une enquête en ligne auprès de pêcheurs récréatifs, que nous avons diffusée avec l'aide de pêcheurs tenant des blogs et de la fédération nautique de pêche sportive en apnée de Normandie. Cette enquête nous a permis d'en apprendre davantage sur leur perception de l'évolution du stock de lieu jaune (Table 6.1) et sur l'estimation qu'ils avaient de la taille de première maturité sexuelle des mâles et des femelles (Fig. 6.1). Les estimations de taille de première maturité sexuelle se ventilent entre 20 et 60 cm, avec une plus forte concentration de réponses entre 35 et 40 cm (Fig. 6.1). La tendance qui ressort pour le ressenti de l'évolution du stock est une diminution de l'abondance et une diminution de la taille moyenne du lieu jaune. De plus, 73.7% des répondants estiment que le lieu jaune est de plus en plus ciblé par la pêche récréative (Table 6.1). Ce résultat est à replacer dans le contexte du moment de l'étude. Le 26 janvier 2015, la Commission européenne annonce la fermeture de la pêcherie de bar pour les chaluts pélagiques en Manche, Mer Celtique, Mer d'Irlande et sud de la Mer du Nord. Il est également imposé aux pêcheurs récréatifs de participer à l'effort en se limitant à trois poissons par personne et par jour. Cette mesure d'urgence dure jusqu'au 30 avril 2015. Hélas, ces limitations arrivent trop tard et ne suffisent pas à enrayer l'effondrement du stock. Le 28 janvier 2016, une nouvelle mesure entre en vigueur et s'étend jusqu'au 30 juin 2016. Cette fois, les prélèvements par pêche récréative sont limités à un poisson par personne et par jour. Le bar est l'espèce la plus ciblée par la pêche récréative en France, et il semble que les limitations sur sa pêche aient incité un report de l'effort de pêche sur le lieu jaune.

Parmi les réponses à l'enquête en ligne, une affirmation qui revient souvent est qu'il est de plus en plus difficile de trouver du lieu jaune près des côtes, et qu'il faut aller de plus en plus loin pour en pêcher. Au large des côtes de Normandie et de Bretagne, les pêcheurs connaissent de mieux en mieux les positions exactes des épaves et améliorent leur technique de pêche. Les bateaux sont de mieux en mieux équipés, et sont capables d'aller plus loin des côtes. Ces informations sont subjectives et peuvent difficilement être utilisées directement dans des modèles d'évaluation de stock. Cependant, avec un plan d'échantillonnage rigoureux et un questionnaire adapté et testé, les enquêtes auprès des pêcheurs peuvent informer les modèles sur l'évolution de la capturabilité et de l'effort, sur la répartition préférentielle des poissons selon leur taille, et sur l'évolution des poids moyens. L'étude réalisée par Griffiths et al. (2010) [112] présente une méthode intéressante de collecte de données auprès des pêcheurs récréatifs, appelée l'échantillonnage fondé sur les répondants. Le principe est de contacter un groupe de pêcheurs qui répondront à l'enquête en échange d'une faible compensation financière, puis de leur donner un petit nombre de coupon, au maximum trois. Chaque coupon contient un code unique, et le participant est informé qu'il recevra une récompense pour chaque pêcheur qu'il aura recruté. Chaque recrue auquel il aura donné un coupon vient ensuite participer à l'enquête et reçoit également des coupons.

TABLE 6.1 – Résultats en pourcentage de l'enquête en ligne, d'après les réponses de 142 pêcheurs récréatifs en 2016.

Evolution of :	Pollack abundance	Pollack average size	Pollack targeting by recreational fishery
Increase	2.3	0	73.7
Decrease	44.4	54.8	7.5
Stable	31.6	14.1	0
No opinion	21.8	31.1	18.8

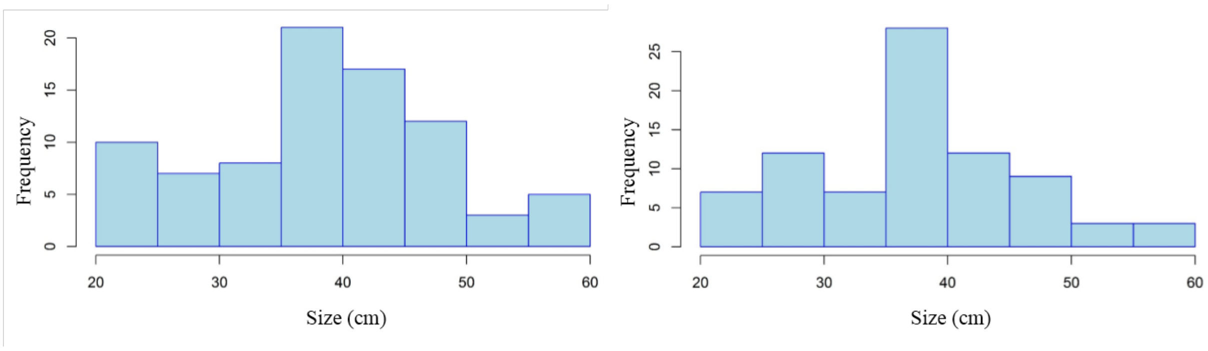

FIGURE 6.1 – Distribution des réponses sur la taille de première maturité sexuelle pour le lieu jaune femelle (a) et mâle (b).

Par ailleurs, la collaboration avec les pêcheurs exerçant la pêche commerciale ou récréative peut permettre de récolter davantage de données de taille, poids, âge et maturité à moindre coût, ce qui est particulièrement intéressant pour les cas des stocks à données limitées. En cas de fortes incertitudes sur les résultats des modèles d'évaluation, le principe de précaution entraîne généralement des taux d'exploitation recommandés plus conservatifs

(Fenichel et al., 2008 [86]). Il est donc dans l'intérêt des pêcheurs d'aider à la collecte de données qui permettra à terme de réduire les incertitudes. Les données françaises collectées dans la Manche et utilisées dans le chapitre 5 ne proviennent pas de poissons achetés. Un grand nombre de données de poids, de taille et d'âge ont été obtenus en criée. Après accord du patron pêcheur, les otolithes étaient prélevés par les ouïes, de manière à ne pas endommager le poisson. En revanche, le lieu jaune étant ramené à terre déjà vidé, il a fallu embarquer avec des pêcheurs afin d'effectuer des prélèvements sur les gonades. Pour le cas des espèces à vie courte telles que la seiche, la collaboration avec l'ensemble des acteurs de la pêche faciliterait la mise en place de systèmes de gestion en temps réel.

Il arrive également que certains pêcheurs récréatifs conservent des données historiques sur leur pêche. Nous sommes ainsi entrés en contact avec un pêcheur de lieu jaune qui conservait des données précises de toutes ses sorties de pêche depuis 1994. Nous avons ainsi pu observer l'évolution du nombre moyen de poissons pêchés par heure de pêche sur les épaves proches de la côte, moyennement éloignés, et loin de la côte (Figure 6.2). On observe une évolution contraire de l'abondance sur les épaves proches de la côte et les épaves à distance moyenne entre 1994 et 2011. Entre 2011 et 2016, l'abondance augmente pour l'ensemble des épaves. Ce genre de données pourrait apporter de l'information sur des évolutions d'abondance locales. D'un point de vue plus général, les approches de science participative sont une piste intéressante à creuser pour récolter davantage de données. Des collaborations accrues entre scientifiques et pêcheurs pourraient faciliter la récolte de données, mais aussi permettre une meilleure communication et une moindre défiance de la part des pêcheurs. L'inclusion des sciences sociales dans les processus de rendu d'avis de gestion, et l'inclusion des pêcheurs dans les processus de décision, permettrait d'atténuer les tensions souvent présentes entre les différents acteurs de la pêche. Cependant, force est de constater que les lobbys ont aujourd'hui un pouvoir énorme, aussi les intérêts de l'ensemble des pêcheurs devraient être représentés, tant ceux de la pêche industrielle que de la pêche artisanale.

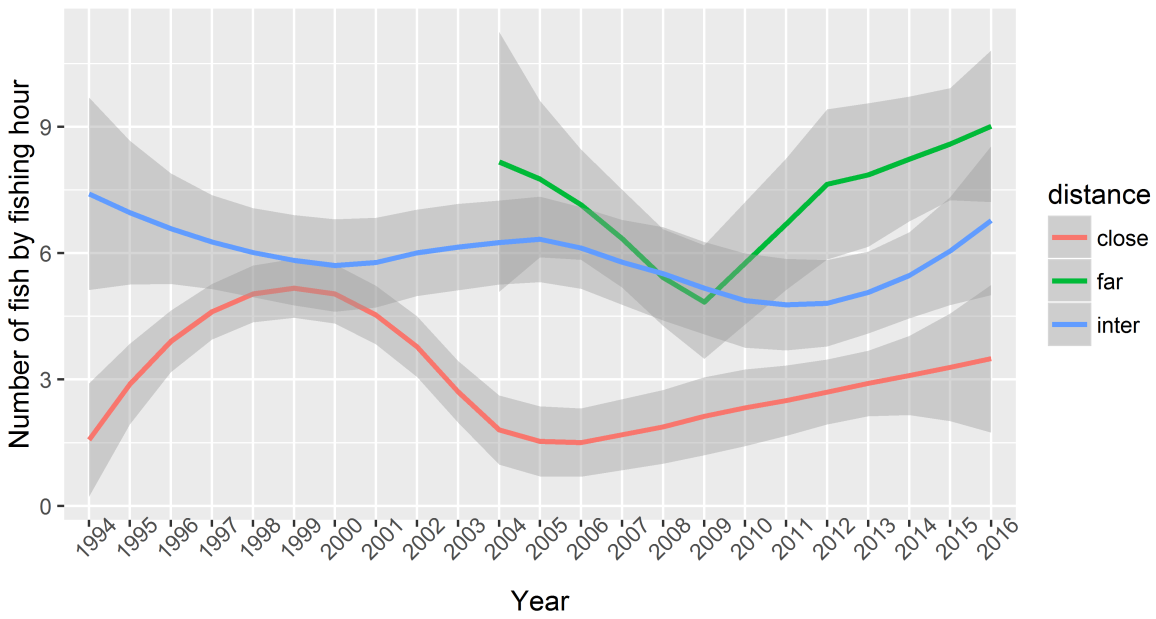

Figure 6.2 – Évolution du nombre moyen de poissons pêchés par heure de pêche, selon l'éloignement à la côte des épaves : « close » pour les épaves à moins de 20 miles de la côte, « inter » pour les épaves entre 20 miles et 40 miles, et « far » pour les épaves au-delà des 40 miles.

Annexes

Annexe A : Détails sur la construction d'un prior pour les paramètres $g_{0,y}$ et $g_{1,y}$

We applied the package mixdist (Macdonald et al., 2011 [171]) to length frequency data obtained from the French Onboard Observer Program (Obsmer) to calculate the individual growth rate for group 1+ individuals (Gr_{1+}). This program aims to collect catch data onboard commercial fishing vessels. External observers follow a specified sampling scheme and collect data on fish kept on board and discarded fish. The number of cuttlefish sampled each year is given in TableA.1 A.1. The mean length of group 1+ individuals was calculated in October and December, as the cohort split-up is of better quality for these months. The Dunn (1999a) [77] length-weight relationship was used to convert mean length into mean weight ($\bar{w}_{1+}$). The variability of mean weight values is plotted on Fig. A.1. The goodness-of-fit of the chi-square statistic was checked, and the fishing seasons where one of the cohort split-up model has a p-value above 0.05 were not used in the growth rate calculation.

For each fishing season where the cohort split-up is reliable, annual growth coefficients Gr_{y1+} were calculated using Eqn A.1, then Gr_{1+} was calculated as the median value of all Gr_{y1+}.

$$Gr_{y1+} = log(\bar{w}_{1+,December}/\bar{w}_{1+,October}) \times 6 \tag{A.1}$$

To calculate the mean growth coefficient for group 0 individuals (Gr_0) we used the package mixdist on length frequency data from CGFS survey:

$$Gr_{y0} = log(\bar{w}_{1,y+1}/\bar{w}_{0,y}) \tag{A.2}$$

where $\bar{w}_{0,y}$ is the mean weight of group 0 individuals in year y and $\bar{w}_{1,y+1}$ is the mean weight of group 1+ individuals in the following fishing season. Gr_0 was calculated as the median value of all Gr_{y0}.

CGFS data from 2006 to 2014 were used. Length data obtained from the mixdist package had an inter-year CV of 0.14 for age 0 and 0.065 for age 1. To calculate the mean growth coefficient of group 1+ individuals (Gr_{1+}), Obsmer data were used (Table A.1). Cohort split-up was reliable for seven years from 2005 to 2014 (Fig. A.1). Length data obtained from the mixdist package had an inter-year CV of 0.058 in October and 0.054 in December. A CV value of 0.1 was used to construct the parameters μ_{g0} and μ_{g1}, used as mean values for the construction of the priors for $g_{0,y}$ and $g_{1,y}$ (Table A.11). We found a value of 2.816 for Gr_0 and a value of 1.542 for Gr_{1+}, with inter-year CVs of 0.13 and 0.64 respectively.

Natural mortality (M) was calculated using the Caddy (1996) [36] gnomonic time division method. This method assumes that M is a simple function of mean lifespan and is constant. A vector of natural mortality-at-age is calculated: the life-span is divided into several intervals whose duration increases proportionally to the age, and natural mortality is assumed to be constant for each interval. The time-division is called gnomonic, and for each interval, a constant number (β) is obtained when multiplying the instantaneous mortality rate by the interval duration. The initial death rate is assumed to be high, and after a few months, a plateau is obtained. An initial number of individuals must be chosen, and exactly 2 survivors must remain after 2 years to ensure population replacement.

The mortality function was fitted with an initial number of hatchlings (N_1) derived from fecundity estimates. Previous studies on cuttlefish fecundity were used to choose values for the initial number of individuals. Mangold-Wirz (1963) [173] reported that females *Sepia officinalis* may spawn from about 150 to 4,000 eggs depending on their size. Richard (1971) [219] estimated numbers of 150 to 500 eggs by counting mature ova only, and a mean number of 2,000 eggs was observed in laboratory culture (Hanley et al., 1998 [117]). Four values of N_1 are tested: 500, 1,000, 1,500 and 2,000.

The two years life span is divided into a number i of smaller time intervals Δ_i. A value of 2/365 is set for the first interval Δ_1. For each interval:

$$N_{i+1} = N_i \times e^{-M_i \times \Delta_i} \tag{A.3}$$

where M_i is the mortality rate for the interval of duration Δ_i.

$$M_i \times \Delta_i = \beta \tag{A.4}$$

where β is a constant.

To create a series of intervals of increasing duration starting at $t = 0$, given a first time interval $\Delta_1 = t_1$, we multiply the time elapsed to the start of each new interval by a constant multiplier, α (Caddy, 1996 [36]).

$$t_n = \sum_{i=1}^{n} \Delta_i, \quad \text{where } \Delta_i = \alpha \times t_{i-1} \quad (i \geq 2) \tag{A.5}$$

Parameters α and β were calculated using iterations to achieve $\sum_{i=1}^{n} \Delta_i = 2$ and $N_n = 2$.

To estimate the natural mortality of group 1+ individuals (M_{1+}), we set the number of time intervals such that the last time interval ends at $t = 2$ years and lasts approximately 12 months. After the division of the lifespan into 10 gnomonic time intervals, we calculated the decline in numbers such that exactly 2 spawners survive by two years of age. To estimate the natural mortality of group 0 individuals (M_0), we calculated the mean mortality value of the 8^{th} and 9^{th} intervals, which matches the period when animals are between 3 months and 12 months old. We tested four possible values for the initial number of individuals (N_1) for 10 gnomonic time-intervals (Table A.2). With 10 time-intervals, the pre-spawning interval was 11.5 months, so the resulting mortality was related to group 1+ individuals. Once the values of individual growth and natural mortality were calculated, we could obtain *Grand mean* μ_{g0} and *Grand mean* μ_{g1}, used for the construction of μ_{g0} and μ_{g1} (Table A.3).

TABLE A.1 – Number of individuals sampled in Obsmer and CGFS. "*" indicates years that were not used for growth rate calculation because one cohort split-up of this year was not reliable.

Obsmer			CGFS	
Year	**October**	**December**	**Year**	**October**
2005	277	252	2005	341
2006	1035	186	2006	344
2007*	245	138	2007	157
2008	409	220	2008	110
2009	526	161	2009	146
2010*	1304	220	2010	147
2011*	655	153	2011	81
2012	755	796	2012	161
2013	1035	334	2013	131
2014	1001	1488	2014	140

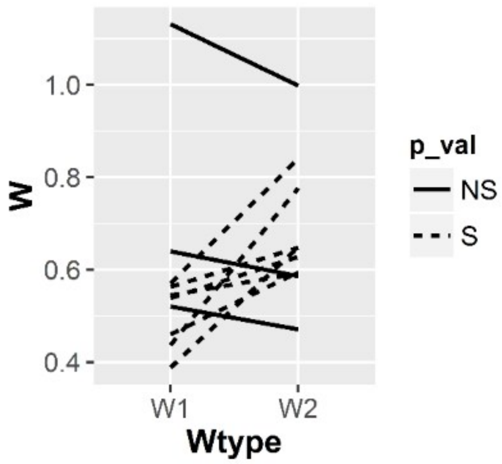

FIGURE A.1 – The variability of mean weight values of group 1+ individuals after cohort split-up of Obsmer length data. W1 is the mean weight in October and W2 is the mean weight in December. Full lines represent the years where p-value of cohort split-up model was not significant (NS). Dotted lines represent the years where p-value of cohort split-up model was significant (S) and therefore used for growth rate calculation.

TABLE A.2 – Estimates natural mortality for different values of N_1 and different pre-spawning intervals.

N_1	a	β	M (group 0)	M (group 1+)	Pre-spawning interval (months)	Number of gnomonic time-intervals
500	0.926	0.552	1.618	0.574	11.5	10
1 000	0.926	0.621	1.821	0.646	11.5	10
1 500	0.926	0.662	1.94	0.688	11.5	10
2 000	0.926	0.691	2.024	0.718	11.5	10

TABLE A.3 – Summary of natural mortality, mean growth coefficient and g parameter.

Age class	Mean mortality	Mean individual growth	Mean biomass growth
0	1.851	2.816	*Grand mean* $\mu_{g0} = 0.97$
1+	0.657	1.542	*Grand mean* $\mu_{g1} = 0.89$

Annexe B : Détails sur le calcul des CPUE à partir des données de la France

To calculate the French LPUE used in this work, we first separated out the catch into two age groups 0 and 1+ for each year and month. Four variables were used in the statistical model to explain the variability of the LPUE: fishing season y, month m, ICES rectangle r and the engine power of the vessel p. No interactions were taken into account. For the engine power, the values were classified into 13 modalities. In the following, $U^{lpue1\_obs}_{y,m,r,p}$ denotes the LPUE abundance indices observed for fishing season y, month m, ICES rectangle r and engine power modality p. To calculate $U^{lpue1\_obs}_{y,m,r,p}$, the catches of group 1+ individuals in kilograms were divided by the effort in number of fishing hours.

We present only the equations related to the calculation of the LPUE time series of group 1+ individuals. The same method was applied for group 0 animals. To account for zero-inflation in the data, a binomial error GLM (Eqn B.1) and a Gaussian error GLM on positive values (Eqn B.2) were developed separately and then combined to provide model estimates of the abundance. Standardized abundance indices $U^{lpue1\_st}_{y,m,r,p}$ were calculated for each fishing season, month, ICES rectangle and vessel power modality as the probability of positive observations multiplied by the expected catch rate conditional to the observations being positive (Eqn B.3).

The binomial GLM model on presence-absence data:

$$logit(U^{lpue1\_obs}_{y,m,r,p})_{0/1} = \alpha_y + \beta_m + \gamma_r + \delta_p + \omega_{y,m,r,p} \tag{B.1}$$

The log-gaussian GLM model on positive data:

$$Ln(U^{lpue1\_obs}_{y,m,r,p})_{>0} = Ln(\alpha_y) + Ln(\beta_m) + Ln(\gamma_r) + Ln(\delta_p) + \varepsilon_{y,m,r,p} \tag{B.2}$$

The prediction of abundance indices based on the combination of the two models:

$$U^{lpue1\_st}_{y,m,r,p} = \frac{e^{logit(U^{lpue1\_obs}_{y,m,r,p})_{0/1}}}{1 + e^{logit(U^{lpue1\_obs}_{y,m,r,p})_{0/1}}} \times e^{Ln(U^{lpue1\_obs}_{y,m,r,p})_{>0}} \times e^{(\frac{\sigma^2}{2})_{>0}} \tag{B.3}$$

where $\omega_{y,m,r,p}$ and $\varepsilon_{y,m,r,p}$ are the residuals for fishing season y, month m, ICES rectangle r and engine power modality p. σ is the standard error of the Gaussian error GLM.

The standardized re-scaled LPUE U^{lpue1}_{y} was calculated for each fishing season as the average on all predicted values divided by the first value of the time series:

$$U_y^{lpue1} = \frac{(\sum_{m,r,p} U_{y,m,r,p}^{lpue1\_st})/N_y^{m,r,p}}{U_1^{lpue1}} \tag{B.4}$$

where $N_y^{m,r,p}$ is the number of predicted values for each fishing season.

Annexe C : Ajustement des modèles LB-SPR et Stock Synthesis aux données de taille

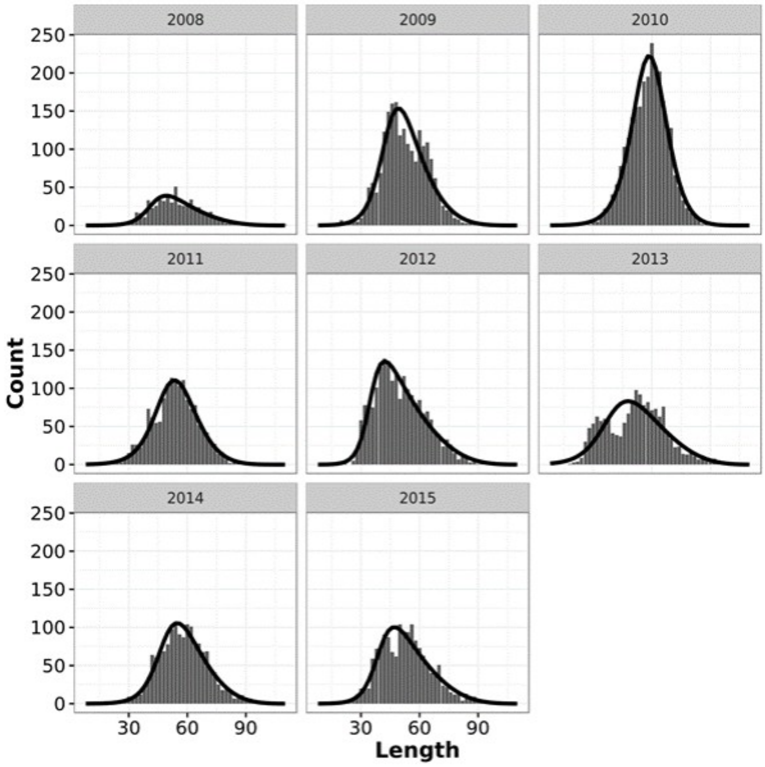

FIGURE C.1 – Fit of the LBSPR model on all length data for each year.

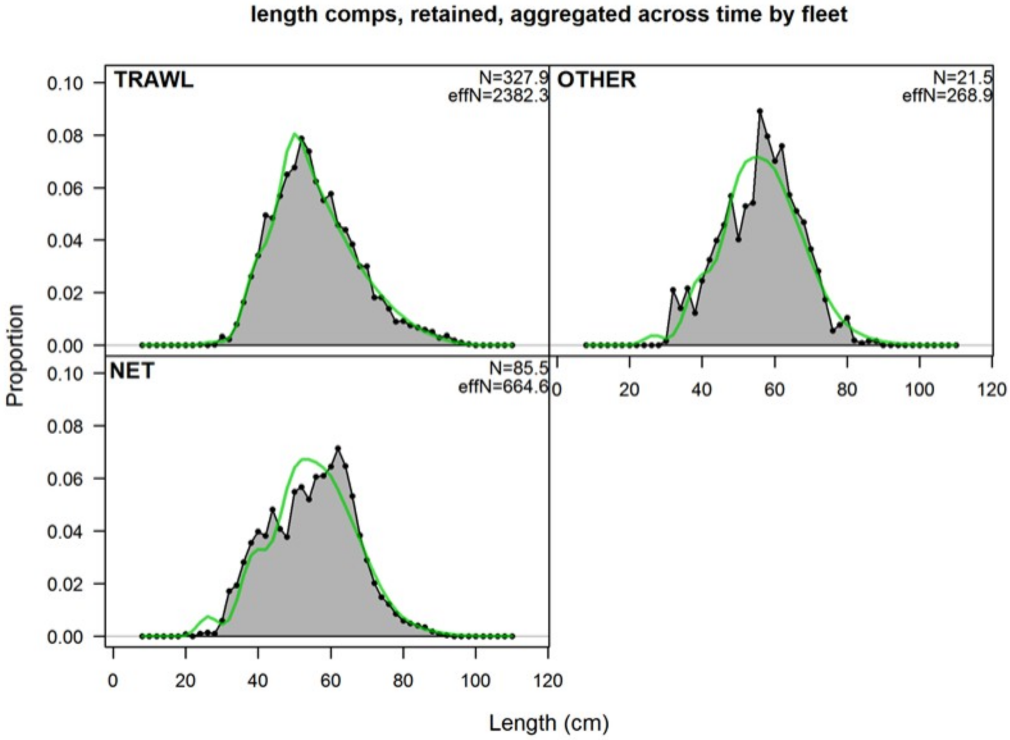

FIGURE C.2 – Fit of the Stock Synthesis model on all length data.

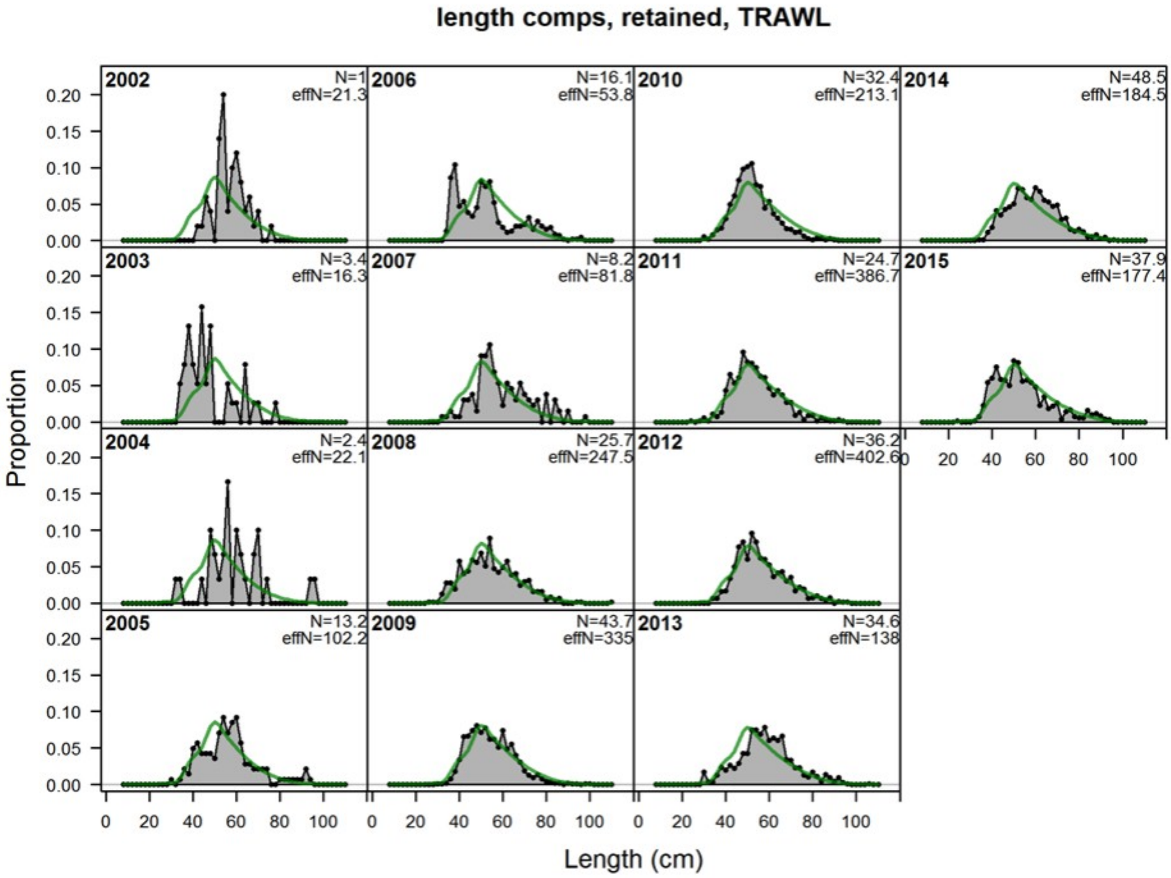

FIGURE C.3 – Fit of the Stock Synthesis model on Trawl length data.

Annexe D : Profils de vraisemblance du modèle Stock Synthesis

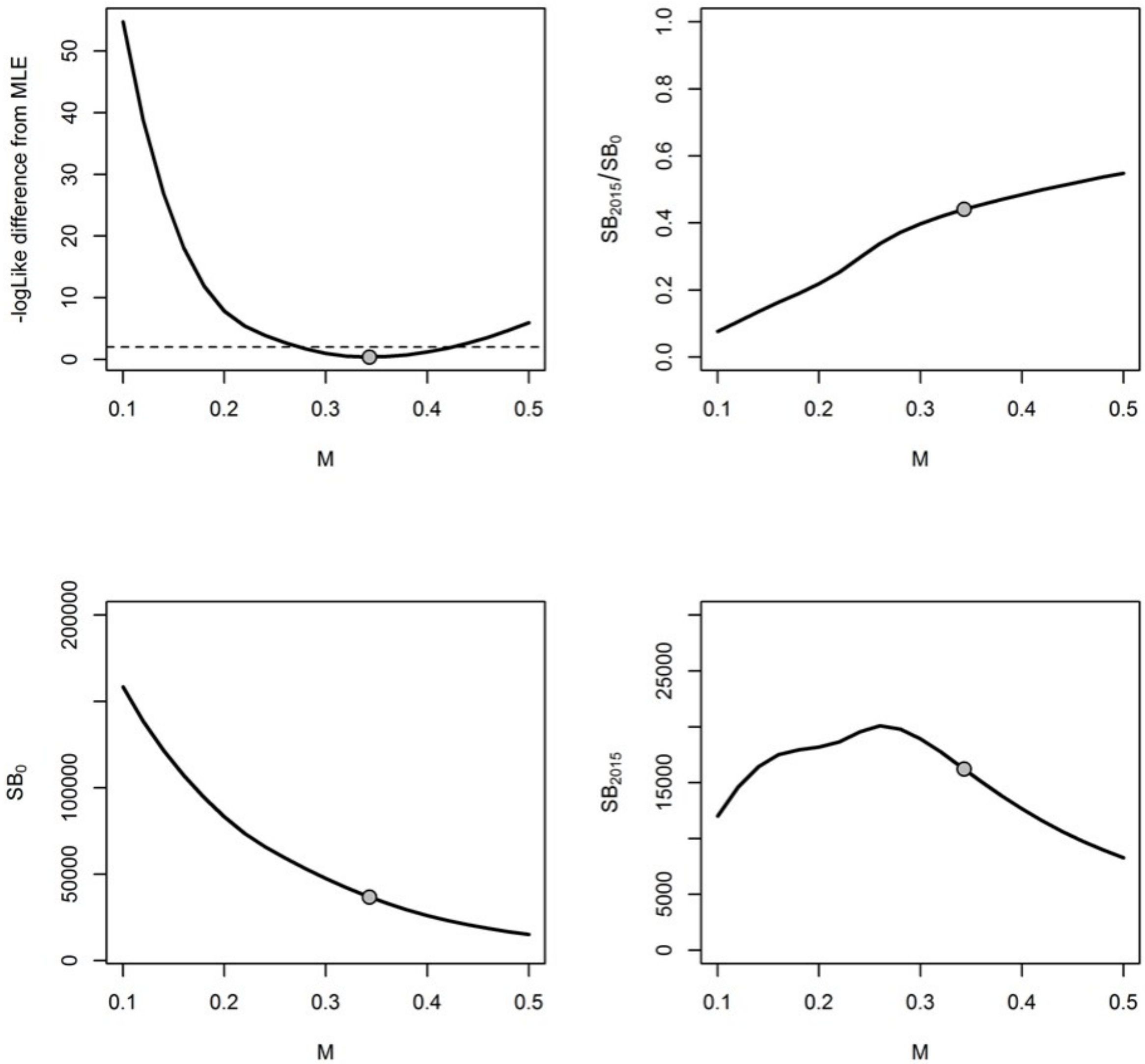

FIGURE D.1 – Profile values on natural mortality parameter.

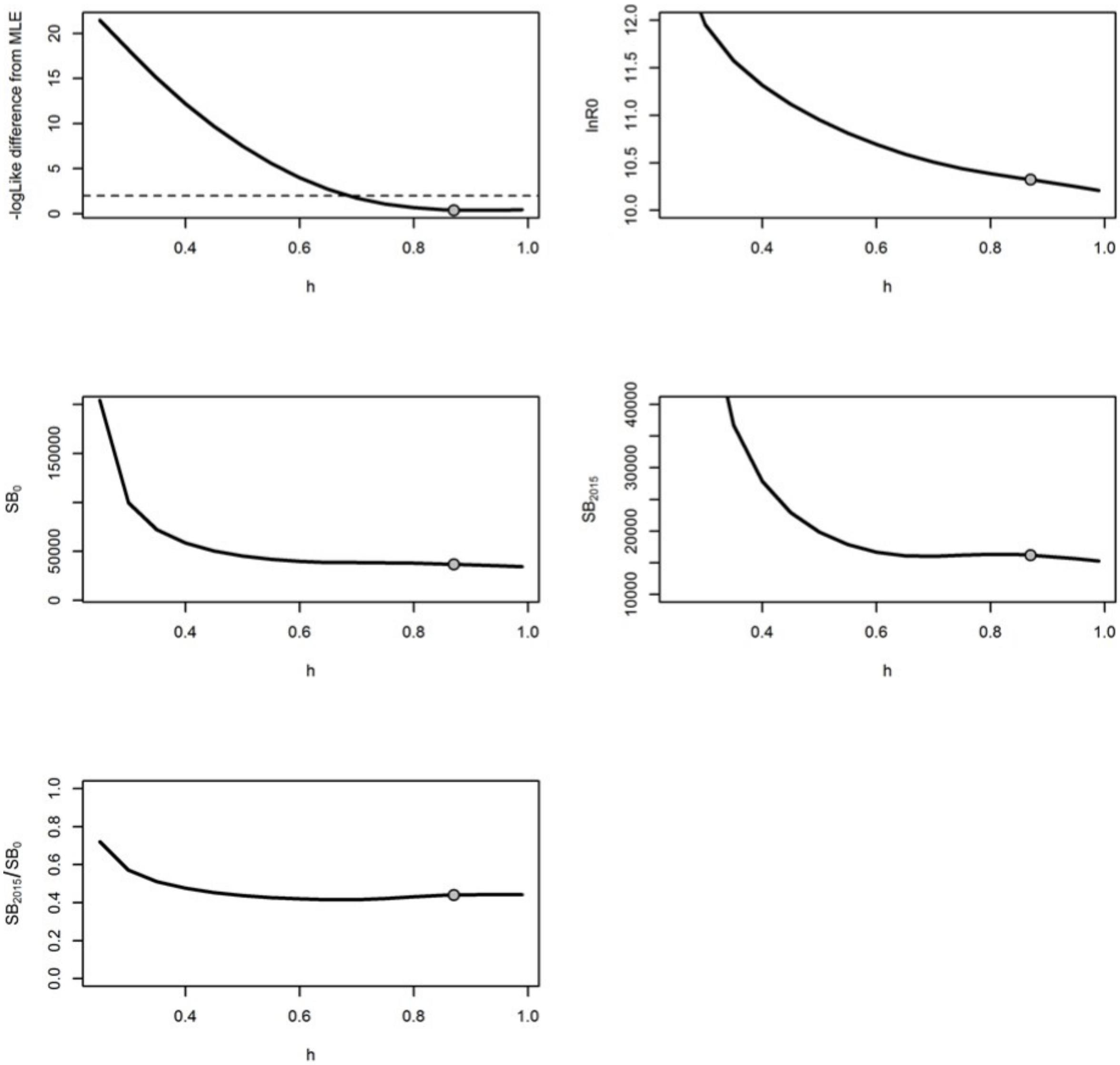

FIGURE D.2 – Profile values on steepness.

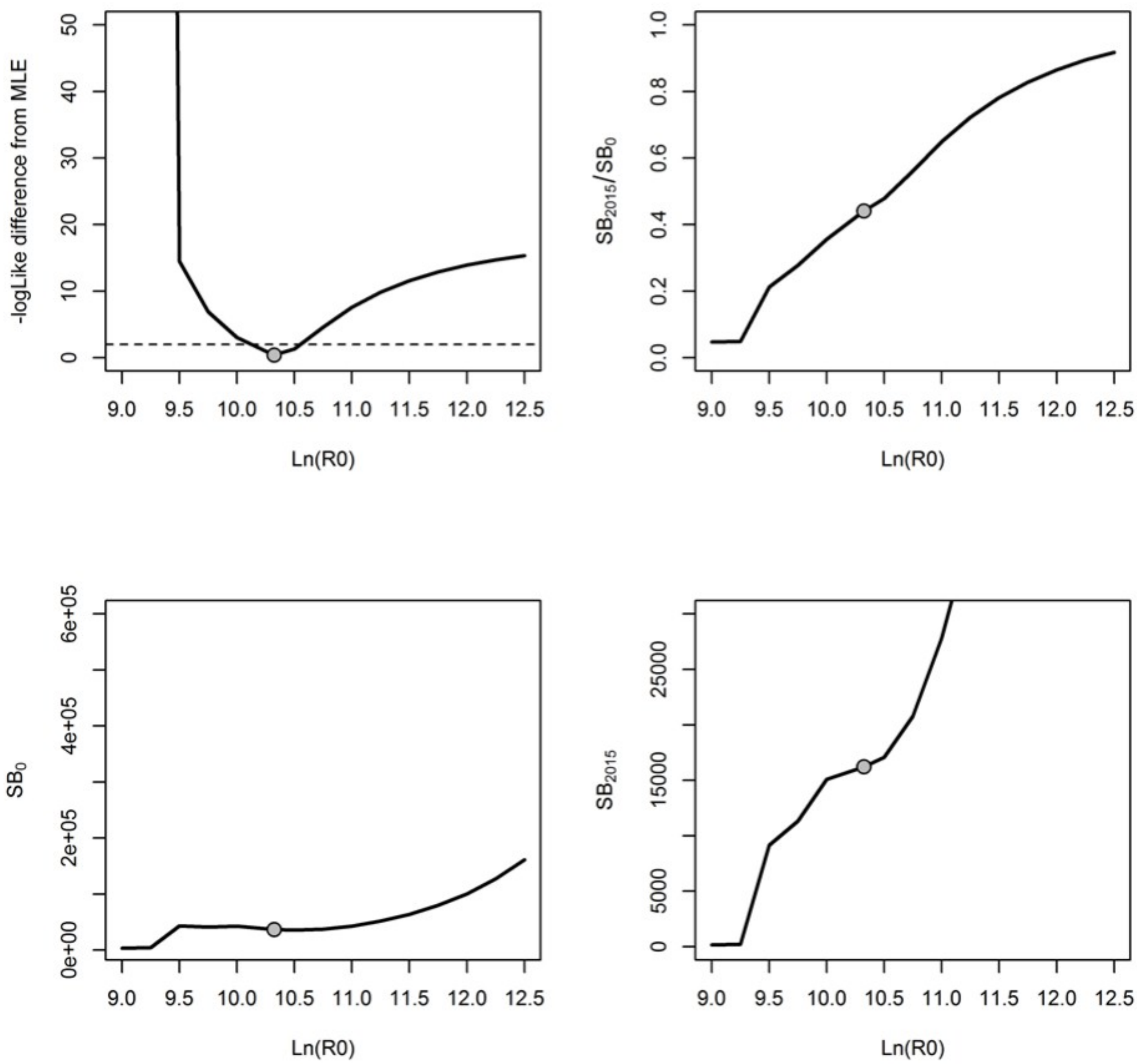

FIGURE D.3 – Profile values on initial recruitment.

Annexe E : Table des résultats du modèle Stock Synthesis

TABLE E.1 – Estimates of parameters obtained from sensitivity analysis runs on model specification.

Label	base model	end sel trawl10	end sel trawl10 top 1	end sel trawl -3	estimated h	estimated h no prior	h 0.8	h 0.97	estimated R	no V
NatM_p_1_Fem_GP_1	0,34	0,34	0,32	0,34	0,34	0,34	0,35	0,34	0,34	0,38
NatM_p_1_Mal_GP_1	0,34	0,34	0,32	0,34	0,34	0,34	0,34	0,34	0,34	0,35
SR_LN(R0)	10,32	10,32	10,24	10,33	10,28	10,21	10,39	10,23	10,31	10,39
SR_BH_steep	NA	NA	NA	NA	0,92	0,99	NA	NA	NA	NA
Q_extraSD_5_SURVEY1	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,15	0,14	NA
Q_extraSD_6_SURVEY2	0,08	0,08	0,09	0,08	0,08	0,08	0,09	0,08	0,06	NA
SizeSel_1P_1_TRAWL	53,50	53,47	53,08	53,50	53,51	53,56	53,55	53,54	53,36	55,43
SizeSel_1P_2_TRAWL	-1,89	0,79	NA	2,73	-1,89	-1,87	-1,87	-1,88	-2,02	0,63
SizeSel_1P_3_TRAWL	4,85	4,85	4,82	4,85	4,85	4,86	4,86	4,86	4,82	5,00
SizeSel_1P_5_TRAWL	-12,59	-12,53	-12,54	-12,59	-12,60	-12,59	-12,60	-12,60	-12,59	-12,74
SizeSel_2P_1_NET	64,44	64,41	63,13	64,46	64,44	64,47	64,51	64,46	64,50	64,95
SizeSel_2P_2_NET	-8,24	-8,29	-8,21	-8,24	-8,24	-8,24	-8,25	-8,26	-8,26	-8,31
SizeSel_2P_3_NET	5,93	5,93	5,89	5,93	5,93	5,93	5,93	5,93	5,93	5,92
SizeSel_2P_5_NET	-11,69	-11,76	-11,61	-11,69	-11,66	-11,68	-11,70	-11,66	-11,68	-11,79
SizeSel_3P_1_OTHER	64,10	64,08	63,04	64,12	64,10	64,13	64,14	64,12	63,81	64,30
SizeSel_3P_2_OTHER	-7,40	-7,38	-7,41	-7,40	-7,40	-7,40	-7,40	-7,39	-7,52	-7,47
SizeSel_3P_3_OTHER	5,72	5,72	5,69	5,72	5,72	5,72	5,72	5,72	5,66	5,69
SizeSel_3P_5_OTHER	-11,04	-11,07	-10,95	-11,04	-11,03	-11,03	-11,05	-11,03	-11,10	-11,14

Label	K 0.2	K 0.16	Linf 96	Linf 100	CV Linf 0.27	Lmat 40	Lmat 48	M 0.2 estimated	M 0.3 estimated	M 0.4 estimated	M 0.34 fixed	M no prior
NatM_p_1_Fem_GP_1	0,36	0,32	0,33	0,34	0,37	0,34	0,34	0,23	0,32	0,37	NA	0,39
NatM_p_1_Mal_GP_1	0,36	0,32	0,33	0,34	0,37	0,34	0,34	0,23	0,32	0,37	NA	0,32
SR_LN(R0)	10,36	10,29	10,30	10,32	10,38	10,31	10,34	9,69	10,20	10,46	10,31	10,35
SR_BH_steep	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Q_extraSD_5_SURVEY1	0,15	0,14	0,15	0,15	0,16	0,15	0,15	0,15	0,15	0,15	0,15	0,15
Q_extraSD_6_SURVEY2	0,08	0,09	0,08	0,08	0,08	0,08	0,08	0,10	0,08	0,08	0,08	0,08
SizeSel_1P_1_TRAWL	53,03	53,94	53,39	53,49	56,56	53,51	53,49	52,38	52,86	54,33	53,44	53,64
SizeSel_1P_2_TRAWL	0,54	0,86	-1,90	-1,89	-1,53	-1,89	-1,89	-1,90	0,62	0,87	-1,90	0,74
SizeSel_1P_3_TRAWL	4,78	4,93	4,86	4,85	5,06	4,85	4,85	4,78	4,80	4,91	4,85	4,86
SizeSel_1P_5_TRAWL	-12,60	-12,56	-12,53	-12,59	-12,77	-12,59	-12,62	-12,41	-12,52	-12,68	-12,62	-12,61
SizeSel_2P_1_NET	63,92	65,05	64,37	64,44	66,81	64,44	64,44	64,32	64,03	65,03	64,40	64,55
SizeSel_2P_2_NET	-8,24	-8,25	-8,26	-8,24	-8,39	-8,24	-8,25	-8,24	-8,27	-8,25	-8,21	-8,25
SizeSel_2P_3_NET	5,87	6,00	5,95	5,93	5,94	5,93	5,93	5,98	5,93	5,94	5,93	5,93
SizeSel_2P_5_NET	-11,76	-11,66	-11,63	-11,69	-11,91	-11,69	-11,64	-11,53	-11,59	-11,76	-11,67	-11,71
SizeSel_3P_1_OTHER	63,71	64,55	64,03	64,09	65,94	64,10	64,10	63,98	63,82	64,51	64,07	64,19
SizeSel_3P_2_OTHER	-7,40	-7,43	-7,37	-7,40	-7,64	-7,40	-7,40	-7,39	-7,40	-7,40	-7,44	-7,40
SizeSel_3P_3_OTHER	5,67	5,77	5,73	5,72	5,71	5,72	5,72	5,76	5,72	5,72	5,72	5,72
SizeSel_3P_5_OTHER	-11,12	-10,95	-10,98	-11,03	-11,24	-11,04	-11,03	-10,87	-10,97	-11,11	-11,00	-11,06

TABLE E.2 – Estimates of spawning biomass, current depletion and initial recruitment obtained from sensitivity analysis runs on model specification (1).

Model name	SB0	SPB 2015	Current depletion	Total yield SPR targeted	Initial recruitment
base model	36815	16224,9	0,441	7259,04	30444,5
end sel trawl 0	36875	16247,8	0,441	7258,84	30401,5
end sel trawl 0 top 1	40028	17506,5	0,437	7269,04	28047
end sel trawl -3	36763	16204,3	0,441	7258,97	30487,3
estimated h	35904	15931	0,444	7172,27	29121,3
estimated h no prior	34527	15280,7	0,443	7002,63	27151,8
h 0.8	37964	16356,4	0,431	7338,96	32457,7
h 0.97	34914	15484,6	0,444	7054,47	27705,8
estimated R	37257	12985,6	0,349	7243,26	30083,3
K 0.2	34841	15150,3	0,435	7201,65	31650,9
K 0.16	39267	17751,5	0,452	7364,75	29468
Linf 96	38053	17038,2	0,448	7320,91	29588,5
Linf 100	36918	16291	0,441	7263,91	30364,8
CV Linf 0.27	32151	13492	0,420	7039,16	32225,9
Lmat 40	37862	17202,1	0,454	7355,11	30169,5
Lmat 48	35166	14757,9	0,420	7117,66	30905,7
M 0.2	50045	12360,1	0,247	6565,55	16181
M 0.3	39388	16358,1	0,415	7112,43	26993,6
M 0.4	34444	15973,2	0,464	7421,55	34842,6
M 0.34	37342	16353,4	0,438	7241,52	30161
M no prior	26715	12745,3	0,477	7487,04	31202,5
no V	29970	13351,1	0,445	7266,5	32640,5

TABLE E.3 – Estimates of spawning biomass, current depletion and initial recruitment obtained from sensitivity analysis runs on model specification (2).

Model name	SB0	SPB 2015	Current depletion	Total yield SPR targeted	Initial recruitment
base model	36814,7	16224,9	0,441	7259,04	30444,5
catch S3	32410,5	14451,5	0,446	7097,77	31697,5
catch S2	36378	15709,4	0,432	7171,95	29802,3
no FR	37373,7	18210,5	0,487	7648,23	34195,9
no IR	36400	15617,9	0,429	7181,97	29714,4
no L	36838,6	19202,4	0,521	7740,23	30255,1
no net L	37790,3	16244,8	0,430	7214,16	32831,1
no other L	37457,2	16455,1	0,439	7166,03	32215,2
no recre	30114,8	17788,3	0,591	6747,43	30925,7
no trawl L	36977,5	19117,4	0,517	7682,87	31581
recre 0-4000	41843	15002,7	0,359	8291	33858
recre 2000	40036,9	20028,8	0,500	8208,83	36589,5
recre 4000	50334,2	22925,6	0,455	9869,56	43493,9

Annexe F : Analyses de sensibilité pour le modèle Simple Stock Synthesis

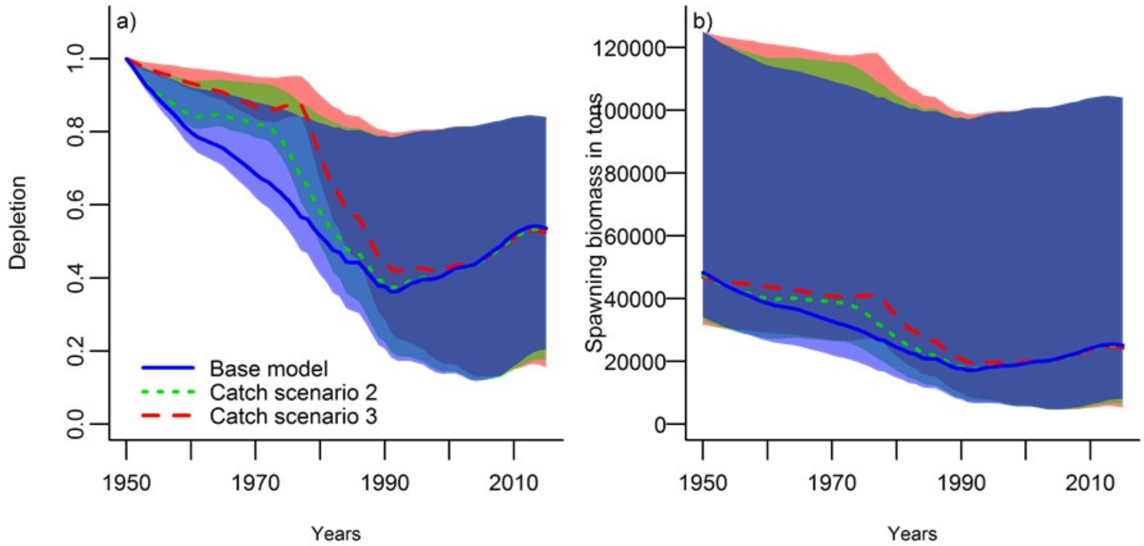

FIGURE F.1 – Results of SSS models based on various specifications on the commercial catch.

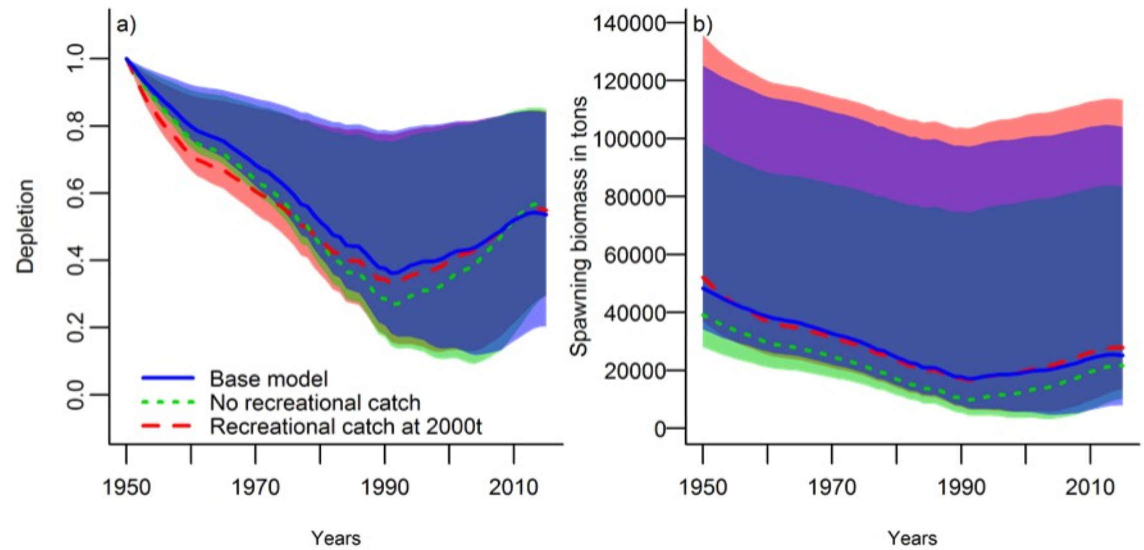

FIGURE F.2 – Results of SSS models based on various specifications on the recreational catch (1).

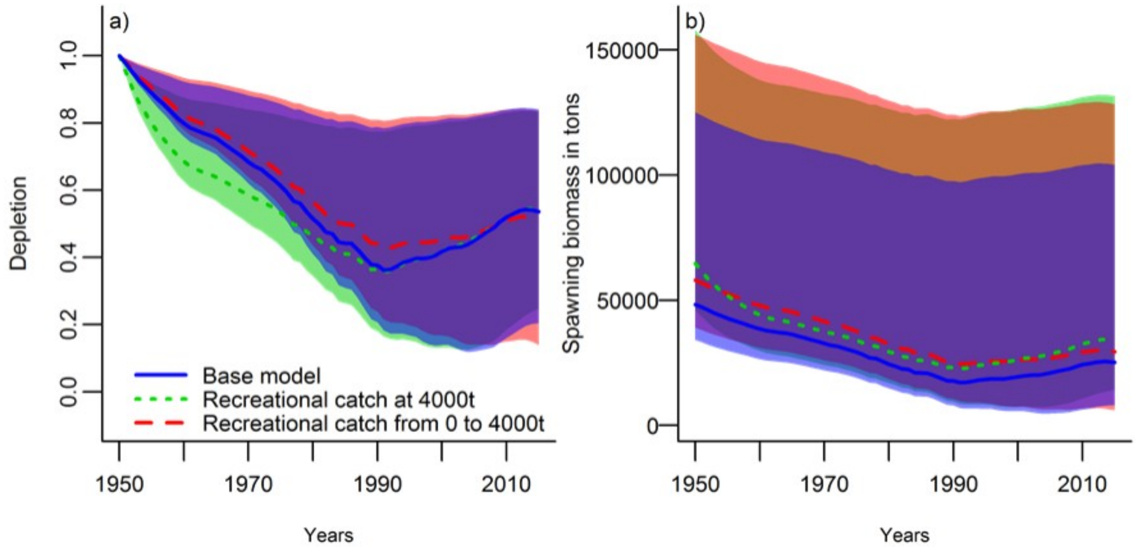

FIGURE F.3 – Results of SSS models based on various specifications on the recreational catch (2).

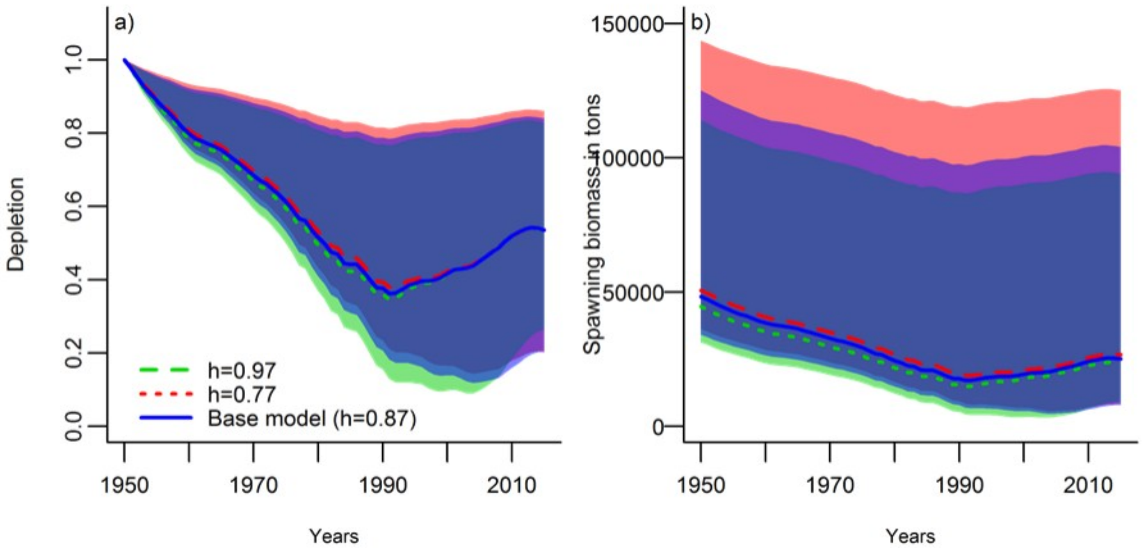

FIGURE F.4 – Results of SSS models based on various specifications on the stepness.

Annexe G : Résultats complémentaires obtenus avec le modèle LB-SPR

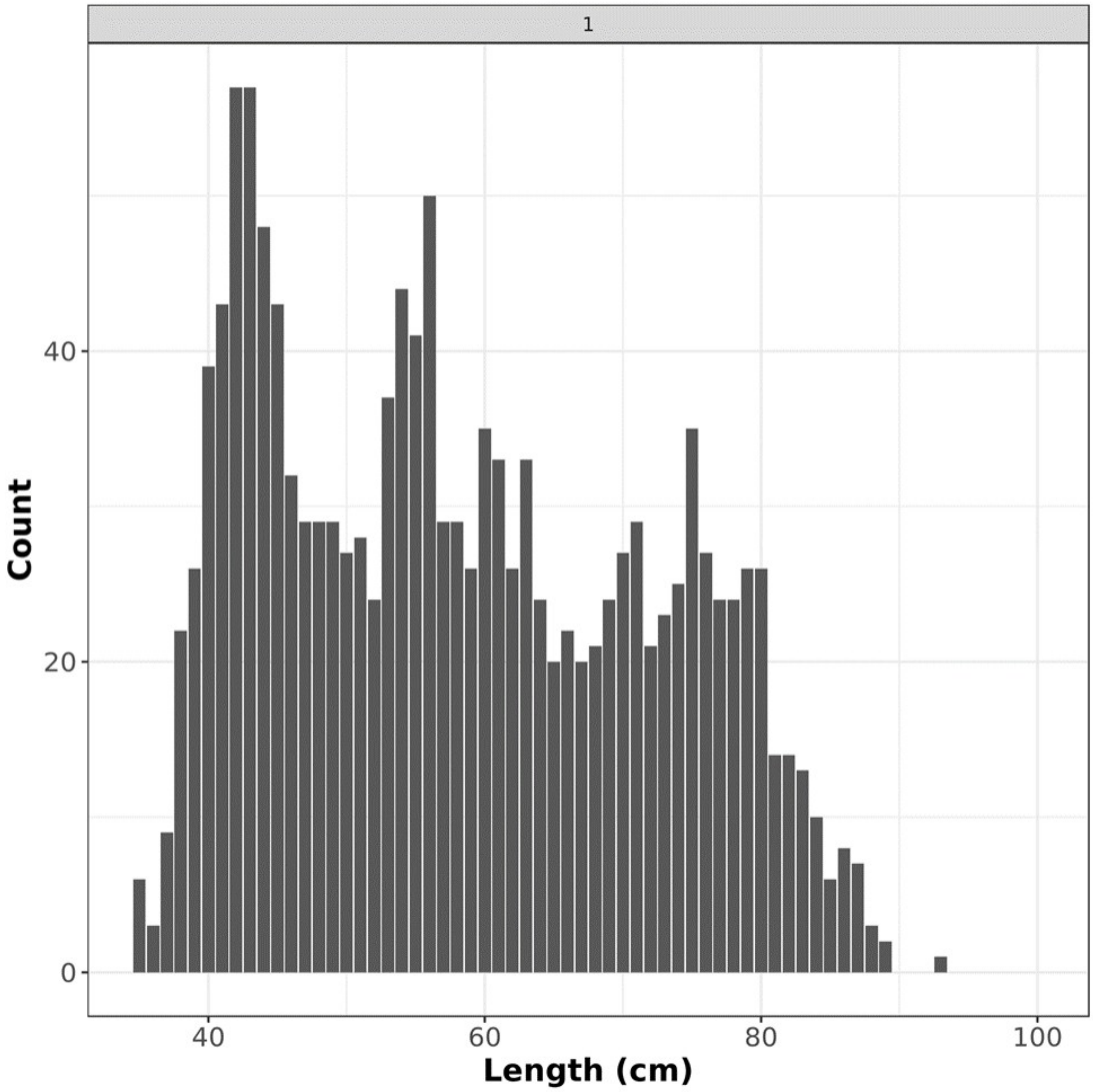

FIGURE G.1 – Size distribution of pollack in 1987. Data come from a small report found in the IFREMER laboratory from Port-en-Bessin. The source could not be clearly identified. A link could be done with the report from Abbes (1991) [2].

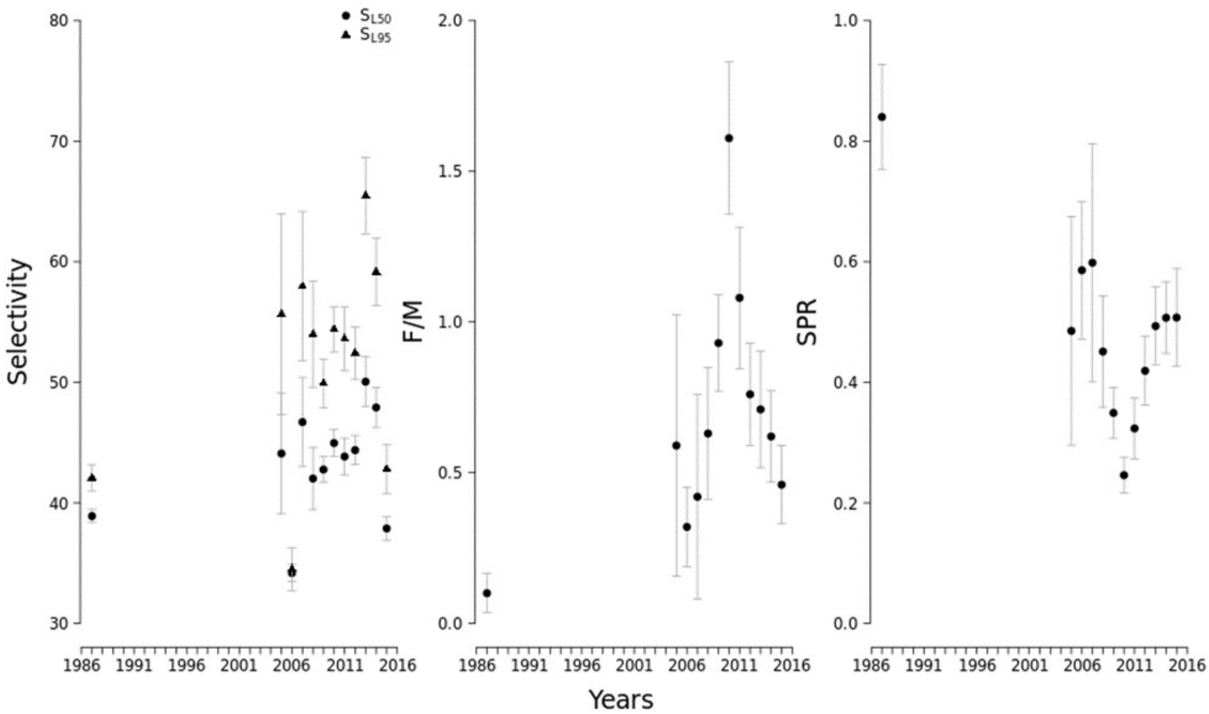

FIGURE G.2 – Results of the LB-SPR model including the size sampling from 1987.

Productions scientifiques

Publications

Alemany, J., Rivot, E., Foucher, E., Vigneau, J., and Robin, J-P. 2017. A Bayesian two-stage biomass model for stock assessment of data-limited species: an application to cuttlefish (*Sepia officinalis*) in the English Channel. Fisheries Research, 191: 131-143.

Alemany, J., Cope, J., Foucher, E., Vigneau, J., Rivot, E., and Robin, J-P. *in prep*. General guidelines for providing MSY advice for data-limited stocks.

Alemany, J., Foucher, E., Rivot, E., Vigneau, J., and Robin, J-P. *in prep*. Stock assessment models for the English Channel stock of cuttlefish.

Alemany, J., Cope, J., Foucher, E., Vigneau, J., Rivot, E., and Robin, J-P. *in prep*. Quantifying stock status of the relatively data-limited stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion using a flexible age-structured modelling framework

Alemany, J., Cope, J., Wetzel, C., Foucher, E., Vigneau, J., Rivot, E., and Robin, J-P. *in prep*. Setting catch limit in a data-limited situation, case study of the stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion.

Alemany, J., Foucher, E., Rivot, E., Vigneau, J., and Robin, J-P. *in prep*. Update of the life-history parameters of pollack (*Pollachius pollachius*) using a Bayesian hierarchical model.

Communications orales

Alemany, J., Foucher, E., Rivot, E., Vigneau, J., and Robin, J-P. 2015. Cuttlefish stock assessment. European Working Group on Cephalopod Fisheries (WGCEPH), 8-11 June 2015, Tenerife, Spain.

Alemany, J., Rivot, E., Foucher, E., Vigneau, J., and Robin, J-P. 2015. A Bayesian two-stage biomass model applied to the English Channel stock of cuttlefish (*Sepia officinalis*). ASC 2015 - ICES annual science conference, 21-25 September 2015, Copenhagen. http://archimer.ifremer.fr/doc/00379/49066/.

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Alemany, J., Rivot, E., Foucher, E., Vigneau, J., and Robin, J-P. 2015. Modèle Bayésien de biomasse à deux stades pour la seiche de Manche. Séminaire AMEDEE – Atelier méthode d'étude de la dynamique des exploitations halieutiques, 15 Octobre 2015, Ifremer Nantes. halieutique.agrocampus-ouest.fr/amedee/presentations/octobre_2015/Alemany.ppsx.

Alemany, J., Foucher, E., Rivot, E., Vigneau, J., and Robin, J-P. 2016. Stock à données limitées : quels enjeux pour le lieu jaune de Manche – Mer Celtique ? Séminaire AMEDEE – Atelier méthode d'étude de la dynamique des exploitations halieutiques, 21 Avril 2016, Agrocampus Ouest Centre de Rennes. http://halieutique.agrocampus-ouest.fr/amedee/presentations/avril_2016/Juliette%20Alemany.pdf.

Alemany, J., Cope, J., Foucher, E., Vigneau, J., Rivot, E., and Robin, J-P. 2017. Assessment of the stock of pollack in the Celtic Seas Ecoregion. European Working Group for the Celtic Seas Ecoregion (WGCSE), 9-19 Mai 2017, Copenhagen.

Alemany, J., Cope, J., Foucher, E., Vigneau, J., Rivot, E., and Robin, J-P. 2017. Une plateforme de modélisation flexible structurée en âge pour estimer le statut d'un stock à données limitées : le lieu jaune (*Pollachius pollachius*) de la mer Celtique. Colloque « Pêches et changements globaux » de l'Association Française d'Halieutique, 28-30 Juin 2017, Ifremer Nantes.

Alemany, J., Cope, J., Foucher, E., Vigneau, J., Rivot, E., and Robin, J-P. 2017. Une plateforme de modélisation flexible structurée en âge pour estimer le statut d'un stock à données limitées : le lieu jaune (*Pollachius pollachius*) de la mer Celtique. Journées scientifiques de l'UMR BOREA, 5-7 Juillet 2017, Université de Caen.

Alemany, J., Cope, J., Foucher, E., Vigneau, J., Rivot, E., and Robin, J-P. 2017. Quantifying stock status of the relatively data-limited stock of pollack (*Pollachius pollachius*) in the Celtic Seas Ecoregion using a flexible age-structured modelling framework. ASC 2017 - ICES annual science conference, 18-21 September 2017, Fort Lauderdale, Florida.

Poster

Alemany, J., Foucher, E., Vigneau, J., and Robin, J.-P. 2015, May. Stock assessment models for short-lived species in data-limited situations: case study of the English Channel stock of cuttlefish (*Sepia officinalis*). Poster presented at the 30th Lowell Wakefield

symposium: 'Tools and Strategies for Assessment and Management of Data-Limited Fish Stocks', Anchorage, Alaska. http://archimer.ifremer.fr/doc/00377/48773/.

Rapports scientifiques

Alemany Juliette, Foucher Eric, Rivot Etienne, Vigneau Joel, Robin Jean-Paul. 2016. Stock assessment of the English Channel stock of cuttlefish with a two-stage biomass model. ICES Working Group on Cephalopod Fisheries and Life History (WGCEPH), Ref. ICES CM 2015/SSGEPD:02 pp.84-98, 16p. http://archimer.ifremer.fr/doc/00377/48774/.

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Vulgarisation scientifique

Participation à la rédaction du livre « Des Léviathans, Regards d'artistes et de chercheurs sur le rapport des sociétés à l'Océan » pages 177-183 avec l'association Périophtalme.

Participation au concours « Ma thèse en 180 secondes ». URL de la vidéo officielle : https://youtu.be/lBENa7PPzuc.

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