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Surexploitation des ressources halieutiques : habitat, récifs artificiels et apprentissage

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A ma famille.

Résumé

Cette thèse a pour thème central l'étude de deux problèmes soulevés dans les pêcheries modernes, la dégradation des habitats et le manque d'informations, qui comptent parmi les causes les importantes de la surexploitation des ressources halieutiques.

Les deux premiers chapitres sont consacrés à l'examen du problème de la dégradation des habitats marins liée notamment aux activités de pêche destructrices. Le modèle de Gordon-Schaefer est prolongé afin de tenir compte de l'impact négatif de la pêche sur les habitats. Les conséquences pour la gestion sont analysées et l'importance de la prise en compte des habitats dans le développement des programmes de gestion des ressources halieutiques est mise en évidence. Le modèle élaboré est ensuite utilisé pour évaluer les bénéfices économiques des récifs artificiels, un outil de gestion auquel font de plus en plus appel les gestionnaires des pêcheries artisanales pour répondre à la dégradation des habitats.

Enfin, dans le troisième chapitre, le rôle de l'information pour une pêche durable est examiné lorsque la ressource est en accès libre. Si, dans les deux premiers chapitres, il est supposé que les informations complètes sont disponibles pour l'élaboration des recommandations de gestion, dans la dernière étude, la décision concernant l'exploitation des ressources halieutiques est prise dans un contexte où aucune information sur la ressource n'est accessible. Cette décision est prise individuellement par chaque pêcheur qui opère dans la pêcherie. En développant un modèle multi-agents, nous montrons l'impact de l'apprentissage des pêcheurs sur la dynamique globale du système halieutique.

Mots clés : Gestion des pêches ; Modèle de Gordon-Schaefer ; Habitats ; Récifs artificiels ; Apprentissage ; Modèle de Roth-Erev ; Pêcheries artisanales.

Abstract

This thesis focuses on two main problems posed in contemporary fisheries : habitat degradation and lack of information. They count among the most important causes of the overexploitation of marine resources.

The first two chapters aim at examining the habitat degradation that is linked to destructive fishing activities. The Gordon-Schaefer model is extended to take account of the negative impact of fishing on the habitats. The consequences for fisheries management are analyzed and the importance of taking into account habitats in the development of fisheries management programs is highlighted. Then the extended model is used to evaluate the economic benefits of artificial reefs, a management tool to which frequently resort the managers of small-scale fisheries to mitigate the effects of habitat degradation.

Finally, in the third chapter the role of information for sustainable fisheries is examined under open access. If in the first two chapters it is assumed that there is complete information, in the last study this assumption is relaxed - no information on the resource is known. The decision concerning the exploitation of marine resources is made individually by each fisherman that operates in the fishery. By developing an agent-based model, we show the impact of individual learning on the global dynamics of the system.

Keywords : Fisheries management ; The Gordon-Schaefer model ; Habitats ; Artificial reefs ; Learning ; The Roth-Erev model ; Small-scale fisheries.

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Introduction générale

Problématique

Cette thèse s'articule autour de trois essais qui abordent le problème de la surexploitation des ressources halieutiques. Les ressources halieutiques sont étudiées dans le cadre de l'économie des ressources naturelles. Cette littérature considère les ressources comme des stocks à exploiter rationnellement. La question est alors de savoir quel est le taux optimal d'extraction (Hotelling, 1931). Les ressources naturelles sont classifiées en deux catégories, épuisables et renouvelables selon qu'elles affichent la capacité de se reproduire ou non. Vu que les ressources halieutiques sont des organismes vivants capables de se reproduire, ils sont considérés comme des ressources renouvelables. L'existence d'un renouvellement rend plus difficile le problème du taux optimal d'extraction (Pearce and Warford, 1993). Les décisions actuelles, qui altèrent le stock de la ressource, peuvent avoir des conséquences sur la ressource dans les périodes à venir.

Les ressources halieutiques comme la plupart des ressources naturelles sont des biens communs ce pour quoi elles nécessitent d'être gérées. Les usagers des ressources halieutiques échouent à tenir compte des coûts que leur prélèvement peut imposer sur les autres usagers. En conséquence, elles sont souvent surexploitées comme les pêcheurs sont incités à exploiter la ressource le plus rapidement possible.

Leur gestion pose d'autant plus de difficultés que, sauf quelques exceptions, les populations halieutiques sont mobiles et ne sont pas visibles avant d'être capturées. Puisqu'elles sont mobiles et habitent dans un monde dont les frontières sont difficiles ou très coûteux à faire respecter, il était difficile, au moins dans le passé, d'instaurer des droits de propriétés sur de telles ressources. L'appropriation réelle du poisson n'intervient qu'avec sa prise. Or, selon l'étude séminale de Hardin (1968), l'absence de droit de propriétés bien définis conduit inévitablement à une surexploitation de la ressource en accès libre et, éventuellement, à sa disparition. Cette situation a été pertinemment décrite comme "everybody's access is nobody's property" (Bromley, 1989). Ainsi, une ressource halieutique en libre accès est l'objet d'une surexploitation biologique et économique. L'économie des ressources naturelles se penche sur la conception des politiques de gestion qui permettraient d'éviter "la tragédie des biens communs".

Il n'en reste pas moins que cette "tragédie" n'est pas toujours inéluctable. Il existe des cas réels où les usagers d'une ressource naturelle se mettent d'accord sur les règles d'exploitation de la ressource afin de prolonger son extraction. De tels cas ont été rapportés par Ostrom (1990) dont les travaux marquent le début d'une nouvelle branche de la littérature économique qui examine l'action collective et les arrangements institutionnels qui en résultent. Cette littérature étudient les conditions sous les quelles ces arrangements peuvent émergés et permettre une gestion efficace par la communauté des usagers concernés, notamment la capacité des usagers à coopérer. La question essentielle est de savoir pourquoi certains utilisateurs d'une ressource naturelle réussissent à bien s'organiser et d'autres non. D'après Ostrom, la compréhension de ces conditions est essentielle pour l'élaboration des politiques de gestion efficaces. Dans la présente thèse, nous ne nous référons pas aux systèmes auto-organisés mais partons d'une situation plus typique où les pêcheurs ne coopèrent pas.

Quels sont donc le statut et les tendances actuels des pêcheries et de leur gestion ? Les ressources halieutiques constituent une source d'alimentation importante pour de nombreux pays. Les captures annuelles des pêches océaniques à l'échelle mondiale totalisent environ 80 millions de tonnes, soit une valeur d'environ 80 milliards de dollars (Sumaila and Munro, 2009). Quoique ces pêches ne soient qu'une source modeste d'emploi dans les pays développés, elles continuent à être une source importante d'emploi dans les pays en voie de développement. Il a été estimé que les pêches océaniques mondiales employaient jusqu'à 200 millions de personnes.

Comme le fait remarquer Clark (2005), la crise actuelle dans les pêcheries mondiales peut être résumée comme "trop de bateaux chassent trop peu de poissons". Il existe beaucoup d'exemples d'effondrements de pêcheries dus à la surpêche telles que la pêche à la morue dans le Nord du Canada, un nombre conséquent de pêches au saumon, pêches aux crustacés, pêches à la sardine et au hareng. La dégradation des habitats a également eu des impacts négatifs considérables sur des stocks de poissons importants notamment sur la pêche au saumon. A l'heure actuelle, d'après FAO, le secteur de la pêche est surinvesti, essentiellement en raison du régime de libre accès, les coûts d'exploitation augmentent, les marges de profit diminuent. Un tiers au moins des principales zones de pêche dans le monde sont surexploitées. L'absence de la gestion de l'accès à la ressource ou l'effondrement des systèmes traditionnels de régulation dans beaucoup de pêcheries une fois que les engins de pêche sont devenus plus mobiles et plus efficace (Berkes *et al.*, 2001) sont à l'origine de l'augmentation de l'effort effectif dans le secteur de la pêche ce qui a entraîné un déclin global des ressources halieutiques. La dégradation des écosystèmes côtiers constitue une autre source de préoccupation grandissante puisqu'ils renferment près des deux tiers de l'ensemble des poissons pêchés dans le monde à un stade ou un autre de leur cycle de vie. Le WRI (2001) estime qu'environ un tiers des écosystèmes côtiers du monde est considéré comme très menacé. Parmi les causes de telles dégradations comptent la surpêche et les méthodes de pêche destructives. Du point de vue économique, la dégradation des habitats entraîne une baisse de la production de poisson (Fluharty, 2000; FAO, 2006) accompagnée de l'accroissement des coûts d'exploitation. Chaque année, la perte de biodiversité coûte des milliards à l'économie mondiale (CE, 2008) affectant en premier lieu les économies en voie de développement et réduisant les possibilités de lutte contre la pauvreté.

Dans l'analyse de ces questions, la dynamique des ressources halieutiques occupe une place centrale. Le renouvellement de la ressource est gouverné par des phénomènes biologiques. Il existe trois classes de modèles qui décrivent la dynamique des populations halieutiques : les modèles de stock-recrutement, modèles du type Beverton-Holt et les modèles de surplus de production. Ces modèles sont utilisés pour estimer à la fois le niveau actuel et le niveau souhaité du stock de poissons et pour déterminer le niveau préféré de captures. Les modèles de stock-recrutement relient le recrutement futur au niveau du stock actuel. Les modèles du type Beverton-Holt (Beverton and Holt, 1998) séparent les populations halieutiques en cohortes selon l'âge ou la taille. La dernière classe de modèles est basée sur le modèle de Gordon-Schaefer (Gordon, 1954; Schaefer, 1954) qui est largement appliqué aux ressources halieutiques et à d'autres ressources naturelles. Les modèles de surplus de production omettent les différences entre les cohortes et les mortalités et modélisent simplement les interactions entre la biomasse et sa croissance.

En économie de la pêche, le renouvellement des ressources halieutiques est en général décrit à l'aide des modèles de surplus de production qui s'appuient sur un modèle démographique - le modèle de Schaefer (1954). A cette première dynamique, naturelle, se superpose une deuxième, économique (Scott, 1955; Smith, 1968; Clark, 2005). Leurs interactions définissent le niveau d'exploitation de la ressource ainsi que sa compatibilité avec les caractéristiques biologiques de la ressource.

Le premier modèle bio-économique dit modèle de Gordon-Schaefer a été proposé par Gordon (1954) qui introduit dans le modèle les coûts d'exploitation et le prix de la ressource. La solution au surinvestissement proposée par Gordon consiste à autoriser ou déléguer la propriété de la pêcherie à un seul et même titulaire. Si la dimension économique n'est pas prise en compte, ce propriétaire unique s'efforcera d'exploiter la pêcherie de sorte qu'un surplus de la population soit prélevé à perpétuité sans altérer le niveau du stock. Si ce surplus prélevable est maximal, on parle du rendement maximum soutenable (Maximum Sustainable Yield) qui reste l'objectif de beaucoup des pêcheries contemporaines (Clark, 2005). C'est un niveau de rendement qui est calculé uniquement sur la base des caractéristiques biologiques de la population. La solution qui intègre également les caractéristiques économiques de la pêcherie suggère d'équilibrer le coût marginal de chaque unité d'effort supplémentaire avec le revenu marginal que cette unité produira. Ce faisant, le propriétaire de la pêcherie exercera le niveau d'effort nécessaire pour produire le maximum de rente soutenable (Maximum Economic Yield).

Même aujourd'hui, l'approche traditionnelle à la gestion des pêcheries repose presque exclusivement sur les modèles de dynamique des populations, avec le rendement maximum soutenable comme un paradigme dominant (Clark, 2006). Les différents régimes de quotas de pêche considérés en général comme un instrument efficace pour la gestion des ressources halieutiques (Wilen, 2000; Newell *et al.*, 2005; Costello *et al.*, 2008) sont définis à partir de la recommandation issue du rendement maximal soutenable (Wilen, 2000). De même, le maximum de rente soutenable est considéré comme un objectif principal dans un nombre de pêcheries (Norman-Lopez and Pascoe, 2011). Il est donc important de construire ces références à partir d'un modèle qui décrit les phénomènes biologiques et économiques ayant lieu dans les systèmes halieutiques avec assez de précision et des données suffisamment précises afin d'éviter de donner des recommandations erronées qui risquent de conduire à l'effondrement des stocks halieutiques.

Le modèle de Gordon-Schaefer a ainsi connu un large nombre de raffinements (Wilen, 2000). Les principales modifications comprenaient l'intégration de l'aspect dynamique du problème (Clark, 2005), l'introduction du cadre multi-espèces en explicitant les relations trophiques qui existent entre différents espèces concernées (Boncoeur *et al.*, 2002; Finoff and Tschirhart, 2003; Gascuel, 2005) et la spatialisation du modèle (Sanchirico and Wilen, 1999, 2001, 2005). Les problèmes d'optimisation associés à ces modèles ont été résolus, en règle générale, à l'aide de la programmation dynamique, des techniques de la théorie des jeux et de l'analyse de l'équilibre.

Jusqu'ici, nous avons brièvement présenté la littérature en économie de la pêche qui s'appuie sur l'analyse de l'équilibre et la programmation dynamique. Cependant, la littérature, qui emploie les techniques de la théorie des jeux pour aborder le problème de la surexploitation des ressources halieutiques, est également considérable. En particulier, elle vise à répondre à la question pourquoi la surpêche peut en effet être une décision économiquement rationnelle (Bailey *et al.*, 2010). Les premiers travaux en économie de la pêche faisant recours à la théorie des jeux (Munro, 1979; Levhari and Mirman, 1980) considèrent deux joueurs qui partagent la même ressource. Les joueurs représentent en général deux pays côtiers ou deux groupes de joueurs formés, par exemple, en fonction du type d'engin de pêche. Grâce à l'application des méthodes de la théorie des jeux, ont été modélisée et analysée, entre autres, la pêche à la morue Arctico-norvégienne impliquant les chalutiers au large et les pêcheurs côtiers (Armstrong and Flaaten, 1991; Sumaila, 1995, 1997), la pêche au thon rouge entre l'Australie et le Japon (Kennedy, 1987) et la pêcherie industrielle pélagique partagée par le Chili et Pérou (Aguero and Gonzalez, 1996). Ces études se sont intéressées non seulement aux gains qui pourraient être générés grâce à la coopération entre les deux parties mais aussi à l'examen des facteurs qui favoriseraient cette coopération (Trisak, 2005). Au cours des années, cette littérature a été enrichie par l'application des jeux répétés (Sumaila, 1995; Kronback and Lindroos, 2006) et séquentiels (Hannesson, 1995; Laukkanen, 2003) impliquant ou non plus de deux joueurs (Kaitala and Lindroos, 1998; Arnason *et al.*, 2000; Lindroos *et al.*, 2007) aux questions relatives à la gestion des ressources halieutiques ce qui a permis de modéliser les interactions entre les pêcheurs, nations ou autorités publiques de façon encore plus réaliste.

Dans la présente thèse, les méthodes traditionnelles de l'analyse de l'équilibre et la programmation dynamique sont utilisées dans les deux premiers chapitres pour aborder le problème de la surexploitation des ressources halieutiques à la lumière de la dégradation des habitats marins. Comme nous l'avons fait remarquer plus haut, la perte et la dégradation des habitats gagne de l'ampleur les dernières décennies et nécessite l'élaboration des programmes de gestion fondés sur des résultats théoriques. Pour ce faire, nous prolongeons le modèle de Gordon-Schaefer en y incorporant les effets négatifs de la pêche sur les habitats et nous nous interrogeons sur la manière dont la prise en compte de l'impact de la pêche sur les habitats modifie les recommandations traditionnelles. Ensuite, nous continuons l'analyse de ce problème en passant outre les frontières traditionnelles qui circonscrivent la régulation actuelle des pêcheries. Celle-ci est souvent qualifiée comme défaillante. L'échec des instruments de régulation traditionnels est causé en partie par leur tendance d'analyser les ressources halieutiques séparément de leur milieu aquatique ce qui a amené à proposer des mesures dont les impacts dépassent largement la gestion du niveau des stocks et celui des captures. L'une de telles mesures suscitant actuellement un grand intérêt auprès des gestionnaires publics ainsi que des pêcheurs consiste à créer artificiellement des habitats propices au développement de la biodiversité marine avec l'immersion de récifs artificiels. Nous nous penchons ici sur les bénéfices économiques potentiels d'une telle politique de gestion des ressources halieutiques et cherchons à savoir à quel degré elle peut répondre au problème de la dégradation des habitats.

Pour examiner le rôle d'information qui a fait l'objet du troisième chapitre, nous avons adopté l'approche agents-centrée[1] qui est de plus en plus sollicitée par les économistes des pêches (Soulié and Thébaud, 2006; Wilson *et al.*, 2007; Little *et al.*, 2009). Elle est particulièrement adaptée à l'analyse des situations d'informa-

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[1] Agent-Based Modeling

tion limitée. L'accès à des informations crédibles est important car une des conditions nécessaires pour toute stratégie de gestion est la disponibilité des évaluations récentes du stock (Clark, 2006). De telles évaluations sont souvent coûteuses et imprécises, ce à quoi on peut s'attendre pour une ressource qui est à la fois mobile et invisible. Puisque les poissons ne peuvent pas être directement observés comme les arbres ou les plantes, constater combien de poissons sont dans la mer ou combien peuvent être prélevés sans affecter la durabilité de la pêcherie est problématique. Plusieurs moyens de réduire le besoin en évaluations précises du stock ont été mis en avant y compris l'utilisation des quotas sur l'effort plutôt que des quotas sur les captures (Clark, 2006) et la création des aires marines protégées afin d'éviter les erreurs de gestion (Lauck *et al.*, 1998; Doyen and Béné, 2003). Pourtant, le manque d'information a effet non seulement sur les décisions d'un gestionnaire éventuel mais aussi sur les décisions individuelles des pêcheurs. Nous nous intéressons ainsi, dans le dernier chapitre, au rôle de l'apprentissage individuel dans le cas des agents (pêcheurs) décentralisés ayant des informations limitées.

Méthodes

Le présent travail de recherche s'appuie sur deux approches différentes : l'approche économique conventionnelle et l'approche agents-centrée. Dans l'approche conventionnelle, il est en général supposé que les agents économiques sont homogènes ou qu'il existe au plus deux ou trois catégories d'agents (Arthur, 2006) ; qu'ils sont rationnels, c'est-à-dire que leur objectif est la maximisation de l'utilité ; qu'ils anticipent et calculent très vite les conséquences de leurs actes. Ces hypothèses permettent d'analyser des phénomènes économiques avec un modèle suffisamment simple pour produire des résultats analytiques explicites. Le comportement des agents, qui est en réalité le fruit de processus complexes où interviennent de nombreux facteurs, est supposé être exprimé par des fonctions mathématiques simples. Cette approche a connu un grand succès et a permis d'obtenir un certain degré de compréhension. Les deux premiers chapitres, étudiant les situations où les agents disposent d'informations complètes, rentrent dans le cadre de l'approche conventionnelle. Dans le troisième chapitre, ce sont les expériences passées différentes pour chaque agent qui sont au coeur de notre analyse. Nous ne pouvons donc pas traiter les agents comme homogènes. Même si les agents sont homogènes au départ (comme nous le supposons dans notre étude), ils ne peuvent pas être au même endroit au même moment et, ainsi, ils ont des histoires différentes et deviennent hétérogènes (Bruun, 2004). L'approche agents-centrée qui est une approche algorithmique permet de relâcher l'hypothèse d'homogénéité des agents de même que l'hypothèse de rationalité (en particulier, l'hypothèse de connaissance commune et de capacités de calcul illimitées) qui a été remise en question par les économistes depuis le travail de Simon (1955). Puisque, pour les analyses qui traitent les agents individuellement, les formulations analytiques sont souvent très complexes, les modélisateurs ont souvent recours à des calculs numériques ce que nous sommes également amenés à faire dans notre dernière essai.

Nous avons ainsi deux raisons suivantes pour lesquelles nous nous recourrons à l'approche agents-centrée : la possibilité de modéliser le comportement individuel des pêcheurs qui n'est pas forcément rationnel et d'analyser les situations où les informations sont limitées. Dans le cadre de cette approche, afin de décrire le comportement des agents et son évolution au cours du temps, on leur associe en général un modèle d'apprentissage selon lequel ils révisent leurs décisions.

Même s'il est communément accepté par les économistes que les individus ne se comportent pas de manière optimale, la littérature économique sur l'apprentissage a un lien avec l'optimisation. Pour décrire l'apprentissage des agents économiques, les économistes font souvent appel à l'apprentissage bayésien qui concerne l'apprentissage individuel d'un agent et suppose que l'individu établit un ensemble d'hypothèses sur les situations qu'il confronte (). Chaque hypothèse correspond à une assertion probabiliste sur l'occurrence d'un évènement. Ces probabilités sont recalculées à chaque pas de temps. La décision de l'action est basée sur la maximisation des utilités espérées de chaque action. Pourtant, deux remarques critiques ont été mises en avant. Premièrement, les humains ne sont pas en mesure d'effectuer les calculs nécessaires pour réviser proprement les probabilités des évènements. Deuxièmement, les humains ne considèrent pas un large nombre d'hypothèses concurrentes en même temps.

Un nombre d'études a montré que face à des décisions complexes sous informations limitées, les individus ne prenaient pas des décisions qui seraient cohérentes avec les estimations des probabilités bayésiennes et la théorie de l'utilité espérée. Il a été constaté que l'évaluation des probabilités conditionnelles était souvent une tâche difficile pour les individus (Holland, 2008). Ils ont recours aux règles de décisions simples basées sur des analogies et des modèles de conduite plutôt que sur le principe d'utilité (McFadden, 1999, 2006).

Dans notre étude, nous avons choisi l'apprentissage par renforcement qui est parmi les modèles d'apprentissage dominants en économie (). L'apprentissage par renforcement est basé sur un phénomène psychologique suivant : si l'action conduit à un résultat positif, la fréquence de cette action augmente ; si elle entraîne un résultat négatif, sa fréquence diminue (Duffy, 2006). Il ne suppose donc pas de réflexion consciente sur la situation comme c'est le cas avec l'apprentissage bayésien ou d'autres apprentissages s'appuyant sur les croyances. Selon l'apprentissage bayésien, les individus savent formuler les hypothèses ainsi que calculer les probabilités de chaque évènement tandis que, selon l'apprentissage par renforcement, les individus ne font qu'observer le gain engendré par l'action choisie et transformer les probabilités de choisir une action en fonction de cette observation (ils ne sont pas conscients qu'ils agissent de manière probabiliste).

Dans ce qui suit, nous présenterons les questionnements et les motivations des trois chapitres qui constituent cette thèse.

Habitats

Puisque le fonctionnement des écosystèmes marins n'est pas entièrement étudié, les modélisateurs font des hypothèses simplificatrices sur le comportement de la ressource halieutique (Wilen, 2000; FAO, 2003; Armstrong, 2007). Bien que des modèles simples réussissent dans certaines situations à servir de bonne référence, parfois des hypothèses trop éloignées de la réalité sont responsables de l'effondrement des populations marines (Wilson *et al.*, 1994; Dhoray and Teelucksingh, 2007) particulièrement dans les pêcheries artisanales (Mahon, 1997; Berkes *et al.*, 2001). Le manque de ces connaissances scientifiques, le manque d'information sur les paramètres biologiques et économiques des systèmes halieutiques et la dépendance de ceux-ci de plusieurs facteurs responsables de la variabilité en dynamique de la ressource empêchent d'atteindre les objectifs des pêcheries (Sethi *et al.*, 2005; Vardas and Xepapadeas, 2010). On constate que les ressources halieutiques disparaissent rapidement (Botsford *et al.*, 1990; Jackson *et al.*, 2003; Worm *et al.*, 2006) accentuant le besoin de passer aux modèles intégrant la biodiversité (Hanna, 1999; Manickchand-Heileman *et al.*, 2004; Akpalu, 2009).

Dans les deux dernières décennies, un grand nombre de prolongements du modèle standard de Gordon-Schaefer a été proposé où certaines hypothèses biologiques et économiques trop contraignantes avaient été relâchées (Wilen, 2000; Rodwell *et al.*, 2003; Schnier, 2005; Reithe, 2006). La dimension spatiale a été intégrée à la fois dans la dynamique biologique et économique (Sanchirico and Wilen, 1999, 2001, 2005), les chaînes trophiques ont été prises en compte (Boncoeur *et al.*, 2002; Christiansen and Walters, 2004; Gascuel, 2005) et, récemment, l'importance du lien habitat-ressource a été mise en avant (Armstrong and Falk-Petersen, 2008). C'est cette dernière littérature qui nous intéresse dans le premier chapitre de cette thèse.

Parmi les hypothèses simplificatrices qui concernent le lien habitat-ressource, on rencontre l'hypothèse de capacité de charge invariable dont nous tentons de s'affranchir. La notion de capacité de charge est ainsi une notion centrale dans ce chapitre. Elle peut avoir des interprétations différentes selon la discipline en question. En économie de la pêche, la capacité de charge définit une limite à la croissance de la ressource due à la rareté de l'espace, de la nourriture et d'autres facteurs. Elle représente donc un stock maximum : la ressource ne peut pas se régénérer à des niveaux supérieurs à la capacité de charge de l'écosystème où elle existe.

Il a été montré que ce niveau du stock dépendait de l'état des habitats (Hakoyama *et al.*, 2000; Griffen and Drake, 2008) qui, à son tour, est sujet à des pressions anthropogéniques importantes. Les travaux portant sur les effets de la pêche sur les habitats marins deviennent de plus en plus nombreux. La sensibilité des habitats aux activités de pêche a été montrée par un grand nombre d'études Auster *et al.* (1996); Roberts and Sargant (2002); Mangi and Roberts (2006). La capacité de charge des habitats peut diminuer par suite de l'utilisation des méthodes de pêche destructives (FAO, 2006). L'intégration du lien entre les habitats, les activités de pêche et la ressource dans les modèles bio-économiques standards présente ainsi un prolongement substantiel. L'omission des habitats de ces modèles peut avoir des implications considérables pour les pêcheries (Armstrong and Falk-Petersen, 2008) : la destruction des habitats est considérée comme une des causes de l'effondrement des pêcheries même celles qui sont régulées (WRI, 2001). Nous développons ainsi la dynamique biologique de la ressource en introduisant le lien entre la capacité de charge, qui reflète à un certain degré l'état des habitats, l'effort de pêche et la ressource. Etant donné que la pêche a une incidence non négligeable sur la capacité de charge à travers la dégradation des habitats, il est plus réaliste de considérer la capacité de charge comme variable et dépendante de l'effort de pêche. C'est une façon simple de prendre en compte la dégradation des habitats. Nous examinons l'impact de la négligence du lien entre la capacité de charge et l'effort de pêche sur la conception des outils de gestion traditionnellement utilisés dans les pêcheries. Deux prolongements du modèle de Gordon-Schaefer ont ainsi été développés. Dans l'un, la capacité de charge est considérée comme une fonction des activités de pêche. Dans l'autre qui semble mieux représenter l'évolution des habitats, la capacité de charge est dotée de sa propre dynamique similaire à celle utilisée pour décrire la dynamique du stock de poissons. Dans ce dernier cas, il s'agit d'un modèle à deux espèces en relation symbiotique où la capacité de charge est considérée comme une "espèce" dont la capture n'apporte rien en termes de profits. Un cadre multi-espèce pour modéliser les habitats a déjà été évoqué par Armstrong and Falk-Petersen (2008). Dans les deux prolongements, l'impact négatif de la pêche sur les habitats et, en conséquence, sur la ressource est introduit à travers la capacité de charge.

En étudiant ces modèles, nous avons démontré de manière analytique que la négligence du lien entre la capacité de charge et les activités de la pêche pourrait être responsable de la surestimation des niveaux du stock correspondant au rendement maximal soutenable (Maximum Sustainable Yield, MSY) et au maximum de rente soutenable (Maximum Economic Yield, MEY) et ainsi empêcher d'atteindre les objectifs visés. De plus, dans le cas du deuxième prolongement qui est supposé mieux décrire les processus réels de l'écosystème, l'omission du lien habitats-ressource peut avoir une incidence encore plus importante sur la pêcherie. La surestimation de la capacité de pêche est également observée dans le cas dynamique.

Ces résultats sont en cohérence avec les tendances observées pour les pêcheries contemporaines. L'effondrement des stocks commerciaux est souvent causé par les erreurs de la détermination des quotas sur les captures basée sur l'évaluation des niveaux de stock MSY et MEY (Roughgarden and Smith, 1996; Sethi *et al.*, 2005). La littérature économique actuelle appelle ainsi à la précaution dans la détermination des Totaux Autorisés de Captures (TAC) et soutient l'importance de la prise en compte des différents éléments de l'écosystème, des interactions avec des espèces non cibles et des différentes facteurs de variabilité de l'écosystème (Emery *et al.*, 2012).

Récifs artificiels

L'examen du problème de la dégradation des habitats est poursuivi dans le deuxième chapitre. Puisque la productivité des stocks à long terme est liée à la capacité de charge de leur habitat, il est intéressant du point de vue tant biologique qu'économique d'améliorer l'habitat en créant d'une manière écologiquement rationnelle des récifs artificiels, structures artificiels remplissant le rôle des habitats naturels, qui peuvent influer positivement sur la capacité de charge (FAO, 2006). Les bénéfices écologiques et économiques des récifs artificiels ont été mis en évidence par de multiples suivis réalisés aux Etats-Unis, au Japon, en France, Espagne et dans beaucoup d'autres pays. Aux Etats-Unis, les bénéfices économiques totaux estimés s'élèvent jusqu'à des centaines de millions de dollars (Ditton *et al.*, 1999; Johns *et al.*, 2001; Sutton and Bushnell, 2007). Au Japon, le budget annuel de près d'un milliard d'euros est consacré aux financements et à la recherche de ce type d'aménagements (Pioch, 2007). En France, les récifs artificiels est une politique de pêche particulièrement répandue en Méditerranée. Contrairement aux Etats-Unis où c'est essentiellement les récifs artificiels de loisir qui sont utilisés, en France, les aménagements des fonds marins rentrent dans le cadre d'une politique d'appui aux pêcheries commerciales (les récifs de production et les récifs de protection). Le premier essai a été réalisé à Palavas-les-Flots en 1968, au Languedoc-Roussillon, région pionnière en matière d'immersion de récifs artificiels (Véron *et al.*, 2008). A partir de 1985, des projets plus importants ont été mis en place à Agde, Gruissan, Port la Nouvelle, Canet, Saint-Cyprien, pour en citer quelques un, et certains ont été ensuite étendus.

Depuis quelques années, la région PACA est également devenue un site important d'immersion de récifs artificiels. La mise en pratique de tels aménagements a débuté en 1983 avec la création du Parc Marin de la Côte Bleue où l'installation de récifs artificiels a été accompagnée par une mise en place des réserves marines. Le projet récifs le plus significatif en PACA a été réalisé en 2007-2010 dans la baie du Prado à Marseille.

Certains sites où les récifs artificiels ont été immergés ont fait l'objet des études et suivis réguliers qui ont confirmé que les récifs artificiels étaient capables de produire un large éventail de bénéfices économiques (Jensen, 2002; Adams *et al.*, 2009). En particulier, ils servent à améliorer la productivité de la ressource (Bohnsack *et al.*, 1994; Santos and Monteiro, 1998; Claudet and Pelletier, 2004) et par la suite la rentabilité économique de la pêcherie (Whitmarsh and Pickering, 1995, 1997; Whitmarsh *et al.*, 2008). Nous nous intéressons à ces structures en tant qu'un outil de gestion des pêcheries commerciales qui vise à améliorer leur rentabilité économique en palliant au manque d'habitats. Grâce à leurs propriétés écologiques, les récifs artificiels ont connu un grand succès dans les pêcheries artisanales (Véron *et al.*, 2008).

Bien que devenu un outil de gestion assez répandu dans les pêcheries artisanales, la littérature économique fournit peu de recherches portant sur les récifs artificiels. Quelques tentatives de modéliser les effets des récifs artificiels ont été faites dans le cadre du modèle bio-économique de Gordon-Schaefer (Whitmarsh and Pickering, 1995, 1997; Boncoeur, 2008). En général, les modélisateurs traduisent l'effet habitat induit par l'amélioration de la qualité des habitats par une augmentation du taux de croissance de poissons et/ou une augmentation de la capacité de charge. Une telle approche de modélisation coïncide avec celle adoptée pour décrire l'effet habitat engendré par une réserve et étudier son impact sur la taille de la réserve nécessaire pour produire les niveaux du stock et des prélèvements correspondant au cas d'un propriétaire unique (Armstrong, 2007; Flaaten and Mjolhus, 2010; Yamazaki *et al.*, 2010).

Il est évident que les réserves et les récifs artificiels sont deux mesures de gestion des pêcheries différentes dans le sens où les réserves contrôlent l'accès alors que les récifs n'impose aucune contrainte sur l'accès. La littérature précédente prend en compte cette différence. Cependant, aucune distinction n'est faite à l'égard de l'effet habitat. L'effet habitat des récifs a une différente nature que celui d'une réserve. Dans le cas des récifs, cet effet est atteint grâce à la création des habitats tandis que, dans le cas d'une réserve, il résulte de l'élimination de la pression de pêche dans la zone de réserve et donc de l'absence d'une pêche destructive. Si les récifs artificiels sont immergés et ne sont pas accompagnés d'interdiction de l'accès (comme dans la réserve), la ressource continue à être prélevée et les habitats continuent à être dégradés par des engins de pêche destructifs. Ainsi, les réserves et les récifs diffèrent également en termes d'effet habitat. Pour pouvoir mesurer correctement les impacts économiques des récifs artificiels et évaluer sa performance en tant qu'une réponse à la dégradation des habitats, il est nécessaire de tenir compte de ces nuances lorsque les effets des récifs artificiels sont modélisés et intégrés dans les modèles de pêche. C'est l'objectif du deuxième chapitre. Nous nous démarquerons de la littérature précédente en considérant les effets négatifs de la pêche sur les habitats qui sont omis de l'analyse bio-économique actuelle (Whitmarsh and Pickering, 1995, 1997; Boncoeur, 2008). Les bénéfices économiques des récifs artificiels sont ainsi étudiés à la lumière des interactions entre les effets négatifs de la pêche et les effets positifs des artificiels sur les habitats.

Pour exprimer l'effet "habitat" des récifs artificiels, nous introduisons une relation positive entre la capacité de charge et la taille des récifs dans le modèle développé dans le premier chapitre. Les questions sur lesquelles nous nous penchons sont les suivantes. Pour quelles pêcheries l'installation des récifs artificiels peut-elle apporter des bénéfices économiques ? Qu'apportent-ils si la pêcherie est en libre accès et elle n'est régie par aucune règlementation ? Sous quelles conditions est-il optimal de mettre en place les récifs artificiels si un cadre dynamique est considéré ? Dans quelle mesure la performance économique des récifs artificiels est dépendante du taux de dégradation des habitats ?

Il est important de noter ici que les explications que nous avons données ci-dessus concernent les récifs artificiels de production c'est-à-dire les structures censées produire de la biomasse. Il existe également un autre type de récifs artificiels dits "de protection" qui empêchent l'accès à certains types d'engins destructifs. Nous nous intéressons à ce type de dispositif en tant qu'un outil de contrôle d'accès. Nous avons ainsi exploré la performance des récifs artificiels sous les quatre régimes suivants : accès libre, contrôle de l'effort, contrôle des engins de pêche via les récifs artificiels de protection ou combinaison des deux contrôles.

Selon nos résultats, la politique publique sous forme de récifs artificiels est en mesure de générer des bénéfices économiques si elle est accompagnée d'un contrôle d'accès à la zone des récifs. Toutefois, sous certaines conditions, l'objectif traditionnel du rendement maximal soutenable peut être atteint même en accès libre grâce à l'installation des récifs artificiels. Dans le cas dynamique où deux variables de contrôle sont considérées, la taille des récifs artificiels et le niveau d'effort de pêche, nous avons trouvé la stratégie optimale qui établit les conditions sous lesquelles l'immersion des récifs artificiels améliore la rente économique de la pêcherie par rapport au scénario où le seul instrument de gestion est le contrôle de l'effort.

Apprentissage

Les deux premiers chapitres font appel à une analyse économique conventionnelle qui traite les systèmes halieutiques comme contrôlables à condition que des informations suffisantes soient disponibles. Or, les pêcheries se caractérisent souvent par un manque d'information (Holland, 2008). Presque toutes les décisions concernant l'exploitation des ressources halieutiques sont sujettes à de nombreuses sources d'incertitude (Sethi *et al.*, 2005). La quantité de ressource halieutique ainsi que son taux de régénération ne peuvent pas être connus avec exactitude. De plus, nous ne connaissons pas toutes "les règles de changement" qui gouverneront les dynamiques futures (Walters and Martell, 2004). Enfin, la dynamique écologique est fortement influencée par des facteurs environnementaux jusqu'à présent imprévisibles.

Ainsi, la contrôlabilité des systèmes halieutiques est une forte hypothèse (Mahon *et al.*, 2008). L'approche standard d'optimisation basée sur l'hypothèse d'information parfaite qui est souvent adoptée en économie de la pêche n'est donc pas toujours en mesure de fournir une solution adéquate relative à la gestion d'une pêcherie donnée. Il est donc enrichissant d'étudier les situations où les informations disponibles sont insuffisantes pour appliquer correctement les recommandations traditionnelles.

En plus d'être un obstacle pour la construction d'une stratégie de gestion efficace, le manque d'information empêche aussi les pêcheurs de prendre des décisions pertinentes concernant l'exploitation de la ressource. Les pêcheurs sont souvent forcés de prendre des décisions en se basant sur des informations fragmentaires. Des études expérimentales ont montré que les usagers d'une ressource naturelle, ne sachant que très approximativement sa quantité, avaient tendance de la surestimer et, par la suite, de surexploiter la ressource (Foddy *et al.*, 1999). C'est ainsi le comportement individuel des pêcheurs décentralisés face au manque d'information qui nous intéresse dans le dernier chapitre. Le problème de la surexploitation des ressources halieutiques étant un problème intertemporel, les décisions intertemporelles des pêcheurs sont au coeur de cette étude. La dynamique de la ressource, décrite ici par le modèle standard de Gordon-Schaefer, se superpose ainsi à la dynamique des décisions des pêcheurs. En employant l'approche agents-centrée permettant de représenter explicitement des comportements individuels, nous nous interrogeons sur l'impact de l'apprentissage individuel, qui détermine la façon dont les décisions de pêche évoluent au cours du temps, sur la dynamique globale du système socio-environnemental en question lorsque les informations sont limitées. En étudiant deux modèles d'apprentissage par renforcement, nous examinons comment ils affectent les décisions intertemporelles concernant le niveau d'effort exercé et, plus généralement, leur impact sur le comportement de long terme du système entier. Deux situations en fonction de l'état du système observé sur le long terme sont distinguées : la situation où la ressource s'effondre et la situation où elle est préservée et indéfiniment prélevée.

Le modèle d'apprentissage par renforcement choisi est le modèle de Roth-Erev (Roth and Erev, 1995) qui décrit bien des comportements myopes. Après avoir fait tourner des simulations, nous avons remarqué que le modèle Roth-Erev conduisait à l'effondrement de la ressource. Pour les agents dotés de cet apprentissage, le profit qu'ils tirent de l'exploitation de la ressource à la période t est engendré uniquement par leur décision de pêche prise à la période t. Pourtant, les décisions passées affectent l'état actuel de la ressource via sa capacité de se reproduire. Aussi la négligence de l'interdépendance temporelle dans ce modèle d'apprentissage est une des causes de l'effondrement de la ressource observé dans nos simulations. Pour tenir compte de cette caractéristique du système halieutique, nous avons prolongé le modèle de Roth-Erev de sorte que les agents fassent un lien entre le profit actuel et à la fois à l'action passée et à l'action actuelle associant un certain poids à chacune de ces deux actions. En faisant varier ces poids, la dynamique globale du système a été examinée.

La dynamique de la ressource a été décrite par le modèle de Gordon-Schaefer. Les paramètres de la dynamique biologique ont été ajustés aux données collectées pour une pêcherie artisanale à Marseille. En faisant tourner des simulations pour notre prolongement du modèle de Roth-Erev, nous avons constaté que l'introduction du lien entre le profit actuel et l'action passée changeait radicalement la dynamique du système. Dans la plupart des cas, les agents apprenaient à exercer des efforts de pêche suffisamment bas pour assurer la pérennité de la ressource et la prélever indéfiniment, contrairement aux agents qui considéraient uniquement la période actuelle.

En conclusion, les travaux réalisés dans cette thèse ont abordé deux grands thèmes qui marquent de plus en plus la littérature bio-économique actuelle : la dégradation de l'habitat marin qui menace l'avenir des écosystèmes marins et le manque d'information qui est particulièrement prononcé pour les ressources halieutiques. Les conséquences de la prise en compte de la dégradation des habitats pour la gestion traditionnelle des pêcheries ont été examinées et le rôle des récifs artificiels en tant qu'outil de gestion des ressources halieutiques à travers la restauration des habitats a été exploré. Enfin, l'impact de l'apprentissage individuel des pêcheurs sur l'exploitation de la ressource est analysé dans un contexte d'information fragmentaire.

1

Modélisation des impacts négatifs de la pêche sur les habitats marins et les implications pour la gestion des ressources halieutiques

Incorporation of habitat concerns in the Gordon-Schaefer model

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Abstract

In the Gordon-Schaefer model, widely used to design fisheries management policy, environmental carrying capacity is assumed to be constant. We develop two extensions to the Gordon-Schaefer model, which incorporate carrying capacity as reflecting the state of marine habitats. Because marine habitats are very sensitive to fishing activities, carrying capacity is assumed to be dependent on fishing effort. In the first model, carrying capacity is a decreasing function of fishing effort, while, in the second, it is a dynamic variable subject to habitat dynamics. Based on these models, we demonstrate that the main outcomes of the Gordon-Schaefer model are drastically modified when carrying capacity is thought to be reduced by destructive harvesting highly affecting habitats. We conclude that, when habitat destruction is observed in the fishery, either habitat component should be characterized in the model, or traditional policies should be combined with more prudent measures. Recommendations are given for optimal management and applications of the presented models are discussed, in particular, for Marines Protected Areas and Artificial Reefs.

Keywords: Bioeconomic modelling, Gordon-Schaefer model, Marine habitats, Marine protected areas, Artificial reefs

1.1 Introduction

There have been many attempts to preserve fishing resources using various management tools such as access limitations, quotas, taxes or subsidies. Most of such fisheries management recommendations stem from the traditional approach to fisheries economics (Clark, 1990, 2006) based on the seminal studies by Schaefer (1954) and Gordon (1954). Over the years, it has become obvious that these attempts have not succeeded in avoiding the severe decline of commercial species and of marine resources in general (for instance, see Daw and Gray, 2005). It is economic tools in particular that do not seem fully appropriate for resource conservation because of the pressure on non-target components of marine ecosystems (see for example Reiss *et al.*, 2010, in the case of TACs). The incidental capture of targeted species and other components of marine ecosystems, the "by-catch" problem, is one of the major issues commercial fisheries face, since it can seriously disturb the functioning of marine ecosystems (Hall *et al.*, 2000).

As a result, not only are most commercial stocks currently overexploited (Lauck *et al.*, 1998; Castilla, 2000; FAO, 2006), but entire trophic webs and habitats may be disrupted at the ecosystem level (Harrington *et al.*, 2005). In the last two decades, a new perspective on fisheries management is promoted (see, for instance, Pikitch *et al.*, 1998; Worm *et al.*, 2006; Powers and Monk, 1988). According to them, ecosystem attributes must be integrated into management and successful management cannot be achieved without a clear understanding of biological processes at an ecosystem level. A major challenge is to incorporate this new approach into the management of marine resources in the standard mathematical models traditionally used in fisheries economics.

The standard framework for fisheries economics was developed from the seminal studies by Schaefer (1954) and Gordon (1954). This model, referred to as the Gordon-Schaefer model (hereafter, G-S model), is considered as a good basis for policy design and has allowed resource managers to obtain quantitative recommendations. Of course, this model is a simplification of the real processes occurring in marine ecosystems but it is precisely for this simplicity that it have received such success among fisheries managers. Yet, an increasing attention to habitat and other ecosystem issues gave rise to more complex models. The G-S model was adapted in different ways to include habitat component. In some bioeconomic models, the dynamics of habitat stock were embedded and, in some studies, linked to fish populations (Doyen *et al.*, 2007; Holland and Schnier, 2006). In other models, only habitat effects were accounted for (Armstrong, 2007; Barbier and Strand, 1998). This second body of literature is mainly focused on *positive* habitat effects. We try to contribute to this second literature by proposing models allowing for the adverse effects on habitats as well such as habitat degradation induced by destructive fishing activities.

According to Barbault and Sastrapradja (1995) and Sala *et al.* (2000), habitat degradation is a major threat to marine biodiversity. These authors argue that, in order to protect species and their ecological functions, their habitats should first be protected. Burke *et al.* (2000) show that marine areas have suffered high levels of habitat destruction with about one-fifth of marine coastal areas having been highly modified by humans. In particular, coral reefs, playing a very important role in fish species diversity, continue to decline.

To avoid habitat degradation, various policies have been attempted. In 1992, the European Council established the "Habitats Directive"[1], which puts forward the conservation of natural habitats as one of essential environmental objectives pursued by the European Community. For marine habitats, the directive is aimed at encouraging the conservation of essential habitats in order to maintain marine biodiversity in Europe. Some years earlier (1986) a similar program for the management of marine habitats was developed by the Department of Fisheries and Oceans of Canada. Its objective was an overall net gain in productive capacity of marine habitats by means of the active conservation of the current productive capacity of habitats, the recovery of damaged marine habitats and the development of habitats. In the last decades, fisheries management tools such as marine protected areas (hereafter MPAs, see Sanchirico and Wilen, 1999, 2001, 2005; Kar and Matsuda, 1998) and artificial reefs (hereafter ARs, see Pickering and Whitmarsh, 1997; Pickering *et al.*, 1998) have been receiving increasing attention since they are thought to help restore depleted fisheries and degraded ecosystems.

Clearly, such approaches need to refer to reliable economic theory. However, the field of fisheries economics offers little theoretical support regarding the management of marine habitats. In general, habitat fluctuations are accounted for through stochastic modelling, which views the impact of these fluctuations on the resource as a source of uncertainty (Hanson and Tuckwell, 1978; Vardas and Xepapadeas, 2010). Few studies define a more explicit relationship. In particular, Holland and Schnier (2006) studied the possibility of implementing an individual habitat quota system to achieve habitat conservation via economic incentives. The authors adapted the G-S model by integrating habitat stock as a variable endowed

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[1] Council Directive 92/43/EEC of 21 May 1992 on the "conservation of natural habitats and of wild fauna and flora".

with its own dynamics. By simulating the model, they investigated the conditions in which the individual habitat quota regime is more cost-effective than MPAs. However, no connection was established between resource and habitats in the model. Yet, Naiman and Latterell (2005) clearly state that fish production is dynamic both in species and in habitats.

In the economics of terrestial renewable resources, this connection is taken into account. Terrestial ecologists argue that the relationship between a terrestial resource and the state of its habitats can be introduced in three different ways: through an effect on the growth rate of the resource, through an effect on the carrying capacity of the resource or an effect on both (see, for instance, MacCall, 1984; Barbier and Strand, 1998). Skonhoft (1999) takes the second relationship for terrestial animal species - the carrying capacity of the resource is an increasing function of its habitat. Habitat is regarded as land that can have, for example, agricultural uses. He analyzes the optimal management of the resource with two control variables: hunting pressure and the size of the area used for agriculture. Hunting is assumed to have no effect on the availability of habitats for wild species and agricultural production is the only factor that affects it.

By contrast, the nature of fishing activities is such that marine habitats can be significantly deteriorated by fishing units employing destructive fishing gear (Turner *et al.*, 1999). As in Skonhoft (1999), we adopt the assumption that habitats and carrying capacity are positively linked. There are experimental studies that underpin this claim for marine resources. Griffen and Drake (2008) examined the behavior of Daphnia magna, small planktonic crustaceans, and found that the carrying capacity of this species is influenced by its habitat size and quality and is correlated with extinction time: both larger habitats and higher quality habitats support populations with higher carrying capacities (for theoretical support, see also Pimm *et al.*, 1988; Hakoyama *et al.*, 2000). Hence, habitat variability results in variability in carrying capacity: if habitats in the marine area improve (degrade), so does carrying capacity.

We propose two different standpoints to take into account potential habitat degradation due to destructive harvesting[2]:

1. carrying capacity is a function of fishing effort;
2. carrying capacity is a variable endowed with its own dynamics entirely dependent on habitat dynamics.

The first standpoint allows for instantaneous impact of fishing effort on carrying capacity. The second accounts for the evolution of carrying capacity subject to both habitat restoration (natural or man-made habitat rehabilitation) and habitat degradation. Carrying capacity is hence time-dependent and the impact of fishing is not instantaneous. This latter standpoint corresponds to that proposed by Armstrong and Falk-Petersen (2008) where they evoke the possibility of modelling habitat modifications by adopting multi-species framework. In this sense, we could say that this model constitutes a particular case of symbiotic relationship (commensalism) between two "species" - fish stock and habitats - where fish stock benefits while habitats are unaffected.

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[2] In real ecosystems, the relationship between habitat complexity and fish species richness and abundance is more complex than assumed in the present paper. In particular, Gratwicke and Speight (2005) find that different components of a habitat have different impacts on fish populations. Some are good predictors of the variation in observed species richness, others of total fish abundance. The workshop on "Economics and biological impacts of ARs" organized by Aix-Marseille University in 2010 addresses this issue.

The single-species G-S model is hence adapted to take into account the degradation or improvement of marine habitats and to produce new quantitiative fisheries management recommendations. Carrying capacity is no longer a parameter and becomes a function of fishing effort in the first extension of the G-S model and a state variable in the second. By analyzing these models, we demonstrate that neglecting habitat dynamics can lead to inappropriate design of fisheries management tools.

In the next section we present the two models. In section 3 biological and bionomic equilibrums are characterized. Then Maximum Sustainable Yield (MSY) and Maximum Economic Yield (MEY) are determined in this new framework. In section 4 the problem of optimal management is addressed. In section 5, we explain the advantages of the models and portray their potential applications. Finally, we discuss and conclude.

1.2 The model

We first describe the standard G-S model, then we detail how habitat concerns are incorporated into it.

1.2.1 The Gordon-Schaefer model

Following Schaefer (1954), the biomass x of a given fish species obeys the following equation:

$$\dot{x} = F(x) - H(x, E) \tag{1.1}$$

where $F(x)$ is the natural growth rate of the fish population while $H(x,E)$ is the harvest rate at the fishing effort $E = E(t), 0 \leq E \leq E_{max}$.

The standard assumptions on the above functions are as follows (Clark, 1990):

$H(x,E) = qEx$ where q is the catchability coefficient, $q > 0$;

$F(x) = rx\left(1 - \frac{x}{K}\right)$ with r the intrinsic growth rate, $r > 0$, and K the environmental carrying capacity, $K > 0$.

The function F is called the logistic function. This function was first formulated by Verhulst in 1838 in order to study population growth. He assumes that growth is limited by the availability of resources like light, space, nutrients or water. According to this formulation, the population increases at rate r up to a given K, the saturation level. In the context of fishery, the resources for growth are provided by marine habitats, which offer to fish food and protection.

1.2.2 Incorporating habitat considerations

In the G-S model, it is assumed that fishing activities only impact the fish by reducing its quantity. In our model, another source of fishing mortality is accounted for, specifically, habitat degradation caused by the use of destructive fishing practices and methods, which worsens condition for the growth of fish. Since any disturbance of the ecological functions of habitats implies a decline in their carrying capacity (Turner *et al.*, 1999), it seems appropriate to model the negative habitat effects through carrying capacity[3] in the following manner:

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[3] We simplify by affirming that damaging habitats influences only the carrying capacity of the area. A decline in fish quality is a possible consequence of such destructive fishing affecting the economic value of the species in question.

1. carrying capacity is a decreasing function of fishing effort, i.e. $K = K(E)$;

2. carrying capacity is a state variable endowed with its own dynamics:

$$\dot{K} = D(K) - G(K, E) \tag{1.2}$$

   where $D(K)$ represents the growth rate of the carrying capacity K and $G(E, K)$ stands for the loss rate of K due to destructive harvesting.

Further, we refer to these extensions to the G-S model as the $H1$ and the $H2$ models respectively.

The $H1$ model assumes an instantaneous negative impact of fishing on K, $\frac{\partial K}{\partial E} < 0$, because of habitat degradation.

In contrast to the $H1$ model, in the $H2$ model, carrying capacity is a time-dependent variable. The function $D(K)$ is assumed to reflect the time-dependent growth of the fauna and flora populations of habitats on which the targeted fish species is ecologically dependent. This growth can be driven by both the natural recovery of habitats and their artificial recovery through, for example, the creation of new habitats (ARs).

Different situations can be depicted via the choice of the functions D and G. When habitat rehabilitation processes are stronger than destructive processes, i.e. $D > G$, carrying capacity increases. The extreme case is $G = 0$, which represents either the use of habitat-friendly fishing methods, or the complete absence of fishing in the area. Conversely, if $G > D$, carrying capacity decreases and eventually drops to a critical level at which fish goes extinct.

Since marine areas cannot support an infinite quantity of fish, in both models, carrying capacity is bounded by an upper limit $K_{\max}$.

1.2.3 The $H1$ model

By specifying the function $K(E)$, we obtain the following model:

$$\dot{x} = rx\left(1 - \frac{x}{K}\right) - qEx, \tag{1.3}$$

with initial conditions $x(0) = x_0$ and

$$K(E) = K_{\max}\left(1 - \theta E\right), \tag{1.4}$$

where $K_{\max}$ is the "virgin" level (upper bound) of carrying capacity, θ stands for the instantaneous loss rate of carrying capacity, $\theta \geq 0$.

The parameter θ is a key parameter of this model. It represents the sensitivity of the marine environment to existing fishing practices and techniques. Depending on θ, different outcomes are expected. High θ describes fishing techniques having a considerable impact on marine habitats. The lower θ, the more habitat-friendly the fishing activities in the area. When the fishing activities are not destructive at all, $\theta = 0$, we obtain a particular case of the $H1$ model - the G-S model.

1.2.4 The $H2$ model

The $H2$ model describes the behaviour of two state variables x and K, each endowed with its own dynamics:

$$\dot{x} = rx\left(1 - \frac{x}{K}\right) - qEx, \tag{1.5}$$

$$\dot{K} = \tau K\left(1 - \frac{K}{K_{\max}}\right) - \gamma EK \tag{1.6}$$

$$x(0) = x_0, K(0) = K_0$$

where τ is the growth rate of carrying capacity driven by habitat recovery, $\tau > 0$, γ is the destruction coefficient, $\gamma \geq 0$, and $K_{\max}$ stands for the maximum possible carrying capacity, $K_{\max} > 0$.

In the $H2$ model, the key parameter is γ, which, as θ, reflects the sensitivy of habitats to the employed fishing gear.

We assume that, in the same manner as the function F, the function D obeys a logistic law. This law is chosen to reflect the growth of plant and animal communities populating habitats, which are involved in the growth of the carrying capacity for the target fish species.

Let us state the properties of the model (1.5)-(1.6) with regard to the modifications the G-S model has undergone.

1) The properties of the fish growth function $F(x,K) = rx\left(1 - \frac{x}{K}\right)$.

F is concave in K: (1a) $\frac{\partial F}{\partial K} > 0$ and (1b) $\frac{\partial^2 F}{\partial K^2} < 0$. According to (1a), fish stock grows faster in a marine area with larger carrying capacity. (1b) indicates that the contribution of carrying capacity to fish growth decreases as carrying capacity increases.

2) The properties of the carrying capacity growth function $D(K) = \tau K\left(1 - \frac{K}{K_{\max}}\right)$.

D is concave: $\frac{\partial D}{\partial K} > 0$ and $\frac{\partial^2 D}{\partial K^2} < 0$. In the same manner as for the fish stock, there is a saturation level for the carrying capacity.

3) The properties of the carrying capacity loss rate $G(K,E) = \gamma EK$:

(3a) $\frac{\partial G}{\partial K} > 0$ and (3b) $\frac{\partial G}{\partial E} > 0$. For the function G, we have adopted the same assumptions as for the harvest function H. Assuming that larger habitats are characterized by higher carrying capacity, (3a) means that higher losses in carrying capacity are expected in larger habitats (larger surface and living populations are exposed to fishing gear). In the same vein, (3b) states that the higher the fishing pressure on habitats, the greater the damage inflicted on them and therefore the higher the losses in carrying capacity.

1.3 Equilibrium analysis

1.3.1 Biological equilibrium with harvesting

Equilibria are determined and the behavior of the steady states of the $H1$ and $H2$ models is analyzed in this subsection. In the $H1$ model, the steady states are found from the equation $\dot{x} = 0$ and, in the $H2$ model, from the system of equations $\dot{x} = \dot{K} = 0$. The positive steady states of (2.1)-(1.4) and (1.5)-(1.6) are $\overline{x}_{H1} = K_{\max}(1-\theta E)\left(1-\frac{qE}{r}\right)$ and $\overline{x}_{H2} = K_{\max}\left(1-\frac{\gamma E}{\tau}\right)\left(1-\frac{qE}{r}\right), \overline{K}_{H2} = K_{\max}\left(1-\frac{\gamma E}{\tau}\right)$ respectively.

Since the $H1$ model consists of only one state equation and its structure is not very different from that of the G-S model, it is not difficult to verify that its steady state is stable as in the G-S model. We now look at the behavior of the system of equations (1.5)-(1.6) at the steady state. For this purpose, the system (1.5)-(1.6) is linearized at $\overline{x}_{H2}, \overline{K}_{H2}$. Then, we write the Jacobian of the system

$$V(\overline{x}_{H2},\overline{K}_{H2}) = \begin{pmatrix} qE-r & r\left(1-\frac{qE}{r}\right)^2 \\ 0 & \gamma E-\tau \end{pmatrix}.$$

Due to the positivity condition of $\overline{x}_{H2}$ and $\overline{K}_{H2}$, we obtain negative eigen values $qE-r<0$ and $\gamma E-\tau<0$. Consequently, $(\overline{x}_{H2},\overline{K}_{H2})$ is locally asymptotically stable.

The equilibrium behavior of the two models is similar and depends on the fishing effort E. In particular, the steady-state fish stocks $\overline{x}_{H1}$ and $\overline{x}_{H2}$ coincide when $\frac{1}{\theta}=\frac{\tau}{\gamma}$. The acceptable values of effort are deduced from the positivity condition of both x and K, i.e. $E<min(\frac{r}{q},\frac{1}{\theta})$ and $E<min(\frac{r}{q},\frac{\tau}{\gamma})$ for the $H1$ and the $H2$ models respectively. Therefore, the domain of acceptable efforts for the $H1$ and the $H2$ models is stricter than that for the G-S model. In addition to the usual positivity condition of x, both models require that the positivity condition of K is satisfied to avoid the extinction of the fish population. When $\frac{r}{q}>\frac{1}{\theta}$ (or $\frac{r}{q}>\frac{\tau}{\gamma}$), the set of acceptable efforts reduces as θ (or γ) increases. Thus, even for high $\frac{r}{q}$, also referred to as the biotechnical productivity (btp) of x (Clark, 1990), the fish stock can still be jeopardized because of highly destructive harvesting. We further refer to the ratio $\frac{\tau}{\gamma}$ as the btp of carrying capacity. Of course, it would be more appropriate to speak of the btp of habitats but we justify the use of this term for carrying capacity by assuming that the btp of K is entirely determined by the btp of habitats.

In the extreme case $\theta=\gamma=0$ interpreted as the absence of destructive fishing methods, the equilibrium behavior of our models is identical to that of the standard G-S model. In this case, carrying capacity in all three models equals the "virgin" value, previously noted as $K_{\max}$.

Let us now make a comparison between the equilibrium properties of our models and that of the G-S model. Since the $H1$ and the $H2$ models have an identical equilibrium behaviour, we only examine the properties of one of them. As depicted in Figure 2.1, the steady-state fish stock calculated from the G-S model, given by $\overline{x}_{GS} = K_{\max}\left(1 - \frac{qE}{r}\right)$, is linear in the fishing effort E (see the curve corresponding to $\frac{\gamma}{\tau} = 0$) whereas the $H2$ model displays convex curves for fish stocks (which coincide with the curves given by the $H1$ model provided that $\frac{\gamma}{\tau} = \frac{1}{\theta}$). For all acceptable positive values of effort, the fish stock $\overline{x}_{H2}$ is always lower than $\overline{x}_{GS}$. For a given effort, the gap between the curves (underlined with arrows in Figure 1) is imputable to the loss of habitats induced by the destructive fishing practices and techniques employed in the area. The greater the destruction they cause (the higher $\frac{\gamma}{\tau}$), the larger this gap. But what is more important is the danger of fish extinction (zero fish stock) accentuated by the use of destructive types of fishing gear, clearly illustrated in Figure 2.1. When the btp of K is lower than the btp of x, the critical effort, at which fish extinction is witnessed, is lower than predicted by the G-S model. The lower the btp of K, the lower this critical effort.

In contrast to the G-S model, the $H1$ and the $H2$ models exhibit such features of marine ecosystems as the potential for the fish stock to collapse because of the degradation of habitats, which makes the biological and the economic arguments justifying habitat conservation transparent.

1.3.2 Comparative statics

Three benchmark situations are analyzed in this subsection: Open Access (OA), Maximum Sustainable Yield (MSY) and Maximum Economic Yield (MEY). The concept of the MSY and the MEY arises from the necessity to control the level

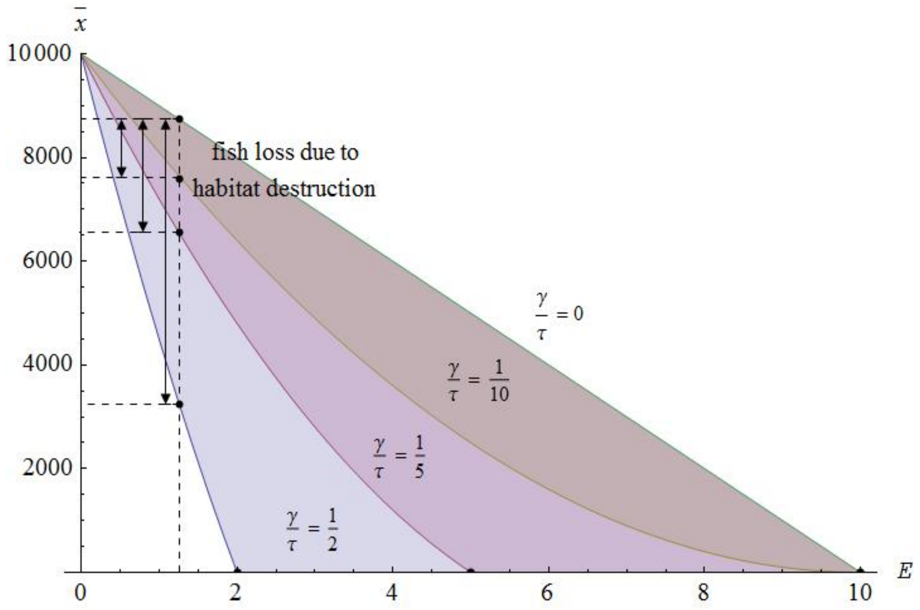

Figure 1.1: Steady-state fish stock for different values of the ratio $\frac{\gamma}{\tau}$ ($K_{\max} = 10000$, $\frac{q}{r} = \frac{1}{10}$). $\frac{\gamma}{\tau} = 0$ corresponds to the G-S model.

of resource extraction in order to avoid overfishing and rent dissipation. The MSY was elaborated so that the maximum level of catches at which fisheries resources can be exploited without exhausting them could be determined, $H_{MSY} = maxF(x)$, and serve as a guideline for fisheries management. Graham (1935) refers to such situation as sustainable fishing. This concept is a common objective of renewable resource management[4]. The MEY stands for the level of resource exploitation at which sustainably harvested resource provides the greatest economic rent. The MEY level is usually lower than the MSY for a non zero cost of fishing.

The economic rent, denoted as R, has a standard form:

$$R(x,K,E) = pqEx - cE \tag{1.7}$$

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[4] In particular, this principle is backed by the European Commission for implementing sustainability in EU fisheries (COM(2006)360).

where p is the constant price per unit of harvested fish and c is the constant cost per unit of effort. The price p and the cost c are exogenous.

The steady-state efforts corresponding to each fisheries regime are presented in Table 1.1. As previously noted, the $H1$ and the $H2$ models produce identical efforts when $\theta = \frac{\gamma}{\tau}$. These efforts exhibit the usual dependences found in the G-S model such as the positive relation to the cost-price ratio c/p in the case of OA and MEY and the positive relation to the btp of x in all three cases. What is not captured by the G-S model is the relationship between the efforts and habitat-specific parameters, the ratio $\frac{\gamma}{\tau}$ and the destruction parameter θ. It can be verified that this relationship is negative. The higher the destruction rates γ and θ, the lower the effort that can be sustained by marine ecosystem.

Table 1.1: Reference points.

	The G-S model	**Extended models**
OA	$E_{\infty}^{GS} = \frac{r}{q}(1 - \frac{c}{pqK_{\max}})$	$E_{\infty}^{H1} = \frac{r}{q} + \frac{1}{\theta} - \sqrt{(\frac{r}{q} - \frac{1}{\theta})^2 + 4\frac{r}{q\theta}\frac{c}{pqK_{\max}}}$
		$E_{\infty}^{H2} = \frac{r}{q} + \frac{\tau}{\gamma} - \sqrt{(\frac{r}{q} - \frac{\tau}{\gamma})^2 + 4\frac{r\tau}{q\gamma}\frac{c}{pqK_{\max}}}$
MSY	$E_{MSY}^{GS} = \frac{r}{2q}$	$E_{MSY}^{H1} = \frac{1}{3}(\frac{r}{q} + \frac{1}{\theta}) - \sqrt{\frac{1}{9}(\frac{r}{q} + \frac{1}{\theta})^2 - \frac{r}{3q\theta}}$
		$E_{MSY}^{H2} = \frac{1}{3}(\frac{r}{q} + \frac{\tau}{\gamma}) - \sqrt{\frac{1}{9}(\frac{r}{q} + \frac{\tau}{\gamma})^2 - \frac{r\tau}{3q\gamma}}$
MEY	$E_{MEY}^{GS} = \frac{r}{2q}(1 - \frac{c}{pqK_{\max}})$	$E_{MEY}^{H1} = \frac{1}{3}(\frac{r}{q} + \frac{1}{\theta}) - \sqrt{\frac{1}{9}(\frac{r}{q} + \frac{1}{\theta})^2 - \frac{r}{3q\theta}(1 - \frac{c}{pqK_{\max}})}$
		$E_{MEY}^{H2} = \frac{1}{3}(\frac{r}{q} + \frac{\tau}{\gamma}) - \sqrt{\frac{1}{9}(\frac{r}{q} + \frac{\tau}{\gamma})^2 - \frac{r\tau}{3q\gamma}(1 - \frac{c}{pqK_{\max}})}$

Two points emerge from the comparison between our models and the G-S model. In unregulated fisheries, fishery managers face two main issues, the depletion of fish populations and habitat degradation, as discussed in the introduction. While, in standard bioeconomic models, only the first problem is addressed, in our model, both problems are brought out. High fishing mortality arises from the absence of control on the fishing effort, habitat degradation from the absence of control on the fishing techniques employed. According to our model, if destructive fishing techniques are used, marine ecosystem cannot sustain an effort as high as in the case of habitat-friendly harvesting (open-access effort is a decreasing function of the habitat destruction paramater, $\frac{\partial E_{\infty}^{H}1}{\partial \theta} < 0$, $\frac{\partial E_{\infty}^{H}2}{\partial \gamma} < 0$), which results in lower harvests. This endagers not only the fishing activities in the area but also other economic activities related to this fishery (such as boat building or bait suppliers).

Second, even if the fishery is managed according to the traditional guidelines such as the MSY or the MEY based on the G-S model, there is still a risk of stock collapse because of an overestimated capacity of the resource to sustain fishing activities. This management error can be dearly paid when highly destructive techniques are employed in the fishery leading to a large gap between the outcomes of the G-S model and that of our extended models.

1.4 Optimal harvesting policy

Consider a sole-owner fishery where the owner of a natural resource (government agency or private firm) have complete knowledge of and control over the fish population. The resource owner seeks to maximize the total discounted present value of economic rents:

$$\underset{0 \leqslant E \leqslant E_M}{Max} J\{E\} = \int_{0}^{\infty} e^{-\delta t}(pqEx - cE)dt \tag{1.8}$$

where E is the control variable and δ denotes the discount rate. The objective function (1.8) is subject to (2.1)-(1.4) in the $H1$ model and to (1.5)-(1.6) in the

$H2$ model.

Optimal fisheries management can be viewed as a problem of optimal strategy for investment in assets in order to maximize the profitability of the fishery (see, for instance, Clark, 1990). In this case, the objective of the resource owner is interpreted in terms of capital assets. He expects the asset to earn dividends. As in the G-S model, there is only one asset in the $H1$ model - fish stock. In the $H2$ model, in addition to fish stock, the resource owner also possess carrying capacity asset.

1.4.1 Optimization problem for the $H1$ model

In order to solve the control problem (2.1), (1.4) and (1.8), we form the Hamiltonian function:

$$\mathcal{H}(x,t,E,\lambda) = R(x,E) + \lambda(F(x,E) - H(x,E)), \tag{1.9}$$

where $\lambda(t)$ is interpreted as the shadow price of an uncaught fish.

The Hamiltonian $\mathcal{H}(.)$ represents the total rate of increase of profits and of fish capital. Two terms on the right side of equation (1.9) are value flows: the first denotes the flow of profits at time t in the objective functional J; the second can be viewed as the investment flow in the fish stock x at time t.

The optimal control $E(t)$ must maximize the rate of increase of total assets. The first derivative of the Hamiltonian (1.9) with respect to the control E

$$\frac{\partial \mathcal{H}}{\partial E} = p\frac{\partial H}{\partial E} - c + \lambda\left(\frac{\partial F}{\partial E} - \frac{\partial H}{\partial E}\right). \tag{1.10}$$

Three solutions for E are possible: either the extremes 0 or E_M, or the interior solution E^*_{H1}. When $\frac{\partial \mathcal{H}}{\partial E} > 0$, i.e. the shadow price λ of fish is sufficiently low, there should be as much fishing as possible. When $\frac{\partial \mathcal{H}}{\partial E} < 0$, i.e. the shadow price λ is sufficiently high, there should be no fishing. When $\frac{\partial \mathcal{H}}{\partial E} = 0$, the control E should be set at its “interior value” E^*_{H1}.

By the Pontryagin conditions,

$$\dot{\lambda} = \delta\lambda - \frac{\partial \mathcal{H}}{\partial x} = \delta\lambda - p\frac{\partial H}{\partial x} - \lambda\left(\frac{\partial F}{\partial x} - \frac{\partial H}{\partial x}\right), \tag{1.11}$$

For the interior solution we obtain:

$$(p-\lambda)\frac{\partial H}{\partial E} = c + \lambda\frac{\partial F}{\partial E}. \tag{1.12}$$

This equation states that the last unit of effort is such that the net value of the marginal product (its market price if caught minus its shadow price if uncaught) equals marginal user cost. The marginal user cost consists of the marginal cost of effort and the marginal losses of fish captial "dividends" because of decreased carrying capacity. This last term (absent in the standard G-S model) allows to account for the negative impact of destructive harvesting on fish growth. In the $H1$ model, this impact is direct whereas in the $H2$ model, as we will see further, it is indirect.

Write (1.11) as:

$$(p-\lambda)\frac{\partial H}{\partial x} + \dot{\lambda} = \delta\lambda - \lambda\frac{\partial F}{\partial x}, \tag{1.13}$$

The left-hand side of equation (1.13) is the marginal net payoff from an uncaught fish i.e. the net value of the marginal product of an uncaught fish plus gains from fish capital. The right-hand side is the marginal net cost of an uncaught fish i.e. the "financial cost" of an uncaught fish minus (plus) the value of "appreciation" (depreciation) at the "biological own rate of interest".

1.4.2 Optimization problem for the $H2$ model

The current valued Hamiltonian for the $H2$ model:

$$\mathcal{H}(x,K,t,E,\lambda,\mu)=R(x,E)+\lambda(F(x,K)-H(x,E))+\mu(D(K)-G(K,E)), \quad (1.14)$$

where, as usual, $\lambda(t)$ is the shadow price of fish and $\mu(t)$ is the shadow price of carrying capacity.

In contrast to the G-S model and the $H1$ model, the Hamiltonian (1.14) consists of *three* value flows: the usual two terms representing the flow of profits and the investment in building up the stock of fish; a third, new, term denoting the flow of investment in the carrying capacity K at time t. Hence, the optimization problem consists in maximizing profits and returns from both the x and K capital assets.

Along with the two capital assets, two types of production are involved in the Hamiltonian $\mathcal{H}$. First, fishing units "produce" fish by harvesting it. Second, they accidentally "remove" a certain amount of habitats due to the use of destructive types of gear[5]. Since this removal of habitats results in a reduced carrying capacity, we can speak of the "removal" of carrying capacity. The fish is a product that can be sold on the market, whereas the removal of K can be viewed as a bycatch.

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[5] In particular, bottom fishing gear is known to remove or scatter habitat substrate (biogenic and sedimentary structures) and non-target benthos.

Given the linear form of harvest and cost functions, the Hamiltonian (1.14) depends linearly on E with coefficient

$$\sigma = p\frac{\partial H}{\partial E} - c - \lambda\frac{\partial H}{\partial E} - \mu\frac{\partial G}{\partial E}, \tag{1.15}$$

referred to as the switching function. As previously, there are three solutions for E depending on the sign of the switching function: $\sigma > 0$, E_M should be applied; when $\sigma < 0$, no fishing takes place; when $\sigma = 0$, we have an interior solution denoted as E^*_{H2}.

The Pontryagin conditions to this problem are written as follows:

$$\dot{\lambda} = \delta\lambda - \frac{\partial \mathcal{H}}{\partial x} = \delta\lambda - p\frac{\partial H}{\partial x} - \lambda\left(\frac{\partial F}{\partial x} - \frac{\partial H}{\partial x}\right), \tag{1.16}$$

$$\dot{\mu} = \delta\mu - \frac{\partial \mathcal{H}}{\partial K} = \delta\mu - \lambda\frac{\partial F}{\partial K} - \mu\left(\frac{\partial D}{\partial K} - \frac{\partial G}{\partial K}\right). \tag{1.17}$$

For the interior solution we obtain:

$$(p-\lambda)\frac{\partial H}{\partial E} = c + \mu\frac{\partial G}{\partial E}. \tag{1.18}$$

Equation (1.18) posits that the last unit of effort is such that the net value of marginal product equals marginal user cost. The marginal user cost consists of the marginal cost of effort and the cost due to reduced carrying capacity measured at the shadow price μ. In contrast to the $H1$ model, the last term here describes a negative impact on carrying capacity and not directly on fish growth.

Write (1.16) and (1.17) as:

$$(p-\lambda)\frac{\partial H}{\partial x}+\dot{\lambda}=\delta\lambda-\lambda\frac{\partial F}{\partial x}, \tag{1.19}$$

$$\dot{\mu}=\delta\mu-\lambda\frac{\partial F}{\partial K}-\mu\left(\frac{\partial D}{\partial K}-\frac{\partial G}{\partial K}\right). \tag{1.20}$$

Since equation (1.11) is identical to (1.19), the same interpretation as in the $H1$ model holds.

The left-hand side of equation (1.20) is recognized as the marginal net payoff from carrying capacity capital. The right-hand side is the marginal net cost. There are four terms describing user costs: the "financial cost" of not "removing" carrying capacity, plus (minus) the value of the depreciation (appreciation) of fish capital and of carrying capacity capital, plus (minus) the value of the marginal increase (decrease) of the loss rate of carrying capacity.

Taking habitats into consideration through carrying capacity dynamics results in a more complex optimization problem. The regulator has to find a tradeoff not only between profits from a fish being caught and the ensuing loss in fish capital, but also between economic benefits from pursuing destructive harvesting and the resulting loss of carrying capacity capital.

1.4.3 Optimal steady state: the G-S model vs. Extended models

We now seek to characterize steady-state solutions in the above control problems. In view of model specifications (2.1)-(1.4) and (1.5)-(1.6), we rewrite Hamiltonians and switching functions

for the $H1$ model:

$$\mathcal{H}_{H1} = (pqx - c)E + \lambda\left(rx\left(1 - \frac{x}{K_{\max}(1-\theta E)}\right) - qEx\right); \tag{1.21}$$

$$\sigma_{H1} = pqx - c - \lambda\left(\frac{r\theta x^2}{K_{\max}(1-\theta E)^2} + qx\right); \tag{1.22}$$

for the $H2$ model:

$$\mathcal{H}_{H2} = (pqx - c)E + \lambda\left(rx\left(1 - \frac{x}{K}\right) - qEx\right) + \mu\left(\tau K\left(1 - \frac{K}{K_{\max}}\right) - \gamma EK\right); \tag{1.23}$$

$$\sigma_{H2} = pqx - c - \lambda qx - \mu\gamma K. \tag{1.24}$$

To find the interior equilibrium solution, we equalize state, costate and switching equations to zero and obtain

for the $H1$ model:

$$x^*_{H1} = K_{\max}\left(1 - \frac{qE}{r}\right)(1-\theta E); \tag{1.25}$$

$$\lambda = \frac{pqE}{\delta + r - qE}; \tag{1.26}$$

$$p - \left(1 + \frac{r\theta(1 - qE/r)}{q(1-\theta E)}\right)\lambda = \frac{c}{qx}, \tag{1.27}$$

for the $H2$ model:

$$x^*_{H2} = K_{\max}\left(1-\frac{qE}{r}\right)\left(1-\frac{\gamma E}{\tau}\right); \tag{1.28}$$

$$K^*_{H2} = K_{\max}\left(1-\frac{\gamma E}{\tau}\right); \tag{1.29}$$

$$\lambda = \frac{pqE}{\delta + r - qE}; \tag{1.30}$$

$$\mu = \frac{rx^2}{K^2}\frac{\lambda}{\delta+\tau-\gamma E}; \tag{1.31}$$

$$p-\left(1+\frac{r\gamma(1-qE/r)}{\tau q(\delta/\tau+1-\gamma E/\tau)}\right)\lambda = \frac{c}{qx}. \tag{1.32}$$

Making the appropriate substitutions, we rewrite equations (1.27) and (1.32) for the $H1$ model:

$$x^*_{H1}\left(1-\frac{qE}{\delta+r-qE}\left(1+\frac{r\theta(1-qE/r)}{q(1-\theta E)}\right)\right) = \frac{c}{pq}, \tag{1.33}$$

for the $H2$ model:

$$x^*_{H2}\left(1-\frac{qE}{\delta+r-qE}\left(1+\frac{r\gamma(1-qE/r)}{\tau q(\delta/\tau+1-\gamma E/\tau)}\right)\right) = \frac{c}{pq}. \tag{1.34}$$

When the future is entirely discounted so that $\delta = +\infty$, equations (1.33) and (1.34) simplify to $x_\infty = \frac{c}{pq}$, which corresponds to the dissipation of economic rent. It can also be verified that the case of $\delta = 0$ where future revenues are weighted equally with current revenues corresponds to the maximization of sustainable rent. Moreover, x^*_{H1}, satisfying (1.33), and x^*_{H2}, satisfying (1.34), decrease with increasing δ toward x_∞. Our problem therefore possesses an equilibrium solution verifying the necessary Pontryagin conditions.

By comparing equations (1.27) and (1.32) to the equivalent equation formulated for the G-S model, namely,

$$p - \lambda = \frac{c}{qx^*_{GS}} \tag{1.35}$$

with $x^*_{GS} = K_{\max}\left(1 - \frac{qE}{r}\right)$, we infer that the optimal steady-state efforts E^*_{H1} and E^*_{H2} deduced from our models are lower than the one calculated from the G-S model, E^*_{GS}.

Without loss of generality, assume that $\frac{1}{\theta} = \frac{\tau}{\gamma} = \frac{r}{q}$. Figure 1.2 illustrates how the optimal efforts are found as an intersection between the unit harvesting cost $\frac{c}{qx}$ when the population level is x and the net value per unit of fish stock. According to this graphical representation, the G-S model indeed recommends higher effort than the $H1$ and the $H2$ models, $E^*_{H1} < E^*_{H2} < E^*_{GS}$. It can be verified that this result also holds for the general case $\frac{1}{\theta} \neq \frac{\tau}{\gamma} \neq \frac{r}{q}$. A high rate of habitat destruction (high θ or γ) could lead to a significant divergence between optimal solutions derived from our models and the G-S model. This finding is in line with the results of the equilibrium analysis carried out in section 3.

The singular controls E^*_{H1} and E^*_{H2} are roots of the following polynomials of degree 3 and 4 respectively:

$$P_{H1}(E) = \left(\frac{\delta}{r} + 1 - \frac{qE}{r}\right)\left(\left(1 - \frac{qE}{r}\right)(1 - \theta E) - \frac{c}{pqK_{\max}}\right) -$$

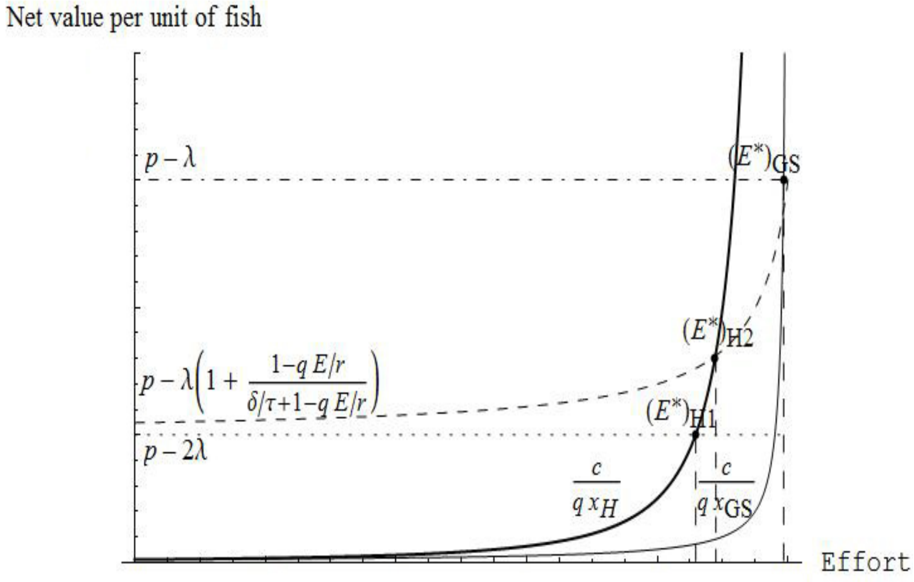

Figure 1.2: This is a schematic representation that allows to compare the optimal steady-state efforts for the G-S, the $H1$ and the $H2$ models. The dotted horizontal line corresponds to the $H1$ model, the dashed curve to the $H2$ model and the dot dashed line to the G-S model. The thick curve represents the unit harvesting cost for the $H1$ and the $H2$ models and the normal curve corresponds to the G-S model.

$$-E\left(1-\tfrac{qE}{r}\right)\left(\tfrac{q}{r}(1-\theta E)+\theta\left(1-\tfrac{qE}{r}\right)\right)$$

$$P_{H2}(E)=\left(\tfrac{\delta}{r}+1-\tfrac{qE}{r}\right)\left(\tfrac{\delta}{\tau}+1-\tfrac{\gamma E}{\tau}\right)\left(\left(1-\tfrac{qE}{r}\right)\left(1-\tfrac{\gamma E}{\tau}\right)-\tfrac{c}{pqK_{\max}}\right)-$$
$$-E\left(1-\tfrac{qE}{r}\right)\left(1-\tfrac{\gamma E}{\tau}\right)\left(\tfrac{q}{r}\left(\tfrac{\delta}{\tau}+1-\tfrac{\gamma E}{\tau}\right)+\tfrac{\gamma}{\tau}\left(1-\tfrac{qE}{r}\right)\right)$$

After introducing the notations $\frac{\delta}{r}=\delta_r$, $\frac{\delta}{\tau}=\delta_\tau$, $\frac{q}{r}=q_r$, $\frac{\gamma}{\tau}=\gamma_\tau$, $\frac{c}{pqK_{\max}}=z_\infty$ the polynomials $P_{H1}(E)$ and $P_{H2}(E)$ can be rewritten as follows:

$$P_{H1}(E)=(\delta_r+1-q_rE)[(1-q_rE)(1-\theta E)-z_\infty]-$$

$$-E(1-q_rE)[q_r(1-\theta E)+\theta(1-q_rE)];$$

$$P_{H2}(E)=(\delta_r+1-q_rE)(\delta_\tau+1-\gamma_\tau E)[(1-q_rE)(1-\gamma_\tau E)-z_\infty]-$$

$$-E(1-q_rE)(1-\gamma_\tau E)[q_r(\delta_\tau+1-\gamma_\tau E)+\gamma_\tau(1-q_rE)].$$

Without loss of generality, let us further assume that $\delta_\tau = \delta_r$ and $\theta = \gamma_\tau = q_r$:

$$P_{H1}(E) = (\delta_r + 1 - q_r E)[(1 - q_r E)^2 - z_\infty] - 2q_r E(1 - q_r E)^2; \tag{1.36}$$

$$P_{H2}(E) = (\delta_r + 1 - q_r E)^2[(1 - q_r E)^2 - z_\infty] - 2q_r E(1 - q_r E)^2(\delta_r/2 + 1 - q_r E). \tag{1.37}$$

Then the leading coefficient of $P_{H1}(E)$ is negative, $a_3 = -3q_r^3$, and the constant term is positive, $a_0 = (\delta_r + 1)(1 - z_\infty)$. It follows that $P_{H1}(E)$ has at least one positive root. It can be verified that this root belongs to the admissible control set, that is to say, it satisfies the x and K positivity condition, $E < \frac{r}{q}$. Similarly, the leading coefficient of $P_{H2}(E)$ equal to b_4 and its constant term equal to b_0 are both positive, as given by $b_4 = 3q_r^4$ and $b_0 = (\delta_r + 1)^2(1 - z_\infty)$. Consequently, there is at least one positive root and, as previously, it satisfies the x and K positivity conditions.

1.4.4 Optimal control scheme

For fishermen to exert the optimal level of effort, divergences between social and private costs and benefits should be corrected. The economic theory based on the G-S model suggests implementing a tax equal to the shadow price λ of fish stock. However, according to our models, a higher tax is required to control both stock and habitat externalities associated with competitive behaviour (see Figure 1.3).

Recall the equations from which the optimal efforts are found:

$$\left(p - \lambda\left(1 + \frac{\partial F}{\partial E}\right)\right)\frac{\partial H}{\partial E} = c; \tag{1.38}$$

$$\left(p-\lambda-\mu\frac{\partial G}{\partial E}/\frac{\partial H}{\partial E}\right)\frac{\partial H}{\partial E}=c; \tag{1.39}$$

$$(p-\lambda)\frac{\partial H}{\partial E}=c. \tag{1.40}$$

The shadow price λ in the left-hand side of the above equations accounts for stock externalities taking place in unregulated fisheries because the cost of harvesting fish increases as the fish stock is depleted. The term to the right of λ in equation (1.39) arises from the previously mentioned symbiotic relation between carrying capacity and fish stock leading to biological externalities. In the $H1$ model where this relation is not explicitly introduced, the externality associated with habitat degradation is taken into account via the direct impact of the destructive harvesting on fish growth, i.e. through the term $\frac{\partial F}{\partial E}$ (see equation (1.38)).

At the steady state, the amount of tax to be paid by fishermen is deduced from equations (1.27),(1.32) or (1.35): $T_{GS}=\lambda$, $T_{H1}=\left(1+\frac{r\theta(1-qE/r)}{q(1-\theta E)}\right)\lambda$, $T_{H2}=\left(1+\frac{r\gamma(1-qE/r)}{\tau q(\delta/\tau+1-\gamma E/\tau)}\right)\lambda$ respectively. The G-S tax allows to internalize only stock externalities whereas the other two taxes take into account both stock and habitat externalities. Moreover, the greater the negative habitat effect caused by destructive harvesting, the higher the taxes suggested by the $H1$ and the $H2$ models.

1.4.5 Special case: $c=0$

If the cost of resource exploitation can be neglected, $c=0$, an explicit analytical steady-state solution can be derived[6]. Considering that $\delta_\tau=\delta_r$ and $\theta=\gamma_\tau=q_r$,

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[6] This case was examined by Plourde (1970).

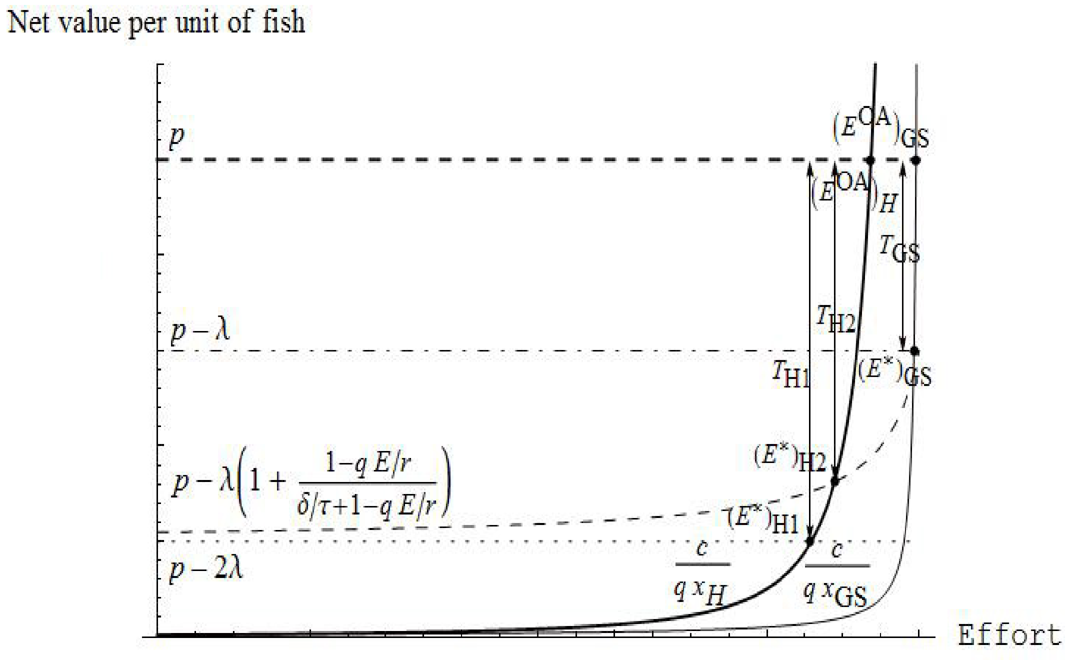

Figure 1.3: This graph portrays how appropriate taxes can lead to optimal efforts. For sake of simplicity, it is assumed here that $\frac{1}{\theta} = \frac{\tau}{\gamma} = \frac{r}{q}$.

the roots of (1.36) and (1.37) are easily found:

$$E^*_{H1} = \frac{\delta_r + 1}{3q_r}; \tag{1.41}$$

$$E^*_{H2} = \frac{1}{6q_r}(3\delta_r + 4 - \sqrt{4 - 3\delta_r^2}). \tag{1.42}$$

Recall that the optimal steady-state effort in the G-S model is $E^*_{GS} = \frac{\delta_r+1}{2q_r}$. By comparing the three models, we obtain $E^*_{H1} < E^*_{H2} < E^*_{GS}$. This result is consistent with the previous, general, analysis. The taxes should be set to $T_{H1} = 2\lambda$, $T_{H2} = 1 + \frac{1/3-\delta_r/2+\sqrt{4-3\delta_r^2}/6}{1/3+\delta_r/2+\sqrt{4-3\delta_r^2}/6}\lambda$. The The $H1$ model recommends the highest tax, the twice of what is traditionally suggested. Figure 1.4 conveys the behavior of the optimal steady-state fish stock for all three models, as given by

$$x^*_{GS} = \frac{K_{\max}}{2}(1 - \delta_r) \tag{1.43}$$

$$x^*_{H1} = \frac{K_{\max}}{9}(2 - \delta_r)^2 \tag{1.44}$$

$$x^*_{H2} = \frac{K_{\max}}{36}(2 - 3\delta_r + \sqrt{4 - 3\delta_r})^2 \tag{1.45}$$

and Figure 1.5 portrays the corresponding optimal steady-state efforts. The effort E^*_{GS} increases faster with δ_r than E^*_{H1} and the gap between the corresponding curves increases as δ_r increases. Conversely, E^*_{H2} becomes closer to E^*_{GS} with increasing δ_r. This difference in the behavior of the $H1$ and the $H2$ models is ensued from the difference in assumptions underlying these models. The $H1$ model describes an instantaneous impact of destructive harvesting on the fish growth whereas the consequences of such harvesting in the $H2$ model is observed only in future. Thus, when society discounts the future, possible losses from high fishing pressure resulting in a strong habitat degradation a long time ahead tend to be neglected in the framework of the $H2$ model to avoid the loss in economic activity today. In the case of the G-S model, these negative habitat effects are not even taken account of. It is hence consistent that the G-S and the $H2$ model suggest to harvest fish to extinction and invest the returns in faster-growing assets for a lower bioeconomic growth rate, $\delta_r = 1$, than predicted by the $H1$ model, $\delta_r = 2$ (see Figure 1.4).

These results are coherent with those obtained for the general case. The optimal effort calculated from the G-S model is overestimated if fishing units do inflict damage on habitats. However, when discount rates are high, errors of estimation become insignificant provided that the $H2$ model is chosen to describe the

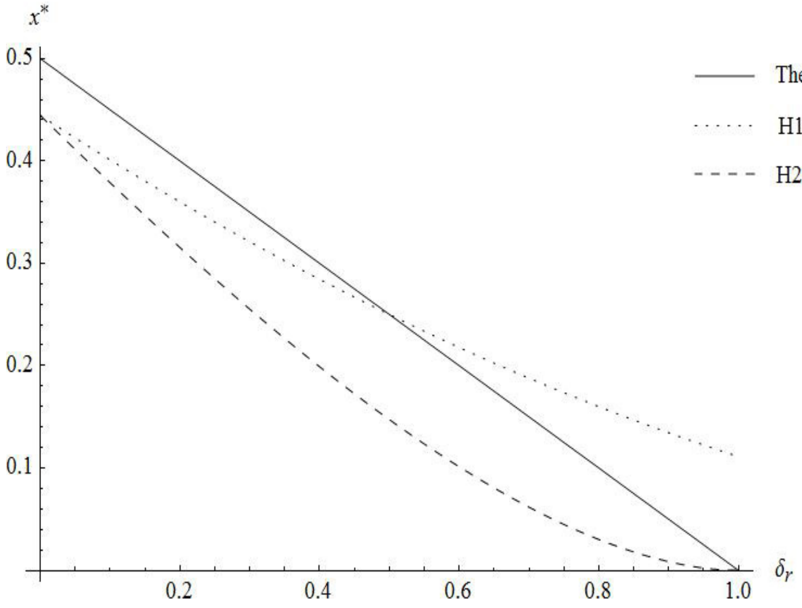

Figure 1.4: Optimal steady-state fish stocks as a function of the bioeconomic growth rate δ_r under zero cost of fishing.

bioeconomic system under consideration. Thus, under a negligeable cost of fishing and sufficiently high discount rate, the optimization problem derived from the $H2$ model can be approximated by the G-S model.

1.5 Model applications

To preserve both fishery profitability and marine ecosystems, management plans may include MPAs, gear zoning or area rotation depending on particular gear and habitat type (Guillén *et al.*, 1994). The use of ARs has also been suggested as a way to prevent trawling which greatly damages marine habitats (see, for instance, Jennings and Kaiser, 1998; Turner *et al.*, 1999) or to favor the reproduction of fish populations by providing means for survival (Pickering and Whitmarsh, 1997). We believe that the extensions to the G-S model developed herein make it more relevant

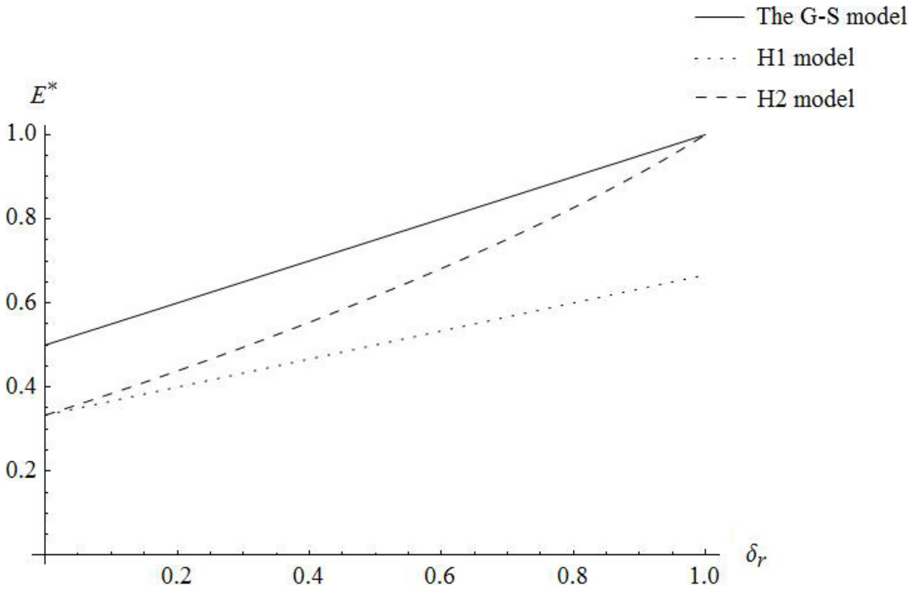

Figure 1.5: Optimal steady-state efforts as a function of the bioeconomic growth rate δ_r under zero cost of fishing.

to assess this wide range of habitat conservation-related policies as compared to the standard G-S model for the following reasons.

First, the $H1$ and the $H2$ models can be applied to a range of gear restriction policies. In coastal fisheries, where habitat deterioration is becoming a very important issue, the use of some types of gear represents considerable danger for coastal ecosystems. Local management agencies handle this problem by introducing gear restrictions prohibiting most destructive fishing practices and techniques. They are enforced through, for instance, extensively using certain types of ARs to prevent bottom trawling. The key parameter θ or γ in the $H1$ model and the $H2$ model respectively, which reflects the destructive power of the fishing gear employed in the fishery, can be used to model this kind of policy. Stricter gear restrictions implies lower γ. The extreme case $\gamma = 0$ represents the use of strictly habitat-friendly types of gear presuming that no adverse effects on habitats are induced.

Furthermore, the $H1$ and the $H2$ models better capture the effects of MPAs, which are expected not only to increase fish biomass but also to favor the recovery of the habitats located within their boundaries (Garcia-Charton and Perez-Ruzafa, 1999; Roberts and Sargant, 2002). Yet, in most papers on MPAs, the effect of reserves on fish populations were modelled through decreased levels of fishing mortality (Ami *et al.*, 2005; Boncoeur *et al.*, 2002; Flaaten and Mjolhus, 2005; Horwood, 2000; Loisel and Cartigny, 2009; Pezzey *et al.*, 2000). This approach disregards positive habitat effects produced by protected areas, especially important when harvesting is destructive. In this case, area closure not only reduces fishing mortality but also prevents habitat degradation. Hence, fish stock recovers more significantly than in the case of habitat-friendly fishing. However, there are some studies which account for positive habitat effects of area closures by adapting the G-S model. In particular, Armstrong (2007) proposes an extension of the G-S model by considering K as an increasing function of the size of an MPA. But, this approach neglects the cause of habitat improvement - the absence of fishing. Carrying capacity being linked to fishing effort within our models, the increase in K driven by area closure is straightforward when E is set to 0.

The same argument holds for ARs used to enhance marine habitat. The literature on this topic is scant and there is still scientific debate about the real benefits of ARs (the attraction-production debate). In the existing literature, a common approach to modelling habitat effects of ARs is to set an increased growth rate r of fish together with an increased carrying capacity K (Pickering and Whitmarsh, 1997; Pickering *et al.*, 1998). However, in the same way as natural habitats, ARs may be damaged by destructive fishing gears. Hence, the positive habitat effects produced by ARs may not last, contrary to what is assumed in the above modelling approach.

Finally, with the $H1$ and the $H2$ models, the positive habitat effects of MPAs can be distinguished from those of ARs. In the existing bioeconomic models, these effects are modelled in a somewhat similar way. Yet, for each of these tools, fish and habitat conservation is achieved by different processes. With MPAs, the conservation is achieved through the elimination of fishing pressure in protected areas, while ARs ensure the recovery of fish and habitats through the creation of new habitats, not necessarily entailing access restrictions. In the framework of our models, the positive effects of MPAs on habitats are straightforward when the fishing effort is set to 0 either in the function $K(E)$ or in the function $G(E, K)$. Habitat effects of ARs are modelled by considering a higher maximal carrying capacity K_{max}.

1.6 Discussion and conclusion

The present paper supports the calls for more caution when making simplifying assumptions on the behavior of marine ecosystems (see, for instance, Wilson *et al.*, 1994). Modellers are often forced to use such assumptions due either to the lack of scientific information or to the excessively complex nature of the real ecosystems, or both. While simple models may work well in some situations, sometimes vulnerable assumptions are responsible for the ultimate population collapses (Shelton and Lilly, 2000; Heithaus *et al.*, 2008). Marine habitats being a very important part of marine ecosystems and very sensitive to fishing activities, neglecting the habitat component may lead to significant management errors, as stressed in this paper.

In particular, we demonstrate that the main outcomes of the G-S model are drastically modified when the danger of reducing the carrying capacity of a marine area because of destructive harvesting is taken into account. Specifically, MSY and MEY, the key fisheries indicators, are overestimated when they are calculated in a traditional way. As a result, when marine habitats suffer considerable damage from fishing activities, fishery policies such as TACs, where allowable catch levels are determined using the G-S model, systematically permit more harvesting than an ecosystem can sustain. This misspecification of effort and catch may explain why some resource stocks and their associated fisheries have collapsed, and underlines the need to integrate habitats into the design of management plans, as put forward by recent studies (for instance, see Naiman and Latterell, 2005).

Misspecification of effort also occurs when the problem of dynamically optimal fishery management is addressed. Both models presented in this paper suggest the implementation of a higher landing tax, as compared to the standard G-S model, in order to take account of the cost of habitat destruction. The more destructive the fishing gear is, the higher the tax should be.

However, to satisfy the informational needs of our models requiring higher quality input data than the standard G-S model, surveys on the quantitative habitat effects of fishing need to be carried out in addition to standard data gathering procedures. The $H1$ model, being less complex than the $H2$ model, is less costly and can be used as a first approximation for producing fishery policies. Although, when the data requirements even of the $H1$ model are too high and costly, excluding habitat considerations from the model is an option, provided that traditional policies are combined with complementary precautionary measures. The creation of networks of protected areas is one such measure capable for alleviating various sources of uncertainty including errors related to model inaccuracies (Grafton *et al.*, 2005; Kahui and Alexander, 2008; Lauck *et al.*, 1998).

The present study opens new prospects for future research. The models developed herein have the potential to provide new insights into the economic performance of ecosystem-based policies such as MPAs and ARs as well as into the impact of gear regulations since, as argued above, they should be more relevant than the existing bioeconomic models. The $H1$ and the $H2$ models clearly establish the relative effectiveness of MPAs and ARs in habitat protection by distinguishing the way they achieve this. From a practical point of view, this distinction is especially important when deciding whether to combine both tools, for instance, when the fishing pressure in the reef areas is too high to enjoy the full benefits of ARs. Depending on local social, cultural and economic context, several management solutions can be considered: MPA alone, ARs alone and the combination of MPA and ARs. Our $H1$ and $H2$ models should offer the means for a more accurate comparison of these scenarios.

2

Les récifs artificiels : une réponse à la dégradation des habitats et à la chute de la production halieutique ?

The Bioeconomic Analysis of Artificial Reefs

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Abstract

This paper focuses on the economic analysis of artificial reefs, which are known to enhance fish production through the provision of new habitats, and demonstrates analytically their potential for fisheries management. This fisheries management solution is primarily promoted in small-scale fisheries where such projects may improve the cost-efficiency of fishing units. The biological research on the topic is abundant whereas economic research is of a much more limited quantity. The existing economic literature lacks rigorous analytical framework for the economic analysis of artificial reefs. A simple extension of the existing bioeconomic models with regard to the positive habitat effect of artificial reefs dependent on their size is developed. The economic analysis undertaken in this study yields more pessimistic results than what is found in the purely ecological analysis and in the surveys conducted for real case-studies. Based on the model developed in our previous study (Udumyan *et al.*, 2010) and slightly modified here, we show that the performance of artificial reefs may be improved through a limitation of inputs to the fishery, gear control or/and an access restriction allowing to ward off the subsequent build-up of fishing pressure in the region and prevent severe degradation of both natural habitats and artificial reefs. Finally, we solve the problem of a dynamically optimal harvesting with the size of artificial reefs as an additional policy variable.

Keywords : Artificial reefs, Reserves, Marine habitats, Bioeconomic modelling, Artificial reef management

2.1 Introduction

The use of controls on input (fishing effort or capacity control) and output (different quota regimes), taxes, subsidies or other economic instruments to manage fisheries is widespread. While in some fisheries, these economic tools succeed in preserving the fishery, many fish stocks continue to decline and the associated fisheries are overcapitalized (FAO, 1996; Jackson *et al.*, 2003; Myers and Worm, 2003; FAO, 2006; Worm *et al.*, 2006). One of the reasons is that ecological attributes of marine ecosystems are neglected when designing fisheries management policies. The traditional single-stock management paradigm usually adopted omits biological relationships such as trophic relationships as well as physical environmental features.

In this context, a new approach has emerged : Ecosystem-Based Management (Browman *et al.*, 2004; Pikitch *et al.*, 1998; Sanchirico *et al.*, 2008), which shifts the fisheries governance focus from managing species independently to the ecosystem-based standpoint. In the last two decades we have thus observed a significant body of literature dealing with multiple patches (Sanchirico and Wilen, 1999, 2001, 2005), trophic webs (Boncoeur *et al.*, 2002; Finoff and Tschirhart, 2003; Gascuel, 2005) or habitat issues (Holland and Schnier, 2006; Armstrong, 2007). Artificial Reefs (ARs) fit into this concept since they achieve fish management goals principally through targeting the restoration of marine ecosystems. By providing new habitats, they improve the biodiversity of a marine area, on one hand, and are thought to improve the revenues of fishermen thanks to their capacity to aggregate fish and provide better growth conditions, on the other (Pickering and Whitmarsh, 1997; Pickering *et al.*, 1998). Although ARs have been used for a long time in small-scale fisheries (the first ARs were immersed in Japan in 17th century), the literature in fisheries economics offers few examples of economic assessment of AR policy (Whitmarsh and Pickering, 1995, 1997) and very few of these studies yield analytical results (to our knowledge, only the study of Boncoeur (2008) has attempted to built a rigorous framework for the analysis of the economic benefits of ARs).

The aim of this paper is to develop a simple bioeconomic model capable of providing a rigorous analysis of AR policy to examine its benefits for fishing communities as well as its drawbacks in various contexts. Using this model we investigate for which kind of fisheries (in terms of resource productivity, harvesting costs, fishing effort exerted, presence or not of access or effort management), ARs can derive significant economic benefits. To do so, we first briefly explain how certain ecological and economic processes prevent fishing units from enjoying the full benefits of AR policy, and find possible responses to them. The past experience on the implementation of AR projects shows that they frequently do not meet the full expectations of the parties involved in project initiation. The main reason for this failure is thought to be incorrect management of ARs or even lack of management (Pickering and Whitmarsh, 1997; Whitmarsh *et al.*, 2008). Second, we find a solution to the problem of dynamically optimal management with the effort and the AR size as policy variables when a single AR project is implemented.

The bioeconomic model of ARs developed herein is adapted from our earlier model (Udumyan *et al.*, 2010)[1], which incorporates the negative impact of destructive fishing on a fish population through carrying capacity. The negative impacts of fishing activities on habitats have been the focus of many recent studies (Auster *et al.*, 1996; Auster, 1998; Turner *et al.*, 1999; Armstrong and Falk-Petersen, 2008).

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[1] For similar models, see for instance Akpalu and Bitew (2011).

Since it is against this backdrop that AR deployment generally occurs, the incorporation of negative habitat impacts, omitted in the previous literature, is essential and will lead to a more accurate analysis. We modify the model (Udumyan *et al.*, 2010) so as to include positive habitat effect as a result of the deployment of ARs and we express this effect in increased environmental carrying capacity for the target species for which the deployed ARs provide shelter. We assume that the increase in carrying capacity is an increasing function of the size of ARs, as Armstrong (2007) did when modeling the positive habitat effect of an MPA. Yet, Armstrong (2007) uses a standard bioeconomic model, the Gordon-Schaefer model, which does not take into account habitat degradation, a vital issue for fisheries where destructive fishing practices and techniques are observed.

Our findings support the need for the management of AR area and highlight the importance of two complementary fisheries management tools for the success of AR policy, effort limitation and temporary reserves[2]. We also demonstrate that, in fisheries where habitats are strongly degraded, the deployment of ARs may not be an economically optimal decision and that their performance can be improved when gear regulation such as the deployment of ARs acting as enforcement devices is put in place. However, we argue that even in the absence of additional management controls, ARs are able to yield some economic benefit such as increased harvests and tuning their size may even allow to accomplish the Maximum Sustainable Yield (MSY) objective[3].

To achieve the dynamically optimal levels, our analysis suggests the creation

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[2] In reserves or no-take zones, all fishing activities are banned. Temporary reserves refer to areas closed for a short period of time.

[3] The MSY objective is a traditional fisheries objective, which is defined as the maximization of sustainable harvests.

of a temporary reserve, which is in line with the arguments raised by fisheries scientists that ARs should not be disturbed by fishing activities to favor their colonization by marine organisms (during this period carrying capacity will gradually increase until the optimal level). We also argue that the reserve should be in place longer as compared to a situation without ARs.

Operating costs seem to play an important role in the decision whether to deploy or not ARs. AR projects do not appear useful in fisheries with very high operating costs. Therefore, even though ARs are expected to reduce harvesting costs through increased fish population, under too high operating costs AR policy is ineffective. The results also suggest that, within the cost range where our solution preconises the implementation of AR policy, the rents generated are higher than those yielded in the absence of ARs.

The paper is organized as follows. The next section details the functioning and the purposes of ARs and reviews the challenges. Section 3 presents our bioeconomic model of ARs and examines the equilibrium properties of the model. Section 4 analyzes the effect of AR policy under different circumstances and management objectives. In section 5, the problem of dynamically optimal management is addressed. Section 6 discusses the main results and concludes.

2.2 ARs in fisheries management : advantages and drawbacks

According to fisheries scientists, ARs assume the role of natural habitats. For certain species (principally rock fish) ARs provide shelter, protecting juveniles from predators. For some species, ARs are also spawning areas (for example, cephalopods). Two main types of AR are distinguished : ARs designed to enhance the resource and generate higher financial returns (Santos and Monteiro, 1998) and ARs built to prevent the use of certain destructive fishing techniques prohibited in the fishery (Guillén *et al.*, 1994). The first kind of reef unit is seen as a tool for sustaining coastal fisheries by mitigating the effects of stock depletion. The second type of AR acts as an enforcement device designed to make resources inaccessible to certain types of gear. In Europe, they are commonly used to exclude illegal trawling from sensitive habitats (Baine and Side, 2003).

However, fisheries scientists are divided on whether ARs act only to attract and aggregate fish or also to increase fish biomass (Bohnsack and Sutherland, 1985; Solonsky, 1985; Bohnsack, 1989; Polovina, 1994). Some studies point to the capacity of certain ARs to act as production enhancers (DeMartini *et al.*, 1994; Sampaolo and Relini, 1994), whereas others show that certain reef units are poorly designed or lack a management strategy (Davis, 1985; Pratt, 1994) dealing with the build-up of fishing pressure that ARs may engender (Pickering and Whitmarsh, 1997).

In this section, we describe challenges posed by the deployment of ARs that will be taken into account in the present study.

2.2.1 Do the observed benefits of AR projects live up to expectations ?

ARs are deployed for a variety of purposes. The most common goals are : enhancement of fisheries yield and production (Seaman and Sprague, 1991; Tsumura *et al.*, 1999), mitigation of local habitat damage or loss (Clark and Edwards, 1999; Baine, 2001), prevention of trawling (Guillén *et al.*, 1994; Relini, 2000), recreational fishery and diving (Ditton *et al.*, 1999; Sutton and Bushnell, 2007) and research on fish populations and epifauna (Bohnsack *et al.*, 1994).

Thus, ARs are expected to yield a range of economic benefits (Whitmarsh *et al.*, 2008). In this study, we are interested in direct use benefits such as increased catches for commercial fishermen. Although surveys conducted worldwide confirm the positive short-term implications of AR projects for both marine ecosystem and fishermen by showing that ARs succeed in increasing catch rates as well as economic returns (Bohnsack and Sutherland, 1985; Bombace *et al.*, 1994; Santos and Monteiro, 1998), whether these benefits are still derived in the long term is not as certain. The economic theory suggests that without management these benefits are bound to dissipate in the long term. Thus, the expected benefits and the real benefits derived from AR development may not match when ARs are the only management instrument.

2.2.2 Different habitat recovery measures need different modeling solutions

Apart from ARs, other habitat-conservation management tools are widely applied. For instance, reserves allow the recovery of habitats located within their boundaries through complete elimination of effort in the area (Garcia-Charton and Perez-Ruzafa, 1999; Roberts and Sargant, 2002). Another example is gear regulation in the shape of a ban on fishing practices and methods that are destructive for the marine environment. The main difference between ARs and these tools is that they achieve habitat conservation by preventing habitat degradation induced by destructive fishing whereas ARs provide new habitats, although habitat degradation can still persist if reef units are not designed specifically for this purpose. The few studies on the bioeconomic modeling of AR effects do not take into consideration this important feature (Whitmarsh and Pickering, 1997; Boncoeur, 2008). This is the reason why the effects of reserves and those of ARs are often confused and are modelled similarly. We show that the model developed in this study leaning on our earlier model provides a framework in which the difference between these tools can be accounted for.

2.2.3 Importance of AR management

While the existing surveys make positive observations on the performance of AR systems, they also point to how the spatial behavior of fishermen changes when ARs are immersed. The opportunities offered by ARs draw fishermen to the AR area once they recognize their benefits, which can lead to an overall increase in fishing pressure in the region. The risk of overexploitation is all the more significant when ARs function as a concentration device that attracts fish from the surrounding areas, rather than as an enhancer. Thus, fished ARs have the potential to lead to severe overfishing (Bohnsack and Sutherland, 1985; Jebreen, 2005).

This point of view is also supported by Baine (2001) who conducts a thorough literature review on the issues raised due to the implementation of AR projects (essentially carried out in North America). With regard to the existing case-studies, he concludes that ARs have the potential to meet the full expectations of their promoters but on condition that prior planning and ongoing management is afforded to ARs. In the same vein, Whitmarsh *et al.* (2008) argues that the implementation of AR projects demands even stricter management (see also Milon, 1989; Grossman *et al.*, 1997; Pitcher *et al.*, 2002).

We identify the conditions under which additional management controls are necessary for the success of AR projects.

2.3 The Bioeconomic Model of ARs and Equilibria Analysis

The model developed herein is based on our earlier model (Udumyan *et al.*, 2010), which integrates the observation, supported by numerous biological studies and surveys, that environmental carrying capacity is strongly related to the state of habitats (see, for instance, Griffen and Drake, 2008). Specifically, through the establishment of this link, the deterioration of habitats caused by destructive harvesting and resulting in decline of carrying capacity for fish populations (Turner *et al.*, 1999) was taken into account. We modify this model so as to incorporate the positive habitat effect produced by AR deployment and to allow for interactions between AR effect and the negative habitat effect of fishing.

2.3.1 Modeling the effects of ARs

According to the conventional bioeconomic model, the Gordon-Schaefer model (Gordon, 1954; Schaefer, 1954), the dynamics of the fish stock x can be described as follows :

$$\dot{x} = F(x,K) - H(x,E), \tag{2.1}$$

where $F(x)$ denotes the natural growth rate of fish and the function $H(t)$ represents harvests.

Standard assumptions are adopted on the above functions :

$F(x,K) = rx(1-x/K)$ with r the intrinsic fish growth rate, $r > 0$, and K the environmental carrying capacity, $K > 0$;

$H(x,E) = qEx$ with q the catchability coefficient, $q > 0$, and E the fishing effort, $0 \leq E \leq E_{max}$. The parameter q relates to the effectiveness of the employed fishing technology. The effort E is "a composite index of all inputs employed for the purpose of realizing this catch" (FAO).

While in the conventional model carrying capacity is a fixed parameter, in this paper, we represent it as a decreasing function of effort following our earlier work (Udumyan *et al.*, 2010) to account for the negative habitat effect of fishing. On the other hand, we model carrying capacity as an increasing function of the size of ARs deployed in the area, which makes the difference with our previous formulation. Thus, specifying the model (2.1), we obtain

$$\dot{x} = rx\left(1 - \frac{x}{(K_{max} + L(\alpha))(1-\theta E)}\right) - qEx, \tag{2.2}$$

where α stands for the size of ARs immersed in the marine area (which may be measured in m^3,$\alpha \geq 0$), $L(\alpha)$ for the amount of carrying capacity by which the maximal carrying capacity increases ($L(\alpha) \geq 0$), θ is the loss rate of carrying capacity per unit of effort ($\theta \geq 0$), and K_{max} represents the maximal possible carrying capacity in the absence of ARs ($K_{max} > 0$)[4].

The function $L(\alpha)$ is increasing and captures the positive habitat effect of

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[4] The positivity conditions of x is satisfied for $E < min\{\frac{r}{q}, \frac{1}{\theta}\}$.

ARs. We assume that $L(\alpha) = \alpha\tilde{K}$ where $\tilde{K}$ is the increase in carrying capacity per reef size unit and $0 \leq \alpha \leq \alpha_{max}$ with α_{max} depending on financial and technical constraints.

The parameter θ embodies the negative habitat effect of fishing and can be interpreted as a destructive power of the employed fishing gear. A fishing technology is thus characterized not only by the catchability coefficient q, measure of efficiency of fish extraction, but also by θ, measure of aggressiveness in regard to habitats[5]. The greater this parameter, the more destructive the fishing gear. On the other hand, $\theta = 0$ reflects the use of a habitat-friendly gear. In this case, carrying capacity is at its maximal value, which is either $K_{max} + \alpha\tilde{K}$ if ARs are deployed or K_{max} otherwise.

ARs acting as gear enforcement devices are modelled by considering θ as a decreasing function of their size :

$$\theta = k_1 - k_2\beta, \tag{2.3}$$

with β as the size of enforcing ARs, $0 \leq \beta \leq \frac{k_1}{k_2}$.

If $\beta = \frac{k_1}{k_2}$, habitat degradation as a result of destructive fishing activities is entirely prevented.

2.3.2 The reserve effects vs. the AR effects

Although the reserve effects differ from the AR effects, they are usually modelled in a similar way. But are the differences between these effects so significant that they

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[5] We assume that artificial habitats have the same sensitivity to fishing as natural habitats, i.e. parameter θ is identical for both types of habitats.

should be taken into account ? The effects that reserves are thought to produce are two-fold. First, the recovery of fish populations through the elimination of fishing mortality caused by fishing activities. Second, the rehabilitation of fish habitats by removing destructive fishing gear from the area[6]. On the other hand, the effects of ARs have essentially impact on habitats through the creation of new habitats and only indirectly on fish populations. In this case, ARs do not necessarily move away destructive fishing gear and habitat degradation can still persist. Therefore, we can tell that the effects of these two management tools do considerably differ since there is only one direct effect, habitat effect, in the case of ARs. However, even if both tools only produced habitat effects, we have seen that they are achieved through different processes and thus may have different management implications. It is hence important to distinguish these effects, and to do so the model should include the link between fishing activities and the state of habitats as we did in Udumyan *et al.* (2010).

In our model, reserve effects are reached by setting the effort E to 0. The elimination of fishing mortality corresponds to the absence of catches $H = qEx = 0$; the rehabilitation of habitats to increased carrying capacity $K = K_{max}$. The AR effect does not involve any access restriction and thus has no impact on catches but also leads to increased carrying capacity $(K_{max} + \alpha\tilde{K})(1 - \theta E)$. However, this increase is subject to the effort exerted in the area : the higher E, the lower the increase in carrying capacity. Thus, our model indeed captures the differences between these two, in some way similar, management tools.

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[6] This second effect only recently have been included into the conventional model (Armstrong, 2007).

2.3.3 Economic assumptions and evaluated scenarios

The implementation of an AR policy. We assume that ARs can be deployed only once, in period 0. Function $C_1(\alpha)$ denotes a discrete investment in an AR project developed for fish population enhancement, which is incurred in period 0 and is related to the labor and materials spent for the design, construction and immersion of ARs. Function $C_2(\beta)$ refers to the costs of the deployment of ARs that enforce gear regulation. A single payment is assumed for each AR project, thus neglecting any on-going maintenance and management costs.

Economic rent. Each period of time, fishing units spend a constant cost c per unit of effort to harvest fish and sell it on the market at a constant price p. The cost c includes the costs of operating vessels (fuel, supplies etc.) plus opportunity wages of captain and crew (Clark, 2006). Price p is assumed exogenous since, in small-scale fisheries where AR projects are usually promoted, the overall quantity offered on the market is not large enough to affect the market price and thus agents are price takers. The total revenues derived from the fishery after the immersion of ARs is $R(x,E) = pqEx - cE$.

For the problem of dynamically optimal harvesting, we relax the assumption of constant price by considering a downward sloping demand function $p = a - bH$.

Combined management scenarios. When an AR project is implemented, it can be combined with complementary fisheries management tools to produce a larger habitat effect and avoid potential negative implications of this policy explained in the previous section. Table 2.1 summarizes different scenarios that we analyze in further sections.

As Table 2.1 states, three different fisheries management objectives are considered : the Maximum Sustainable Yield (MSY) and the Maximum Economic Yield (MEY), which are the traditional fisheries management objectives (see, for instance, Clark, 1990), and the maximization of discounted rents of fishery. Depending on these objectives, two main groups of scenarios are outlined, referring to either a static model or a dynamic model.

The assumption $\theta = 0$, required in some scenarios to obtain explicit analytical results, can be interpreted as the implementation of gear regulation in the concerned area prior to or at the same time as the deployment of an AR project (this combination of tools is frequently observed in real-world fisheries) or that fishing units were employing habitat-friendly gear in the first place.

In the same vein, the assumption of fixed and exogenous effort may be the result of arrangements between local fishermen[7] or could be imposed by a local authority, who does not necessarily succeed in finding the optimal effort level with regard to the fisheries objective, for example, due to scarce information on the resource and marine ecosystem in general giving little room for appropriate management of fishery inputs or outputs (Holland and Brazee, 1996; Lauck *et al.*, 1998; Boncoeur *et al.*, 2002; McGoodwin, 2003).

2.3.4 Biological equilibria

In this subsection, we examine the equilibrium behavior of the presented model. Expression for biological equilibria is found and analyzed. The biological equilibria

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[7] For instance, in the French Mediterranean, these arrangements are worked out by the institutions called "Prud'homie", which were developed many centuries ago by local fishermen who early became aware of the necessity of managing the resource.

Table 2.1 – This table conveys the examined fisheries management regimes. The parameter δ denotes the discount rate. We call enforcers the ARs designed to exclude some types of destructive gear while enhancers refer to the ARs aimed to enhance the fishing.

Management objective	**Type of reef units**	**Other tools**	**Policy variables**	**Assumptions**
MSY	Enhancers	None	α	$\theta = 0$
MEY	Enhancers	Effort control	E	
$Max \int_0^\infty e^{-\delta t} R(t)dt - C_1(\alpha)$	Enhancers	None	α	E parameter
$Max \int_0^\infty e^{-\delta t} R(t)dt - C_1(\alpha) - C_2(\beta)$	Enhancers, Enforcers	None	α, β	E parameter
$Max \int_0^\infty e^{-\delta t} R(t)dt - C_1(\alpha)$	Enhancers	Effort control	E	$\theta = 0$
$Max \int_0^\infty e^{-\delta t} R(t)dt - C_1(\alpha)$	Enhancers	Effort control	α, E	$\theta = 0$

are derived from the equations $\dot{x} = 0$. The model given by (2.2) possesses one positive steady state :

$$\overline{x} = (K_{max} + \alpha \tilde{K})(1 - \theta E)(1 - qE/r); \qquad (2.4)$$

This steady state is locally asymptotically stable (the calculations are very similar to those made for the conventional model, for details see Clark, 2006). The analysis of the steady state of the system will allow the model assumptions to be verified.

As expected, the positive habitat effect due to the deployment of ARs results in higher steady-state fish stock (according to the first multiplier in equation (2.4)). The second multiplier in expression (2.4) accounts for destructive harvesting resulting in the deterioration of both natural and artificial habitats whereas the third multiplier refers to the fishing mortality caused by fishing. With respect to the second multiplier, when destructive harvesting takes place ($\theta > 0$), any additional unit of effort reduces the ecological benefits of ARs. If fishing is not allowed in the AR area as in reserve, according to our model formulation, ARs fare the best from the biological point of view. When the area is open to fishing and the fishing effort cannot be regulated, the prohibition of destructive types of gear ($\theta = 0$) is the second-best solution for the improvement of ecological benefits of ARs.

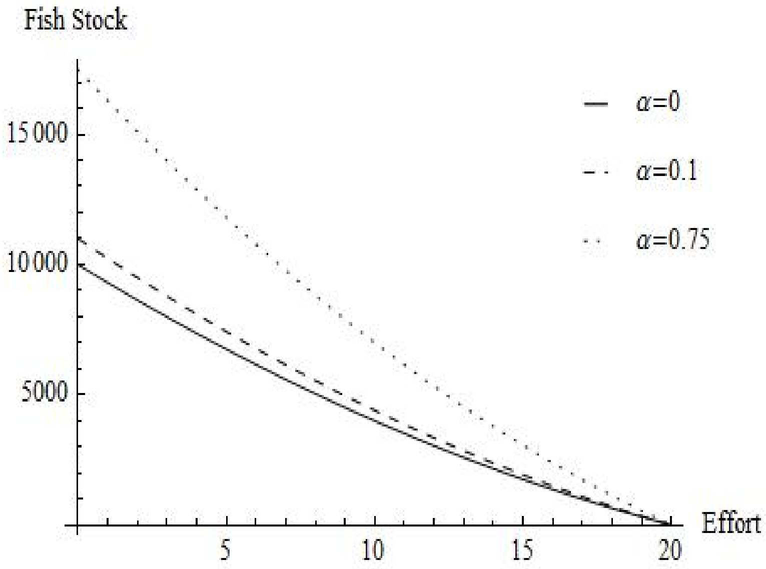

Figure 2.1 – The steady-state fish stock as a function of effort is displayed for different values of α. The parameter values are $r = 0.1, q = 0.005, \theta = 0.02, K_{max} = 100000, \tilde{K} = 10000$.

Figure 2.1 compares steady-state fish stocks for different sizes of AR projects (dashed and dotted curves) with the fish stock produced in their absence (solid curve). According to this graphical sketch, the gap between the curves decreases as effort increases and the fish stocks corresponding to a positive α (dashed and dotted curves) approach that of the status quo scenario $\alpha = 0$ (solid curve). Therefore, in a heavily fished fishery, there is little ecological benefit from the deployment of ARs, which is a coherent property of the model for two reasons. First, the quantity of fish extracted increases with increasing effort and ARs cannot remedy this since they do not limit fishery input or output nor do they capable of significantly increasing the fish stock. Second, the impact of destructive harvesting on habitats amplifies as effort increases and, at high levels of effort, this strongly impairs the positive habitat effect of ARs. At lower efforts, the gap between the curves broadens accentuating the positive consequences of an AR project. The ecological benefits of ARs (measured in fish stock) increase as α increases.

2.4 Economic and ecological impacts of ARs in different fishery contexts

The role of an AR policy in achieving fishery objectives such as the MSY, the MEY or the maximization of discounted rents is discussed for different types of regulation already in place in the concerned area.

2.4.1 Achieving the MSY in an open-access fishery

The MSY is a traditional references for sustainable resource exploitation (Clark, 1990). The idea behind the MSY is to determine the maximal quantity of fish that can be extracted without altering the fish stock. This yield level is usually reached through input (effort limitation) or output control (quota). However, Flaaten and Mjolhus (2010) demonstrate that it can also be reached through the creation of reserve. They show that the reserve size can be tuned so as the yield level in the fishing ground (marine area open to fishing enjoying from the creation of reserve through fish migration) attain the MSY level.

In this section, we carry out a similar analysis to examine the circumstances in which the AR size can be tuned so that the yield level satisfy the MSY objective without additional control on input or output. To do so, we analyze the situation of unregulated open access where ARs is the only management tool in place. For the sake of simplicity, we assume that $\theta = 0$.

In an unregulated open-access fishery effort achieves a bioeconomic (or bionomic, as Clark refers to it) equilibrium at the level E_{OA} where fishery revenues match cost, i.e. $pH(x, E) = cE$:

$$E_{OA} = \frac{r}{q}\left(1 - \frac{c}{pq(K_{max} + \alpha\tilde{K}}\right)\right). \tag{2.5}$$

Taking into consideration that the fish stock settles at $x_{OA} = \frac{c}{pq}$, the yield level is $H_{0A}(\alpha) = \frac{cr}{pq}\left(1 - \frac{c}{pq(K_{max}+\alpha\tilde{K}}\right)\right)$. From the form of $H_{0A}(\alpha)$ follows that harvests can be increased through ARs, $\frac{\partial H_{0A}}{\partial \alpha} > 0$. Comparing H_{0A} to the MSY level $H_{MSY} = \frac{rK_{max}}{4}$ obtained for the conventional model, we find the AR size required to reach it :

$$\alpha = \frac{c/pq}{\tilde{K}\left(1 - \frac{pq}{c}\frac{K_{max}}{4}\right)} - \frac{K_{max}}{\tilde{K}}. \tag{2.6}$$

This expression for α is positive if $\frac{c}{pq} \geq \frac{K_{max}}{4}$. This result suggests that in fisheries involving lower harvesting costs, it is not possible to achieve the MSY objective only through the implementation of AR projects as opposed to the case of reserve for which Flaaten and Mjolhus (2010) prove analytically that, in certain conditions, the MSY level can be reached even in zero-cost fisheries.

2.4.2 What can be expected from ARs in a regulated fishery ?

It is evident that AR projects are not capable of improving the fishery rent in an unregulated open-access fishery where the rent is expected to dissipate. The short-term increase in profits engendered by the deployment of ARs as reported by different surveys triggers the process of effort adjustment (entry of new fishing units or/and the expansion of the fishing activities of the existing fishing units) until the rent of the fishery dissipates. Therefore, as in the case of reserve (Flaaten and Mjolhus, 2010), the MEY, which refers to the yield level at which sustainably harvested fish stock produces the greatest economic rent, cannot be achieved without input or output control. Then the question is whether the creation of new habitats through ARs serves in any way given that the effort control is used to accomplish the MEY objective.

To answer this question, we calculate the effort level leading to the MEY in the framework of our model, that is, in the presence of ARs and negative habitat effects of fishing neglected in the conventional model :

$$E_{MEY} = \frac{1}{3}\left(\frac{r}{q}+\frac{1}{\theta}\right) - \sqrt{\frac{1}{9}\left(\frac{r}{q}+\frac{1}{\theta}\right)^2 - \frac{r}{3q\theta}\left(1-\frac{c}{pq(K_{max}+\alpha\tilde{K})}\right)}, \qquad (2.7)$$

According to this expression, there is a positive relation between E_{MEY} and α, i.e. $\frac{\partial E_{MEY}}{\partial \alpha} > 0$. The reason for this lies in the improvement of fishery efficiency imputable to better conditions for fish growth offered by ARs : the unit cost of effort remains unchanged but greater revenues per unit of effort are earned since the population of fish is larger and, therefore, more fish can be captured (in other words, harvesting costs $\frac{c}{qx}$ are lower)[8].

Thus, ARs allow to relax control on effort. This is a convenient implication of AR projects when the calculations of the effort level corresponding to the MEY (in its conventional form) may involve errors of estimation due to the lack of information on key biological or economic parameters and costly data-gathering. In particular, neglecting habitat component in the analysis and, therefore, the problem of habitat degradation could lead to the overestimation of effort (Udumyan *et al.*, 2010). Moreover, ARs may generate higher sustainable rent. For instance, in the case of habitat-friendly fishing it is the result of comparison between $E_{MEY}(\alpha) = \frac{r}{2q}\left(1 - \frac{c}{pq(K_{max}+\alpha\tilde{K})}\right)$, $x_{MEY}(\alpha) = \frac{K_{max}+\alpha\tilde{K}}{2} + \frac{c}{2pq}$ and $E_{MEY} = \frac{r}{2q}\left(1 - \frac{c}{pqK_{max}}\right)$, $x_{MEY} = \frac{K_{max}}{2} + \frac{c}{2pq}$. It is obvious that the fish stock and the effort are both larger for positive α.

2.4.3 ARs in a poorly managed fishery with degraded habitats

In the previous subsections, the present and future benefits were equally discounted, which is why the investment in an AR project assumed discrete in this study did not influence the results. In this subsection, we explore the effects of ARs in fisheries with degraded habitats considering that the fishery objective is the maximization of the expected present value of profit from harvest with the present benefits having more weight for the government agency in charge of fishery management. ARs acting as fishery enhancers is the only management tool and the effort exerted in the area is assumed fixed and exogenous.

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[8] At this point, it is important to mention the difference between operating and harvesting costs. Parameter c refers to the operating costs of fishing and quantity $\frac{c}{qx}$ to the harvesting costs.

To analyze this optimization problem, the cost function $C_1(\alpha)$ of AR project incurred at time 0 is introduced. We suppose that $C_1(\alpha)$ is convex and specify it as follows

$$C_1(\alpha) = d\alpha^{\omega}, \tag{2.8}$$

with coefficients $d, d > 0$ and $\omega, \omega \geq 1$.

According to this formulation, costly AR projects are expressed by high ω and d.

We assume that a single AR project financed by government is realized. There are no costs of management or other expenses related to the deployment of ARs beyond period 0. The size of ARs cannot exceed some upper bound denoted here as α_{max}, the level that embodies technical and financial constraints, $0 \leq \alpha \leq \alpha_{max}$.

Because the AR project is implemented only once, policy variable α is constant over time. Assume that the AR cost function $C(\alpha)$ is strictly convex ($\omega > 1$).

The problem of optimal management is formally represented as

$$\underset{\alpha}{Max} V\{x, E, \alpha\} = \int_0^{\infty} e^{-\delta t}(pqEx - cE)dt - d\alpha^{\omega} \tag{2.9}$$

where α is the control variable, $0 \leq \alpha \leq \alpha_{max}$ and δ denotes the discount rate.

Since both the effort and the AR size are time-independent, (2.9) can easily be reduced to a static optimization problem. First, we find the expression for x by solving differential equation (2.2) :

$$x = (K_{max} + \alpha\tilde{K})\left(1 - \frac{qE}{r}\right)(1 - \theta E). \tag{2.10}$$

Then we substitute (2.10) into the objective integral (2.9) and solve it :

$$\underset{\alpha}{Max} V\{x,E,\alpha\} = \frac{1}{\delta} pqE\left((K_{max}+\alpha\tilde{K})\left(1-\frac{qE}{r}\right)(1-\theta E)-\frac{c}{pq}\right)-d\alpha^{\omega}. \quad (2.11)$$

After some basic calculations, we obtain

$$\alpha^* = \sqrt[\omega-1]{\frac{pq\tilde{K}E(1-qE/r)(1-\theta E)}{\delta d\omega}}, \quad (2.12)$$

where $\omega > 1$[9].

As expected, the optimal size α^* is negatively related to δ, ω and d. The larger the investments required for the implementation of an AR project (high d or/and ω), the lower its cost-effectiveness and, thereby, the smaller the project should be (see Figure 2.2). Similarly, a highly discounting government agency is less motivated in AR projects as compared to a low discounting one since they involve prior investments and the gains from ARs are not immediate. In the extreme case $\delta \to \infty$, ARs as a fisheries management option will not win through, i.e. $\alpha^* = 0$. On the other hand, if $\delta \to 0$, the maximal possible amount of ARs should be deployed, i.e. $\alpha^* = \alpha_{max}$.

On the contrary, the relation to the effort E is not monotonic : $\frac{\partial\alpha^*}{\partial E} > 0$ if $E < \frac{1}{3}\left(\frac{r}{q}+\frac{1}{\theta}-\sqrt{\frac{r^2}{q^2}-\frac{r}{\theta q}+\frac{1}{\theta^2}}\right)$, $\frac{\partial\alpha^*}{\partial E} \leq 0$ otherwise.

Two kinds of fishery are distinguished here with respect to the fishing pressure : moderately and heavily exploited fisheries (see Figure 2.2). In a moderately exploited fishery, the higher the effort is, the higher the size of ARs should be. In a heavily exploited fishery, the opposite is true. From this it follows that, under too high

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[9] Since $\frac{\partial^2 V}{\partial^2\alpha} < 0$, α^* is the maximum of V.

or too low fishing pressure, ARs are of little use while the best results from AR deployment (α^* is maximized) are expected at the effort $\tilde{E} = \frac{1}{3}\left(\frac{r}{q} + \frac{1}{\theta} - \sqrt{\frac{r^2}{q^2} - \frac{r}{\theta q} + \frac{1}{\theta^2}}\right)$, which, as mentioned earlier, is the level satisfying the MEY objective. This result is coherent since under low pressure habitats do not suffer considerable damage as to be in need of ARs. Similarly, under too high pressure damages are so great that ARs are not able to alleviate the negative habitat effects of fishing.

Note also that the lower the AR cost d, the greater the magnitude of $\frac{\partial \alpha^*}{\partial E}$. Thus, the higher d, the less important the regime (moderately and heavily exploited fisheries) under which ARs are deployed when deciding on their size. On the contrary, for cost-effective AR projects, the effort control is crucial since it can significantly improve the economic benefits derived from their implementation.

When comparing the rent yielded in this scenario with that generated in the absence of ARs, we find the level of AR size at which ARs lead to higher rent :

$\alpha < \sqrt[\omega-1]{\frac{pq\tilde{K}E(1-qE/r)(1-\theta E)}{\delta d}}$.

Since the optimal size α^* satisfies this inequality, the management scenario studied here always generates higher rent for a given effort.

Finally, the negative relation of α^* to θ suggests that the use of highly destructive types of gear may considerably undermine the benefits of ARs and that the introduction of gear control may improve the cost-efficiency of ARs. This issue is raised in more details in the next subsection.

2.4.4 Combined with gear control in the shape of enforcing ARs

As was shown in the previous subsection, the use of destructive types of gear may considerably impair the benefits of ARs so that it may not be economically optimal to

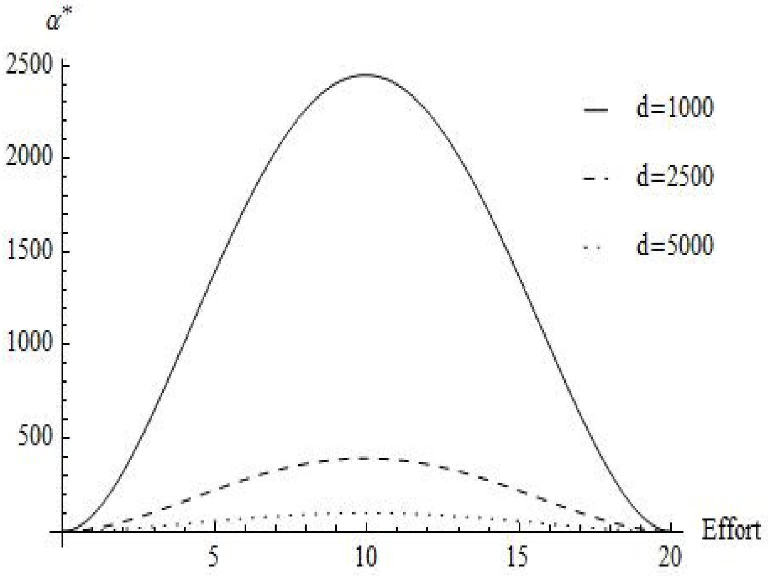

Figure 2.2 – The optimal AR size α^* as a function of effort for different values of the AR cost d. The parameter values are $r = 0.1, q = 0.005, \tau = 0.05, \gamma = 0.001, K_{max} = 100000, \tilde{K} = 10000, p = 15, c = 0.1, \delta = 0.05, \omega = 1.5$.

deploy them. Now cosider that ARs acting as enhancers for fishery are accompanied with a gear control through the deployment of ARs serving as obstacles for some types of destructive gear to prevent fishery losses due to habitat degradation. The sizes of both types of ARs are hence regarded as policy variables.

Assume that the form of the cost function for ARs acting as gear enforcers is identical to that describing the costs of ARs for fish enhancement :

$$C_2(\beta) = s\beta^v, \tag{2.13}$$

with coefficients $s, s > 0$ and $v, v \geq 1$.

To find an analytical solution to the problem of discounted rent maximization, we set $\omega = s = 2$. Thus,

$$\underset{\alpha,\beta}{Max} V\{x,E,\alpha,\beta\} = \int_0^\infty e^{-\delta t}(pqEx - cE)dt - d\alpha^\omega - s\beta^v \tag{2.14}$$

$$\dot{x} = rx\left(1 - \frac{x}{(K_{max}+\tilde{K}\alpha)(1-(k_1-k_2\beta)E)}\right) - qEx, \tag{2.15}$$

where α and β are control variables, $0 \leq \alpha \leq \alpha_{max}$ and $0 \leq \beta \leq \beta_{max}$.

As in the previous scenario, α, β and E are independent of time t, therefore, we easily solve the integral :

$$\underset{\alpha,\beta}{Max} W(\alpha,\beta) = \frac{1}{\delta}(pqEx - cE) - d\alpha^2 - s\beta^2. \tag{2.16}$$

with $x = (K_{max}+\tilde{K}\alpha)(1-(k_1-k_2\beta)E)\left(1-\frac{qE}{r}\right)$.

Then we write down the first-order conditions :

$$\frac{\partial W}{\partial \alpha} = \frac{1}{\delta}pq\tilde{K}E(1-(k_1-k_2\beta)E)\left(1-\frac{qE}{r}\right) - 2d\alpha = 0, \tag{2.17}$$

$$\frac{\partial W}{\partial \beta} = \frac{1}{\delta}pqk_2E^2(K_{max}+\tilde{K}\alpha)\left(1-\frac{qE}{r}\right) - 2s\beta = 0, \tag{2.18}$$

Solving this system of equations, we obtain[10] :

$$\alpha^{**} = \frac{p^2q^2k_2^2\tilde{K}K_{max}E^4\left(1-\frac{qE}{r}\right)^2 - 2\delta spq\tilde{K}E^2\left(\frac{k_1}{k_2}-\frac{1}{k_2E}\right)\left(1-\frac{qE}{r}\right)}{4\delta^2 ds - \tilde{K}^2p^2q^2k_2^2E^4\left(1-\frac{qE}{r}\right)^2}, \tag{2.19}$$

$$\beta^{**} = \frac{2\delta dpqk_2K_{max}E^2\left(1-\frac{qE}{r}\right) - 4\delta^2 ds\left(\frac{k_1}{k_2}-\frac{1}{k_2E}\right)}{4\delta^2 ds - \tilde{K}^2p^2q^2k_2^2E^4\left(1-\frac{qE}{r}\right)^2} + \frac{k_1}{k_2} - \frac{1}{k_2E}. \tag{2.20}$$

---

[10] It can be easily shown that the corresponding matrix of second derivatives is negative-definite on condition that $4\delta^2 ds > \tilde{K}^2p^2q^2k_2^2E^4\left(1-\frac{qE}{r}\right)^2$. In that case, (α^{**},β^{**}) is the maximum of W.

Comparing the optimal AR size α^{**} to that of the previous scenario α^{*} given by (2.12), we find that $\alpha^{**} > \alpha^{*}$ for any level of effort. Higher size of ARs is optimal when gear control in the shape of ARs for enforcement is implemented because they are designed to prevent habitat degradation to some extent. As a result, fishing activities do not impair the positive habitat effect produced by ARs as much as in the absence of such control.

The expressions obtained for α^{**} and β^{**} suggest negative relations to k_1, δ, d and s. The parameter k_1 refers to the rate of habitat degradation in the absence of ARs designed for gear enforcement. Therefore, it is straightforward that the higher this rate, the worse the performance of both types of ARs. The relation to δ is also in line with economic theory. What seems not to be as straightforward is that both α^{**} and β^{**} are negatively dependent not only on the costs required to deploy the corresponding type of ARs but also on that of the other type, $\frac{\partial \alpha^{**}}{s} < 0$ and $\frac{\partial \beta^{**}}{d} < 0$. This points to how their cost-efficiencies are interdependent. The higher s, the lower β^{**} and the weaker the gear control in the area, which impairs the benefits of ARs. In the same vein, the higher d, the lower α^{**} and thus the lower the expected increase in carrying capacity. In that case, the effect of gear control on carrying capacity becomes less significant.

Finally, in the case of $\omega = v = 1$ and $d \geq s$, we find that $\beta^{**} > \alpha^{**}$ for $E > \frac{1}{k_1 + k_2 \frac{K_{max}}{\tilde{K}}}$. There is more need in gear control than in the enhancement of fish carrying capacity when the target fish populations are heavily exploited. The reason is that it would be more cost-efficient to deal with the fishing activities causing habitat degradation than to offset the negative habitat effects of fishing by the positive habitat effects of ARs.

2.5 Dynamically optimal harvesting and AR strategy

In this section, we characterize the dynamically optimal harvesting and AR strategy that maximize the expected present value of profit from harvest given that the present benefits have more weight for the government agency regulating the fishery. We consider that this government agency has absolute control over the level of fishing effort and that the effort restriction is regarded as one of the management instruments at its disposal. Note that to yield explicit analytical results, we assume that the fishing activities in the area are habitat-friendly, i.e. $\theta = 0$.

By assuming linear costs of AR deployment, i.e. $\omega = 1$, we solve the following problem

$$\underset{\alpha, E}{Max} V\{x, E, \alpha\} = \int_0^\infty e^{-\delta t}(pqEx - cE)dt - d\alpha \tag{2.21}$$

subject to the state equation

$$\dot{x} = rx\left(1 - \frac{x}{K_{max} + \alpha\tilde{K}}\right) - qEx, \tag{2.22}$$

$$x(0) = x_0,$$

where α is control parameter and $E = E(t)$ is a time-dependent control variable, $0 \leq \alpha \leq \alpha_{max}$, $0 \leq E \leq E_{max}$.

According to the Pontryagin maximum principle, we build a Hamiltonian of the problem

$$\mathcal{H}(x, t, E, \lambda) = e^{-\delta t}(pqEx - cE) + \lambda\left(rx\left(1 - \frac{x}{K_{max} + \alpha\tilde{K}}\right) - qEx\right), \tag{2.23}$$

where $\lambda(t)$ is known as the shadow price of fish.

The necessary optimality conditions are as follows :

$$\dot{\lambda} = -\frac{\partial \mathcal{H}}{\partial x} = -e^{-\delta t} pqE - \lambda \left(r - \frac{2rx}{K_{max} + \alpha \tilde{K}} - qE \right); \tag{2.24}$$

$$\int_0^\infty \frac{\partial \mathcal{H}}{\partial \alpha} dt - d = \int_0^\infty \frac{\lambda r \tilde{K} x^2}{(K_{max} + \alpha \tilde{K})^2} dt - d \leq 0, \alpha \geq 0, \alpha \left(\int_0^\infty \frac{\lambda r \tilde{K} x^2}{(K_{max} + \alpha \tilde{K})^2} dt - d \right) = 0; \tag{2.25}$$

$$\int_0^\infty \frac{\lambda r \tilde{K} x^2}{(K_{max} + \alpha \tilde{K})^2} dt - d \geq 0, \alpha \leq \alpha_{max}, (\alpha - \alpha_{max}) \left(\int_0^\infty \frac{\lambda r \tilde{K} x^2}{(K_{max} + \alpha \tilde{K})^2} dt - d \right) = 0; \tag{2.26}$$

$$\frac{\partial \mathcal{H}}{\partial E} = e^{-\delta t}(pqx - c) - \lambda qx = 0. \tag{2.27}$$

The resource should be fished as intensively as possible when $\frac{\partial \mathcal{H}}{\partial E} > 0$, i.e. the optimal effort is E_{max} ; while $\frac{\partial \mathcal{H}}{\partial E} < 0$, no fishing should take place ; if $\frac{\partial \mathcal{H}}{\partial E} = 0$, the effort should be set to its interior value E^*.

According to conditions (2.25) and (2.26), the interior control α^* is found from the following equation :

$$\int_0^\infty \frac{\lambda r \tilde{K} x^2}{(K_{max} + \alpha \tilde{K})^2} dt = d. \tag{2.28}$$

Solving equation (2.27) with respect to λ, we obtain

$$\lambda = e^{-\delta t} \left(p - \frac{c}{qx} \right). \tag{2.29}$$

By substituting (2.29) into (2.24), we find that

$$K_{max} + \alpha \tilde{K} = \frac{r}{\delta} \frac{2x - \frac{c}{pq}}{1 - \frac{r}{\delta} - \frac{c}{pqx}}. \tag{2.30}$$

The control parameter α being independent of time, equation (2.30) is algebraic and therefore $\dot{x} = 0$. This result allows us to calculate the integral in equation (2.28). We solve (2.28) using expression (2.29) for λ

$$\int\limits_{0}^{\infty} e^{-\delta t}\left(p - \frac{c}{qx}\right)\frac{r\tilde{K}x^2}{(K_{max} + \alpha\tilde{K})^2} = d; \tag{2.31}$$

$$\left(p - \frac{c}{qx}\right)\frac{r\tilde{K}x^2}{(K_{max} + \alpha\tilde{K})^2} = \delta d. \tag{2.32}$$

By substituting (2.30) into (2.32), we obtain a cubic equation for x :

$$a_1 x^3 + a_2 x^2 + a_3 x + a_4 = 0, \tag{2.33}$$

where

$$a_1 = \left(1 - \tfrac{r}{\delta}\right)^2 - 4\tfrac{r}{\delta}\tfrac{d}{p\tilde{K}},$$
$$a_2 = \tfrac{c}{pq}\left(4\tfrac{r}{\delta}\tfrac{d}{p\tilde{K}} - \tfrac{r^2}{\delta^2} + 4\tfrac{r}{\delta} - 3\right),$$
$$a_3 = \tfrac{c^2}{p^2q^2}\left(3 - 2\tfrac{r}{\delta} - \tfrac{r}{\delta}\tfrac{d}{p\tilde{K}} - 1\right),$$
$$a_4 = -\tfrac{c^3}{p^3q^3}.$$

The constant a_4 of the corresponding polynomial is negative. If, in addition, the leading coefficient a_1 is positive, there is at least one positive real root. This positivity condition is satisfied for $\frac{d}{p\tilde{K}} < \left(1 - \frac{r}{\delta}\right)^2 \frac{\delta}{4r}$. It states that, if marginal AR cost d or/and discount rate δ are sufficiently low, the examined problem has an interior optimal solution (α^*, E^*). However, considering the form of the objective function, it is expected that the optimal control α^* is not an interior value but lies at an extreme point, either 0 or α_{max}. Therefore, if the constraint in question is verified, it only means that there is an interior solution for the effort control. This interior value E^* is found from $\dot{x} = 0$, or

$$x = (K_{max} + \alpha\tilde{K})\left(1 - \frac{qE}{r}\right), \tag{2.34}$$

using (2.30) and (2.33).

Since the feasible solution of (2.33) is not tractable, it is difficult to interpret it without fixing model parameters. To get an idea of how the optimal controls behave depending on model parameters, we hence conduct numerical calculations. For convenience, we introduce the following notations :

- $z_\infty = \frac{c}{pqK_{max}}$ corresponds to the open-access fish stock level when ARs are not deployed ;
- $\gamma = \frac{\delta}{r}$ is the ratio of the discount rate to the intrinsic growth rate of the population, which is referred to as the bionomic growth ratio (Clark (1990)) ;
- $\omega = \frac{d}{p\tilde{K}}$ is the ratio of marginal AR cost to the present value of the fish sheltered by one unit of ARs given that these latter are entirely colonized. Thus, this aggregated parameter measures the efficiency of an AR project ;
- $L = 1 + \frac{\alpha\tilde{K}}{K_{max}}$ represents the carrying capacity of the area after the deployment of ARs as a proportion of the carrying capacity before ARs were installed.

We thereby examine L instead of α. The optimal control L can be represented as a function of ω when parameters z_∞ and γ are fixed. The following values for z_∞ and γ were tested : z_∞ ranged from 0 to 0.9 in steps of 0.1 and γ was varied in the range 0.1 to 0.9 with steps of 0.2. We only illustrate the case $\gamma = 0.1$, $z_\infty \in [0.6; 0.9]$ with steps of 0.1 as it depicts a typical situation when the effort E^* should be set at its interior value. As expected, the optimal solution for α is attained at one of the extreme points. The curves presented in Figure 2.3 consist of the points (ω, L_{max}) with $L_{max} = 1 + \frac{\alpha_{max}\tilde{K}}{K_{max}}$ at which the optimal AR size switches from α_{max} to 0 for a given α_{max}. For instance, given that $L_{max} = 1.4$ and $z_\infty = 0.9$, the solution to our problem preconizes the deployment of ARs on condition that $\omega \leq 1.36422$, otherwise $\alpha^* = 0$.

The decision to deploy ARs depends, in particular, on the marginal cost c of fishing (which appears in z_∞) and the marginal cost d of AR deployment (aggregated in ω) as well as on the relationship between the two. Not surprisingly, for sufficiently low d it is optimal to deploy the maximal amount of ARs. On the contrary, if the AR project is too costly, it should not be implemented since the costs of the project are lager than the present value of its future benefits.

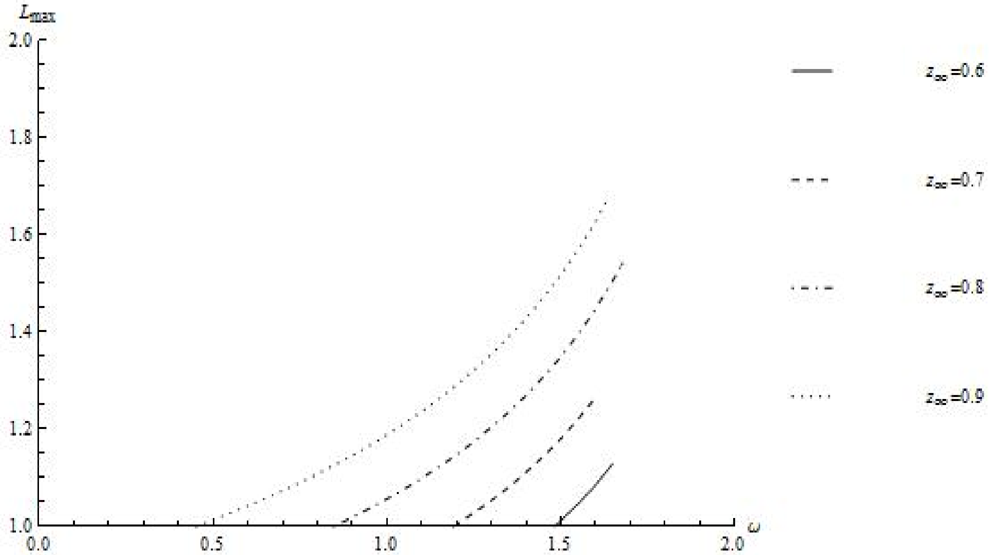

Figure 2.3 – In this graph, the behavior of the optimal control L is plotted as a function of ω for different values of z_∞. The points on each curve correspond to the threshold at which the optimal AR size switches from α_{max} to 0 for a given L_{max}.

For a given L_{max} (or α_{max}), the critical threshold for ω (and therefore for d), where the optimal AR size switches from α_{max} to 0, decreases with increasing c. Therefore, the higher the cost c of fishing, the lower the cost d of the AR project should be for it to be implemented.

For further analysis, imagine now that the maximal amount of ARs is not fixed. The greater the marginal AR cost d is, the lower the harvesting costs $h_c = \frac{c}{pqx}$ should be, which is attained through an AR project of a larger scale (see Figure 2.4).

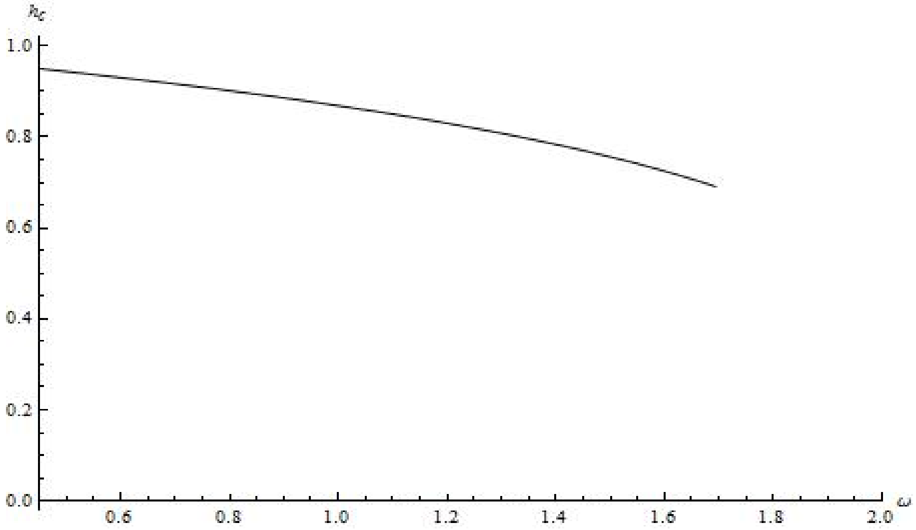

Figure 2.4 – The illustration of the relation between $h_c = \frac{c}{pqx}$ and ω.

In the same vein, for a given d, larger amount of ARs should be immerged for greater operating costs (see Figure 2.5). This property of the optimal solution can be explained as follows. The higher the operating costs, the higher the harvesting costs for the same level of fish stock and therefore the more there is a need for ARs, which are known to reduce harvesting costs.

When the optimal size of ARs is found, the optimal interior effort that belongs

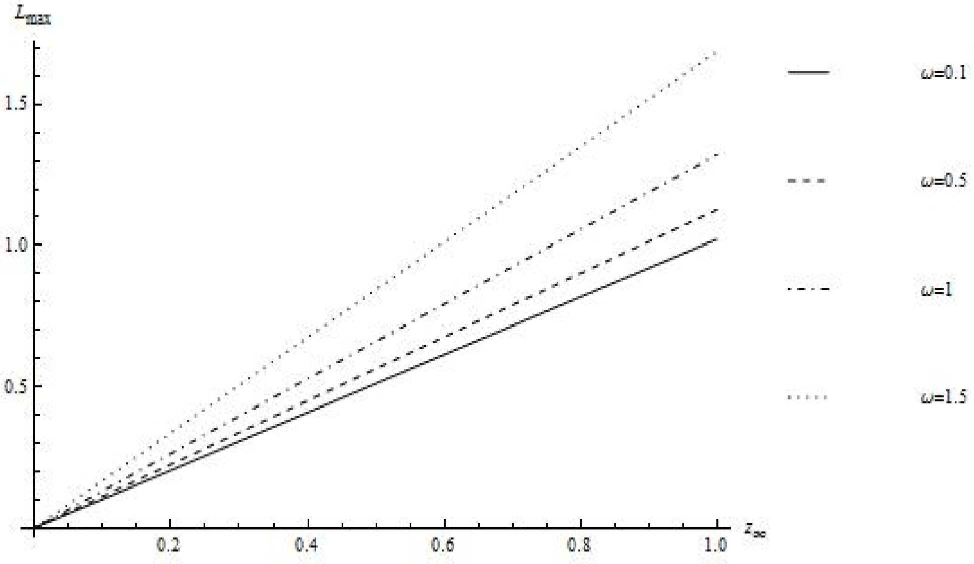

Figure 2.5 – This graph illustrates the behavior of the optimal control L depending on z_∞ for different values of ω.

to the set of admissible controls can be calculated

$$E^*(\alpha^*) = \frac{r}{4q}\left(\gamma + 3 - z_\infty(\alpha^*) - \sqrt{(\gamma+3-z_\infty(\alpha^*))^2 - 8(1-z_\infty(\alpha^*))(\gamma+1)}\right), \tag{2.35}$$

as well as the optimal fish stock

$$x^* = \frac{K_{max}+\alpha^*\tilde{K}}{4}\left(z_\infty(\alpha^*)+1-\gamma+\sqrt{(z_\infty(\alpha^*)+1-\gamma)^2+8\gamma z_\infty(\alpha^*)}\right), \tag{2.36}$$

where α^* is equal either to 0 or α_{max}, $\gamma = \frac{\delta}{r}$ and $z_\infty(\alpha^*) = \frac{c}{pq(K_{max}+\alpha^*\tilde{K})}$ (the corresponding open-access fish stock level).

For $\alpha^* = 0$ problem (2.21)-(2.22) yields the same optimal effort and fish stock as obtained by Clark (1990) in the conventional model without ARs. Another important property of the optimal solution is that the fish stock x^* and the effort E^*, as described by equations (2.36) and (2.35) respectively, are increasing functions of the AR size α. Consequently, these optimal levels are higher than those that result from the conventional model without ARs for any $\alpha^* > 0$.

To sum up, when the fish is captured with a too high cost, the government agency should not expect any gains from ARs and the only tool to be used to manage the resource is the effort control. On the other hand, for a given AR cost d and maximal AR size α_{max}, ARs are seen as a useful management tool within a sufficiently low effort cost range, where they are capable of significantly improving the efficiency of fishermen by reducing harvesting costs through the enhancement of fish population and their aggregation. In that case, the discounted rents of fishery resulting from the deployment of the maximal amount α_{max} of ARs are higher than those yielded without ARs.

For a one-dimensional dynamic problem with one time-dependent control variable, it is the most rapid approach path (MRAP) that is optimal for achieving the interior solution (Clark, 2006). According to it, the optimal path to the obtained interior solution is as follows. As long as $x < x^*$, no fishing should take place ; if, on the contrary, $x > x^*$, the fishing effort should be set to its maximum E_{max} ; otherwise, to the interior solution $E = E^*$. Thus, the optimal solution to the problem (2.21)-(2.22) is described by

$$E(t) = \begin{cases} 0, x < x^* \\ E^*, x = x^* \\ E_{max}, x > x^* \end{cases}$$

and $\alpha^* = 0$ or α_{max}.

In other words, in period 0, ARs of size α^* should be immersed (or not) and a temporary reserve should be established if the target fish population is below the optimal level x^*. Usually, the option of AR deployment is contemplated when the target fish population in the area under consideration needs to undergo significant recovery. That is why it is reasonable to assume that initial stock $x(0) < x^*$. The creation of a temporary reserve is then inevitable and allows ARs to be colonized by fish in order to achieve this optimal fish stock level. The lower the initial population, the longer the reserve will be in place. Since the optimal fish stock is equal or higher than that obtained in the absence of ARs, longer reserve is required than in the optimally controlled fishery without ARs on condition that the model parameters are such that the optimal solution suggests to deploy ARs.

2.6 Discussion and conclusion

In the present paper, we attempt to provide a thorough analysis of the most important management issues that AR policy raises and to answer for what kind of fisheries ARs can represent an economically interesting tool. The model developed earlier (Udumyan *et al.*, 2010) and slightly adapted to take account of the positive habitat effect of ARs offers new insights into their potential to improve the economic performance of the fishery. We show that ARs can be a useful tool for fisheries management provided certain conditions are met. Specifically, the decision whether to deploy ARs strongly depends on certain parameters of the fishery such as harvesting costs, fishing effort exerted in the area, the destructive power of fishing gear employed as well as on the cost-effectiveness of ARs in terms of the increase of carrying capacity they are expected to bring.

The main advantage of the chosen modeling solution is that it provides more accurate analysis by examining the interaction between the positive habitat effect of ARs and the negative habitat effect of fishing, usually neglected in conventional models. This interaction is important, since ARs are designed to offset the negative habitat effect caused by destructive fishing through the creation of new habitats.

Most of the existing biological case-studies and surveys, being only concerned with short-term benefits in fisheries with a weak control of fishing pressure, are too optimistic about the performance of ARs. As soon as economic incentives come into play, these benefits dissolve if no management is afforded to ARs. Without management, while a temporary growth in fish stock and fishery rents as a result of AR deployment can be observed in an unregulated open-access fishery, it is followed by a decline until the rent dissipates. However, not all economic benefits dissipate. ARs are able to increase catches even in an open-access setting. Moreover, their size can be chosen to yield the MSY but under certain conditions, in particular, under sufficiently high operating costs. For low-cost fisheries, ARs may not be suited to achieving the MSY objective under open access, while reserves are shown to be able to do so even for zero cost fisheries (Flaaten and Mjolhus, 2010). Yet, the establishment of a reserve involves monitoring costs and is not easily accepted by fishermen contrary to ARs. The question is whether it makes sense to deploy ARs if no resource rent is generated. If demand is infinitely elastic (p constant) as assumed in this analysis, ARs yield no economic benefits such as consumer and producer surplus. But the integration of a downward sloping demand in the model and its combination with the open-access supply curve found by Copes (1970) for the case of marine resources reveal that a consumer surplus increase whenever ARs produce a higher yield.

For ARs to benefit the fishery in terms of resource rent, input or output controls should be put in place, as found in the literature on ARs. In this study, we have examined how the performance of ARs is improved in an optimally managed fishery through effort control or gear regulation such as the deployment of ARs for gear regulation enforcement. We find that under the effort restriction leading to the MEY, as well as providing increased catches, ARs generate increased resource rent and allow the effort control to be weakened. Provided effort limitation is in place, higher rents can also be expected to be generated when seeking to maximize the discounted rents of fishery, in certain circumstances. In the same vein, in the case of fixed and exogenous effort (the level of which is assumed to embody the existing arrangements in the area), when the discounted rent maximization is sought, we demonstrate that combined with the other type of ARs for gear control enforcement, greater benefits are expected from fish enhancement ARs due to habitat loss mitigation. We find that gear enforcement ARs need to be larger as compared to fish enhancement ARs when high levels of effort are exterted in the area. Moreover, if this two types of ARs are combined, the optimal size of fish enhancement ARs is greater since their cost-efficiency improves when less damage is inflicted on habitats (and thus on them). However, when fishing pressure is excessive, it may be more cost-efficient to improve the performance of the fishery by avoiding habitat degradation primarily via gear enforcement ARs.

When a government agency regulates both the effort and the AR size in a dynamic framework, we argue that a temporary reserve should be set up to allow ARs to be colonized by marine organisms in order to reach the optimal equilibrium levels by following the optimal path. Thus, government agencies who put in place temporary bans on fishing activities in AR areas with this in mind (for instance, in the French Mediterranean (Jouvenel and Faure, 2005; Ami *et al.*, 2008) may be able to follow the near-optimal path on condition that a proper subsequent control of fishing effort is ensured. The reserve should be longer-term than in the case of an optimally managed fishery without ARs. Among other observations, for too high operating costs or/and high costs of AR deployment, ARs may not be ideal. In this case, the optimal fisheries management problem reduces to that posed in the absence of ARs. However, when it is optimal to deploy ARs, higher rents are yielded through the reduction of harvesting costs. It is this ability to increase the efficiency of fishermen that allows AR projects to gain support from local fishing communities. ARs are commonly immersed in areas with poor habitats. In such environments the biological conditions in which fish populations reproduce are poor and operating costs are high. Fishes are difficult to catch and a longer search period is required implying higher fuel expenditure, more wasted bait and labor. This is why costly fisheries are more in need of such projects.

The framework elaborated in this study creates a basis for the further analysis of ARs. The results may be sensitive to some assumptions that were necessary to yield analytical results. Some of them can be relaxed. For instance, a spatial framework can be envisaged linking multiple fishing areas with migration flows. It would be interesting to examine the migration of effort depending on the relative profitability of the areas (Sanchirico and Wilen, 2005). This would allow the problem of the build-up of effort in the AR area to be addressed in a dynamic and spatially explicit framework. Other possible worthwhile extensions would be the incorporation of the concentration effect of ARs (Boncoeur, 2008) as well as on-going management costs. Finally, a multi-species setting would provide a more accurate analysis since ARs have a wider impact on the ecosystem and the biodiversity of the area than assumed in this study.

3

Le rôle de l'information pour l'exploitation durable des ressources halieutiques

Integration of path-dependency in a simple learning model : the case of marine resources

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Abstract

Overexploitation of renewable resources, and more particularly fisheries, is often driven by the lack of information about the state and dynamics of the resource. A solution to this problem stemming from the resource users is proposed in this paper. We use an agent-based model composed of a bio-economic model of Gordon-Schaefer where agents make choices following a very simple learning model. We modify the Roth-Erev learning model so that agents explain their profit not only by current action but also by past action. On the example of a Mediterranean small-scale fishery, we show that this modification radically changes the dynamics of the resource use, which turns out to be sustainable.

Keywords : Renewable resources, Agent-based Simulation, Bioeconomic model of fishery, Roth-Erev model, Incomplete information

3.1 Introduction

Fisheries are said to be renewable resources : stocks of fish replenish themselves from one year to another thanks to the reproduction of individuals. However, fishery depletion is occurring everywhere in the world (FAO, 2006), signalling the need for political and organizational measures both on a theoretical and a practical level.

One of the major causes of natural resource loss and ecosystem degradation (FAO, 1998) is linked to the problem of realistically estimating the degradation of the resource. It is not uncommon to mistakenly predict the absence of overexploitation (Berkes *et al.*, 2001). These errors are dearly paid when the resource estimations are the basis on which the resource manager defines the most appropriate management tool. In general, stocks of biomass in a resource can be perceived either directly through observation or indirectly through evaluation of captures. In fisheries, direct stock observation is very costly and not necessarily accurate. The indirect method of evaluation is accessible not only to fishermen, but also to managers through surveys. Most of the time, the depletion of the resource becomes visible when it becomes hard to catch fish, and at that stage it is often urgent to save endangered species (FAO, 2005). In these situations, fisheries' profits fall and stocks can collapse.

We designed this study to identify the conditions enabling a group of fishermen operating within a small-scale fishery, who only have access to an indirect perception of the resource, to make choices that exploit the resource in a sustainable manner while maintaining profits for the fishermen. The case examined is a small-scale fishery in Marseilles, France, where much is unknown about the resource. As often in economics when dealing with low levels of information, we choose to use an Agent-Based Model to simulate the evolution of choice of agents in their environment. This model is implemented on a bio-economic dynamic framework that models the level of a fishery, where fish reproduce and in which captures have an impact on stock : the Gordon-Schaefer model (Gordon, 1954; Schaefer, 1954). To fit the setting, we place a few agents, who are price-takers and have a homogeneous technology, in an open-access framework.

The agents in the system are in the worst possible situation in terms of information about the resource they use and are hence backward-looking. They know nothing about the resource level and have no idea of the actions and performance of other agents. All they know is which level of effort they chose at each point and which profit they got from this effort. Moreover, they have only one objective : a high profit. With the usual model of reinforcement learning (), the Roth-Erev model, this leads to depletion of the resource. Here we perform a slight transformation on basic reinforcement learning, with agents associating their profit with their past effort rather than their current effort, and this leads to a sustainable level of stock and positive profits (see definition of sustainability in section 3.3). This result is sensitive to the importance of the previous step over the present one and to the number of agents.

The paper is organized in the following manner. In section 3.2, we explain the motivations and technical choices. In section 3.3, we give the main assumptions that lead to the model, and we describe its bio-economic and learning dynamics. In section 3.4, we explain calibration choices and describe the dynamics of simulations depending on parameter sets. Finally in the last section we conclude on the interpretation of these results and their possible impact.

3.2 Literature on common-pool resources : role of information

How to use a renewable resource in a sustainable way is a central issue in today's economy. Individuals need to access the resource to make a living, but the exploitation of a resource has an impact on its capacity to reproduce, which can reduce future use (Ostrom *et al.*, 1994). Several approaches can be taken to address this issue. One very usual way of solving the problem is to establish rules of access (Ostrom, 1990). Our point of view is slightly different, mainly because our study is based on one specific case, a small-scale fishery in Marseilles, where institutional arrangements are not easily accepted by actors using the resource. These fishermen consider, in a "traditional" way, that the management of the resource should be distributed and left to each fisherman's appreciation. Thus, we decided to wonder how a resource can be used in a sustainable way by a non-coordinated pool of agents : what is the relevant information these individuals need so as to be able to conduct their activity in the long term.

Many studies focus on the role of information about the resource and its impact on behaviors, be it in game-theory or through experiments. What these experiences reveal is that even a high level of information does not enable agents to coordinate in a sustainable way and depletion of the resource is unfortunately to be expected in most cases. In section 3.2.2 we explain how Agent-Based Computational Economics, meaning economic analysis based on Agent-Based Simulations, can be used to understand economic systems where agents do not possess full information, in particular, in cases when they do not understand the game they are playing and only perceive their profit in the system. We take one possible approach, which is to develop reinforcement learning for these agents. This learning technique is widely discussed in the literature, and this is why we propose here a variation on the seminal model of Roth-Erev.

3.2.1 Lack of information and over-exploitation

Full information is a very strong assumption since resource size and its regeneration rate are rarely known with precision (Messick *et al.*, 1988). There are experimental studies on the impact of the uncertainty about the resource on harvest behavior. One of the first studies on resource size uncertainty is Budescu *et al.* (1990). They design a repeated single-trial (static) game where the exact size of the resource is unknown to participants who have to decide, without communicating with each other, on their level of exploitation. Their resource follows a uniformly distributed random variable, about which participants only know the lower and upper bounds of the distribution. The width of the interval between these bounds is considered as a measure of uncertainty. If the sum of requests exceeds the available amount of resource, then all players get no payoff. While this payoff rule seems extreme, it takes into account basic features of a variety of ecological systems which can be exploited up to some critical level. The results of these experiments indicate that, as uncertainty increases, so does the quantity of the resource requests, resulting in overharvesting. This finding is replicated several times under different assumptions : symmetric and asymmetric profits, different definitions of uncertainty, simultaneous and sequential requests (Foddy *et al.*, 1999).

The uncertainty about resource dynamics is examined by Hine and Gifford

(1996). They employ a computer-based, real-time interactive simulation, FISH, to create an artificial resource on which a small group of participants manage a fishery over several harvesting seasons. Simulations last for a limited number of rounds or until the resource is depleted. Feedback about the number of resource units remaining in the pool and the number of units harvested by other group members is provided after each round. The resource replenishes itself every round at a variable rate predetermined by the experimenter. The regeneration rate is either known or unknown to participants. No specific information about the magnitude of these rates is given to the participants. The main result of this study is that if the replenishment rate of the resource is unknown, the resource is overharvested as opposed to experimental treatments with a known regeneration rate.

These studies show that in an experimental choice situation, the more uncertain users are about the state of the resource and its dynamics, the more they deplete this resource.

Further, the effects of time dependency in the common-pool resource are addressed by Ostrom *et al.* (1994). Their experimental design allows for probabilistic destruction of the resource depending on the amount harvested by subjects. They introduce a "safe zone" where natural regeneration of the resource allows a certain level of harvesting without damage to the resource. Inside that zone, the probability of destruction is zero. Outside, the destruction probability increases linearly. Thus, in this finitely repeated game, rather than the resource size, it is the conservation of the resource that is at stake. Players know the exact probability of resource destruction depending on the total pressure exerted on the resource. Once the resource has been destroyed, the game ends. The payoff of participants depends on the decisions made both by others and by themselves. Results suggest that the resource is destroyed in every case and, in most cases, very quickly. In order to overcome the observed inefficiencies, Ostrom *et al.* (1994) argue the need for institutional changes balancing harvesting with natural regeneration.

Cardenas *et al.* (in press) give one possible explanation for these inefficiences in the cases where the resource at stake is ecollogically complex. The experiments they conduct reveal the difficulties encountered by real actors in making relevant decisions in response to temporal and spatial features of resource dynamics. These experiments are conceived so that the interactions produce a path-dependency and then the difficulties related to this feature of the game are discussed. In contrast to the previous study, the resource is characterized by its size which is dependent upon the harvesting behavior of the subjects. Their payoff at time t depends on the state of the resource at t. In these experiments, participants know the state of the resource at each time-step and are informed of the dynamic structure of the resource, that is of the impact of each action on the state of the resource. The game is divided into two stages : open-access fishery and harvesting under rules. In the second stage, three access rules are considered for which individuals can vote. These are property rule (restriction of fishing effort), lottery rule (random assignment of fishing locations to participants) and rotation rule (ban on fishing in one of the locations). Overexploitation of the resource occurs in all settings, even, surprisingly, when the resource is accessed under the property rule. Cardenas *et al.* (in press) refer to this situation as a "fishery trap" : once the participants overexploit the resource, even if they realize it, individual attempts to decrease effort are not sufficient to replenish it. In this new setting, it is obvious that even when the dynamics is clearly described, users facing choices have difficulties in understanding precisely the impact of their effort, and they overestimate the ability of the resource to recover from their captures.

A conclusion that can be drawn from these previous studies is that knowledge about resource stock and dynamics is important but not sufficient to avoid depletion of the resource. Thus, we explore another point of view where agents know nothing about the resource. Agents here are only interested in profit, as in the standard economic assumption.

The goal of the current study is to find out whether a simple learning rule could enable agents to avoid this "fishery trap" related to the complex structure of biological and anthropogenic interactions, as well as to be able to make the best decisions under uncertainty arising from this complexity. We rely on a dynamic framework that reflects the temporal dependence of the state of the resource on the agents' current and past actions. The objective behind the learning model is to give the agents the opportunity to perceive their past action as having an impact on their current profit (in line with the assumption that higher current exploitation reduces future yield).

3.2.2 Agent-Based Simulation for economies with incomplete information

In mainstream resource economics, it is often assumed in simple models that a self-owner has perfect knowledge, or at least knowledge on the probabilities of the outcomes. He then maximizes a given objective function for an infinite time horizon (Janssen and Ostrom, 2006). In certain more complex models, still leading to analytical proofs, agents have information about the state of the resource at time t or about its initial state and dynamics (for instance, Sandal and Steinshamn, 2004; Martin-Herran and Rincon-Zapatero, 2005). In these analyses what is looked for are the actions that maximize agents' objective functions at each point in time.

In some papers, resource dynamics not only include the usual components such as fish reproduction and harvest function but also account for effects of increase in sea temperatures, pollution events, other harmful occurrences or temporal variations in the habitat. In these studies, it is supposed that the usual components can be assessed by resource managers (therefore, they are not subject to uncertainty) but the impacts of the latter are unpredictable and referred to as ecological uncertainty, usually described by stochastic dynamics (for instance, Wang and Ewald, 2010).

The Agent-Based tradition which has arisen in economics in recent years is based on a rather different point of view (Tesfatsion, 1997;). The aim of most models is to address the issue of the choice of action when agents have low levels of information and have to learn about the possible outcomes of their actions (). The seminal theoretical reference in this field is the work by Herbert Simon, who developed his research in management science and showed that the representation of agents as being boundedly rational can be more relevant to address real-world issues than substantive rationality (Simon, 1955). Bounded rationality can be interpreted following two axes : either agents have access to perfect information but they are limited in their computing abilities, or they are limited in their access to information. In both cases, they cannot calculate the "best" of all choices in a given situation. His approach led to the appearance of many models, also developed thanks to new calculation tools, in which agents had to rely on their experience and infer from the results of past actions the actions they would want to take in future.

The representation that is chosen to organize agents' learning is very important in examining a problem, since it can have a major impact on overall results (;). Indeed, only in very rare and constrained settings is it possible to show that the rationality of agents has very little impact on the economic dynamics of a system (Gode and Sunder, 1993). Usually the choice of learning algorithm is either based on observed behaviors or is related to the type of information agents can access. A major line of research is thus focused on the issue of representing learning in the most relevant way.

In the context we are interested in, we wish to assume that agents have no prior knowledge about the resource and only learn thanks to their past experience - which is seen as their past actions (in fishing effort) and their results (in profit). A very widely used model based on past information is reinforcement learning (Duffy, 2006), and its most basic model is the Roth-Erev model (Roth and Erev, 1995). This choice is considered to be appropriate for highly uncertain settings where the agents have little information about the resource (Janssen and Ostrom, 2006).

This model is based on a basic psychological observation : actions that lead to reward are chosen more frequently for the future, while actions that lead to punishment are chosen less frequently. This learning allows agents to explore their environment to discover the feedback they can get from their actions, settling into their favorite action after some time, but checking once in a while that their choice is still the best. To attain all these features, the model is based on probabilistic choices : agents are faced with a given set of actions, each of which produces a particular reward at each time-step. In the context of a fishery this reward also depends on the state of the resource at each time-step. The information about these rewards enables them to associate an action with a "propensity" ; all propensities are translated into probabilities of choosing an action when the agent needs to act. This model enables agents to face an exploration-exploitation dilemma (March, 1991). Erev and Roth (1998) have shown that their model explains well the data collected from economic experiments on certain social dilemma games. It embodies the most salient regularities observed in the decision-making behavior of human subjects across a wide variety of multi-agent experimental games.

However, some people have tried to refine this model and adapt it to better fit their own case-studies. The model of Nicolaisen *et al.* (2001) modifies the Roth-Erev rule in a double-auction context, and addresses the problems of parameter degeneracy ; it also eliminates probability updating in response to zero profits. Another variation, Bereby-Meyer and Erev (1998) extends the Roth-Erev model by representing the point delineating the loss and gain domains as a function of expectations, goals, and experience. Finally, a well-known model links reinforcement and belief learning, under a generalized Experience-Weighted Attraction (EWA) learning model (Camerer and Ho, 1999). Janssen and Ahn (2006) even consider the variation of the latter by including fictitious play, social preferences and signalling component in order to show that individuals have other-regarding preferences of inequality aversion and conditionally cooperative preferences. In the latter two versions, the structure of the game needs to be known to agents, since they have to be able to compare their actual utility to what it would have been if they had chosen another action. A learning dynamics that is also used in economic studies is the classifier system : it can be based on the reinforcement learning of Roth and Erev but with context-dependent learning, more suitable to market settings (Kirman and Vriend, 2001;).

In our system, we first made a preliminary study which revealed that the standard Roth-Erev model leads to overharvesting of the resource in our ecological setting. This is in line with the fact that this algorithm can lead agents to choose actions that are near the economic optimum in the setting we chose. As a variation of this model we decided to incorporate the past actions of agents into their decision process. As stated before, we show in this study that this very small change greatly impacts on the efforts that agents choose and as a result on the dynamics of the resource.

3.3 The model

3.3.1 Main assumptions and general framework

Resource and time. Agents[1] are placed in a biological environment represented by a *standard dynamic model of resource.* The biological environment consists of a single resource situated in a single area. Time is discrete and one time-step represents one day. The reproduction of the resource relies on the dynamic developed by Schaefer (Schaefer, 1954) : it is a step-by-step process whose calibration is performed for Marseilles data on a daily basis.

Agents. An Agent has to choose one action at each time-step : the (fishing) effort she exerts on the resource. Agents are homogeneous in terms of choice of actions

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[1] We refer to artificial agents as Agent or Fisherman and real agents as agent or fisherman.

(possible efforts) and learning process ; the number of Agents is given for a set of simulations : this assumption is based on the fact that the small-scale fishery is exploited by small communities to which there is almost no entry (McGoodwin, 2003). We vary the number of Agents, denoted as N, between sets of simulations.

Impact of action. The effort exerted provides fish to the Agents and this has two impacts (following Gordon and Schaefer). The first effect concerns the population level since the harvested fish is no longer in the sea, thus lowering reproductive potential. Hence present and future levels of resource stock are reduced after harvesting. The second effect concerns the Agent profit level and is twofold because the amount of harvested fish depends not only directly on the chosen action but also indirectly on fish stock level (the first effect). The Agent sells this amount on the market, earns money and deduces the profit. As proposed in (Clark, 2006), to calculate profit, the fishing cost is assumed to be proportional to the effort and is the same for all Agents. We also assume that the overall quantity offered on the market by the small fishery is not large enough to affect the market price and thus there is no effect on the individual agent's decision to harvest. Thus agents are price takers. We simplify the situation even more by using a fixed price for the whole simulation. This makes our learning model more efficient and avoids initially having to model price and market dynamics.

Information. Agents are placed in the worst possible situation in terms of information. An Agent observes only the profit she yields and the effort she exerts at both previous and current time-steps. She does not know that other Agents are exerting effort and, therefore, the profit and the effort of other Agents ; she has no information about the state of the resource (stock level) or its reproduction dynamics ; she is not able to evaluate the effect of fishing on the resource. As seen in the following description of the learning algorithm, Agents are totally unaware of "dynamic externalities" that take place in this system (Levhari and Mirman, 1980), the behavior which is frequently exhibited by real fishermen.

Learning. An Agent chooses effort among a set of possible values, ranging from 0 to a maximum, which is identical for all Agents. The Agent learns following a variation of the Roth-Erev model. As in the Roth-Erev, model each possible effort is associated with a propensity (equivalent to a “grade” to evaluate the performance of this effort) ; with these propensities, the Agent uses a *probabilistic choice mechanism* to decide on effort. The possible efforts based on the propensities are discriminated by means of the distinction parameter (β). The propensities are updated according to the profit that is obtained after the effort has been exerted. The updating process, as in Roth-Erev, relies on two parameters : a forgetting parameter (φ), an experimentation parameter (ε). What we add to the learning model is that the profit of the current time-step is assumed to be due not only to the effort that has just been exerted, but also to the action of the previous time-step. Hence the result of a chosen effort is evaluated over two time-steps. The importance of past and present action is weighted with a parameter θ, which is the central parameter of our model and whose influence we test here. The number of Agents is expected to have an impact on learning, since increasing the number of agent makes the impact of an individual’s action harder to perceive for this Agent.

Sustainability. We consider a simulation as sustainable if : 1/ the Agents yield nonnegative profits throughout the simulation ; 2/ The fish stock is increasing except for the first hundred time-steps where the Agents explore the effects of different actions some of which can cause a decrease in fish stock. This definition corresponds to that proposed by BenDor *et al.* (2009).

3.3.2 Resource dynamics and profit of Agents

Agents harvest from the same location. Each chooses her individual effort from the set of possible efforts $\{0, E_1, E_2, ..., E_{max}\}$ and hence all effort exerted on the resource in this location can be aggregated in one total effort E. The evolution of the fish biomass $X(t)$ follows a discrete dynamic equation, where an Agent i harvests H_i fish after exerting an effort E_i :

$$X_{t+1} = X_t + F(X_t) - H(E_t, X_t) \tag{3.1}$$

where $F(X)$ is a function representing the natural growth rate of the fish population, which follows a logistic law (Clark, 1990) :

$$F(X_t) = rX_t(1 - X_t/K) \tag{3.2}$$

with r the intrinsic growth rate and K the environmental carrying capacity (saturation level). Harvests per unit of effort are proportional to the resource biomass, e.g. $H_t = kEX_t$, where k is a catchability coefficient. The economic component of the model is described by the profit to Agent i of effort E_t^i and profit $\Pi_t^i = pH_t^i - cE_t^i = pkE_t^iX_t - cE_t^i$ where p is the price per unit of resource, H_t^i the individual harvests at time t, c cost per unit of effort, and E_t^i is the effort exerted by Agent i at time t. As previously mentioned, the price p and the cost c are fixed and homogeneous.

This model clearly exhibits the property of path-dependency of the resource on past actions. Since current profit depends on the current state of the resource, it depends not only on current effort but also on all past efforts : $\Pi_t = \Phi(X_0, E_1, E_2, ..., E_t)$. The process depends on 5 parameters : p, c, r, K, k.

If we consider N Agents, then the resource dynamics can be rewritten in the following way :

$$X_{t+1} = X_t + F(X_t) - \sum_i H_i(E_t^i, X_t), \tag{3.3}$$

where H_i are the harvests of Agent i and E_t^i is the effort employed by Agent i at time t. We will use this dynamics in the model.

3.3.3 Learning model as a variation of Roth-Erev

The model we use to define Agents' learning is very close to the Roth-Erev original model. Each possible action for an Agent is chosen following the probabilistic model. The propensities associated with each action are updated according to the profit that is obtained. The only difference is that in our case, the propensities associated with actions at both time $t-1$ and t are evaluated with the profit obtained at time t, with respective weights $(1-\theta)$ and θ. Conversely : the profit at time t enables the propensities of the current action and the past action to be changed.

Probabilistic choice of effort

Suppose that each Agent can choose among M actions. The Agents base their choice on aggregated information about past experience, thanks to "propensities" $q_{ij}(t)$. They change over time and define the propensity to play action j in period t for Agent i. Initial (period 1) propensities are equal $q_{ij}(1) = q_{im}(1)$ for all available actions j, m and all Agents i, and $\sum_j q_{ij}(1) = S_i(1)$, where $S_i(1)$ is an initial strength parameter, equal to a constant that is the same for all players, $S_i(1) = S(1)$. The lower the value of initial strengths, the faster the learning. As in Roth and Erev (1995), for initial strengths we choose the same order of magnitude as the payoffs (for details, see section 4.1). We therefore suppose that $q_{ij}(1) = \Pi_{max}(1)$ for all i and j, where $\Pi_{max}(1)$ is the maximal possible profit that an Agent can receive in the first period.

The probability $p_{ij}(t)$ that Agent i plays action j in period t is made according to the exponential choice rule, namely, $p_{ij}(t) = exp(\beta q_{ij}(t))/\sum_m exp(\beta q_{im}(t))$, where β is a distinction parameter that measures the sensitivity of probabilities to reinforcements. There are two extreme cases. First, $\beta = 0$ where the Fisherman randomly chooses the effort he wants to exert without taking into account the profit it yields. Second, if β tends to ∞, the Fisherman always exerts the effort that yields a high profit. In technical terms, parameter β reinforces the differences between the propensities $q_{ij}(t)$. The higher the value of β, the more distinct the values of $q_{ij}(t)$ and it is more probable that the Fishermen would choose a "stable" decision (i.e. an action that is used repeatedly for the rest of a simulation).

Roth-Erev learning algorithm : linking profit to current action

Suppose that, in period t, Agent i plays action j and receives a profit of Π_t^i. Let $R(\Pi_t^i) = \Pi_t^i - \Pi_t^{i\,min}$, where $\Pi_t^{i\,min}$ is the smallest profit in the set of all profits obtained during t periods[2]. Thus, Agent i updates her propensity to play action j according to the rule :

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[2] This definition of the payoff function $R(\Pi_t^i)$ corresponds to that described in a particular case of the model of Bereby-Meyer and Erev (1998).

if $j = C$,

$$q_{ij}(t+1) = (1-\varphi)q_{ij}(t) + (1-\varepsilon)R(\Pi_t^i); \tag{3.4}$$

if $j = NC$,

$$q_{ij}(t+1) = (1-\varphi)q_{ij}(t) + \varepsilon R(\Pi_t^i)/(N-1), \tag{3.5}$$

where C is the action chosen in period t (current action) and NC are the actions that were not chosen in periods t and $t-1$;

φ is classically interpreted as a forgetting parameter that gradually reduces the role of past experience, ε an experimentation parameter that allows for some experimentation, and we define θ as the weight associated with the current action.

The term $\varepsilon R(\Pi_t^i)/(N-1)$ allows the Agents to reinforce the actions not chosen in period t. This way, the Agents do not forget them too quickly. To reinforce them in an equal manner, the function $R(\Pi_t^i)$ is divided by the number of these actions, $N-1$.

Variation : linking profit to past action

In the standard Roth-Erev model, $R(\Pi_t^i)$ is entirely associated with the action I. We transform the Roth-Erev model so that it is possible for the Agent to associate profit in t with its action in $(t-1)$ and to do so we introduce an additional parameter θ that gives weight to past and current action. When $\theta = 0$ only the past action is associated with the profit ; when $\theta = 1$ only the present action is ; when $0 < \theta < 1$ the profit is partly associated with both actions.

The modified propensity updating rule is as follows :

if $j = C$,

$$q_{ij}(t+1) = (1-\varphi)q_{ij}(t) + \theta(1-\varepsilon)R(\Pi_t^i) + \varepsilon(1-sgn(\theta))R(\Pi_t^i)/(N-v); \quad (3.6)$$

if $j = P$,

$$q_{ij}(t+1) = (1-\varphi)q_{ij}(t) + (1-\theta)(1-\varepsilon)R(\Pi_t^i) + \varepsilon(sgn(\theta-1)+1)R(\Pi_t^i)/(N-v); \quad (3.7)$$

if $j = NC$,

$$q_{ij}(t+1) = (1-\varphi)q_{ij}(t) + \varepsilon R(\Pi_t^i)/(N-v), \quad (3.8)$$

where C is the action chosen in period t (current action), P is the action chosen in period $t-1$ (past action) and NC are the actions that were not chosen in periods t and $t-1$;

v is equal to 1 if $\theta = 0$ or 1, otherwise it is equal to 2 ;

$\theta = 1$ corresponds to the standard Roth-Erev model.

Note that the function $sgn(\cdot)$ is introduced only for reasons of generalization and has no interpretation here.

The first term in each equation makes the agents gradually forget their past experience. The second term updates propensities through recent experience weighted by parameters θ or $1-\theta$ and $1-\varepsilon$. Finally, the third term leads to experimentation. It is not null for the actions that are not chosen, neither at t nor at $t-1$ for the case of $0 < \theta < 1$. For $\theta = 0$ these are the actions not chosen at $t-1$ and the actions not chosen at t for $\theta = 1$. Basically, the profit obtained at t, weighted by

ε, is shared equally among the actions that are not reinforced by the second term (there are $N-1$ or $N-2$ actions of this kind).

The proposed learning model does not particularly pertain to the fishermen's behavior but pertains to agents with limited access to information, capable of learning by trial-and-error and in a context where present situation depends highly on past actions.

3.3.4 Parameters tested in simulations and observed indicators

The parameters in our system can be divided into three different groups. First, there are parameters we will fix for all simulations, and whose choice can be justified according to estimation of real-world data (p, c, r, K, k, E). The second set of parameters is composed of all parameters that are related to the usual reinforcement learning algorithm and the associated exponential rule (β, φ, ε). The third set of parameters is composed of those whose influence we actually want to test on the system (θ, N). The complete list of parameters with their range of values can be found in appendix 3.6.1 ; the choice for the first parameters is explained in section 3.4.1 ; the sensitivity analysis for the second set of parameters is explained in appendix 3.6.2.

In this subsection, we explain the simulation protocol and observation choices for testing θ and N. N, the number of Agents, is expected to have an impact on the learning process, since Agents perceive the result of all actions in addition to their own actions. The higher the number of Agents, the less accurate the information for each individual Agent, who has no idea of the others' efforts or profits.

Our main hypothesis in these experiments is that θ has an impact on the perception of which level of effort is the best choice, and this is why we vary θ. Values of θ are 0, 0.1, 0.25, 0.5, 0.75 and 1, where $\theta = 1$ is the usual Roth-Erev model and $\theta = 0$ is the past-only model. Values of N are 2, 8 and 16. We observe more precisely two values of θ which are 0 and 1. We run 30 simulations for each set of parameters with 5000 time steps.

It should be noted that the number of Agents has an impact on another parameter. The maximum overall effort of Agents (sum of all Agents' individual efforts) remains equal whatever the number of Agents, and the number of possible actions for each Agent also remains equal. The list of possible individual efforts E changes accordingly. For two Agents, $E \in \{0; 5; 10; ...200\}$; for 8 agents, $E \in \{0; 1.25; 2.5; ...50\}$; for 16 agents $E \in \{0; 0.625; 1.25; ...25\}$. This scaling allows the same biological system (i.e. with the same biological parameters X_1, K, r, q) to be kept and therefore facilitates comparison between scenarios. At this stage, an alternative could be to consider that as the number of Agents increases, the maximum overall effort on the resource should also increase. However, we want to test the influence of the number of Agents on our learning algorithm, and hence to be in a situation where only one parameter changes. In this case, the Agents are a priori not "at a disadvantage" (in terms of resource scarcity) in being more numerous.

With the fixed parameters we use, it is possible to calculate the main reference points widely used in fisheries management (Clark, 1990) :

1. Bionomic equilibrium, where resource generates zero profits, is obtained if $E_0 = 164.45$, $X_0 = 108.46$, $\Pi_0 = 0$;
2. Maximum Sustainable Yield (MSY), where the sustained harvests are maximi-

zed, is attained for $E_{MSY} = 105$, $X_{MSY} = 250$, $\Pi_{MSY} = 1.932$;

3. Maximum Economic Yield (MEY), where the sustained profits are maximized, $E_{MEY} = 82.22$, $X_{MEY} = 304.23$, $\Pi_{MEY} = 2.093$;

Our model was extensively observed. First, we conducted simulations to understand the dynamics of the system and how learning could qualitatively impact resource use. This will be described in subsection 3.4.2.1, by using step-by-step indicators such as :

- Individual effort
- Fish stock
- Individual profit

After this observation phase, once the regularity of the dynamics seemed to be confirmed and we could evaluate which global indicators would be meaningful, we ran many simulations to obtain quantitative data. The following indicators were observed :

- Proportion of sustainable simulations ;
- Average final fish stock (over the set of sustainable simulations for one set of parameters) and standard deviation of the final fish stock ;
- Average overall final profit (over the set of sustainable simulations for one set of parameters) and standard deviation of the final profit.

3.4 Dynamics of the simulations and discussion

In this section we describe and discuss the results of simulations. First we show how we calibrated the bio-economic model, so that it fits to data on small-scale fisheries in Marseilles. Then, we describe dynamics of typical simulations in a qualitative way, for two extreme cases, where θ is 0 and 1, and explain the reason why the results differ so greatly. We finally give quantitative data for repeated sets of simulations with varying values of θ. We then show how the number of Agents impacts on the evolution of the system, and explain why. The sensitivity analysis of the model to the parameter defining the learning process (φ and ε) is given in appendix 3.6.2, and shows that our main result remains unchanged.

3.4.1 Calibration of parameters

3.4.1.1 Data on small-scale fisheries in Marseilles

Small-scale fisheries in the Mediterranean are difficult to survey. Indeed in this area, a diversity of small-scale fishing units varies its fishing activities depending on the season and the geographical sector. They market the fish by direct sale and these sales are partially illegal. Our model is therefore calibrated on the few existing studies on small-scale fisheries in the French Mediterranean and in France in general. The parameters of the bioeconomic model were adjusted according to the real data provided by Jouvenel and Faure (2005) for the Prado Bay, Marseilles (chosen for the richness of recent data), and more general data describing the French Mediterranean fishery (Berthou *et al.*, 2001). Due to the low number of statistical observations, the goal of the calibration was not to describe the exact behavior of the fish stock and fishermen in Marseilles but for the model to illustrate the realistic evolution of the fish stock as well as the economic situation and performance of small-scale fishing units. We are interested in this study in the daily behavior of fishermen. Each period t therefore represents a day and the bioeconomic parameters of the model are calibrated with respect to this time-step. While the step is unusually short for bioeconomic models., it here provides opportunities for the Agents to learn. The use of the Roth-Erev model, in particular, requires a large number of steps to reinforce decision-making.

First of all, it should be noted that in the Prado Bay the resource is slowly depleting. However the resource is still capable of producing positive profits. These two facts were used for the model calibration. We suppose here that in ten years the resource will deplete to the point of small but negative profits if the same effort is maintained. This assumption makes sense because the Prado Bay is a small area, where if a high effort is applied for too long, we can expect the local collapse of the fish stock.

The approximate amount of effort exerted in this area is deduced based on the survey of Jouvenel and Faure (2005). Furthermore, the experimental fishing conducted in the framework of their survey allowed them to compute catch per unit of effort (CPUE), a widely reported fisheries indicator, i.e. $CPUE = kX = 1618g$.

Another important detail that is reported by Jouvenel and Faure is that fishing nets and bottom lines are the only fishing techniques that are employed in the Prado Bay. Moreover, fishing nets are used more frequently in Marseilles than bottom lines. This fact is taken into account in the calculation of the parameters concerning fishermen.

The price per kilogram of harvested fish is calibrated in accordance with the data on the fishermen's average profits obtained in the fishing grounds of Marseilles (Berthou *et al.*, 2001). The price obtained is very close to the average price of the commercial fish species weighted by the frequency with which they are harvested. According to Berthou *et al.* (2001), sales by fishermen are about 165 euros per day at sea for bottom line fishermen and 334 euros for net fishermen. The cost c per unit of effort is calibrated with respect to the information on the costs of fuel, renewal and purchase of nets and wages of the crew reported by Berthou *et al.* (2001).

Furthermore, in defining maximal possible effort E_{max}, we take into account the restrictions on the length of fishing nets and number of fish hooks that are imposed by the Prud'homie de Marseilles, an institution that was developped many centuries ago by local fishermen who early became aware of the necessity of managing the resource.

Finally, we suppose that the initial fish stock X_1 is 30% of the environmental carrying capacity K. This assumption takes account of the fact that the level of fish stock is lower than the recommended MSY level where the sustained harvests are maximized (for more details see section 3.4.2). All above observations, assumptions and data were necessary to deduce the order of magnitude of the parameters r, k, X_1 and K.

3.4.1.2 Learning model

As for the learning parameters in the standard Roth-Erev model, values $\varphi = 0.1$ and $\varepsilon = 0.2$ show the best fit to the experimental data collected by Erev and Roth (1998) and cover twelve distinct types of human-subject games. The goal of the present paper was to consider how well simple learning models can model the interaction of players who must learn about the game and each other in the course of playing the game. Thus the results of this study are deprived of a particular context and can be used for the current study. According to the sensitivity analysis reported by Roth and Erev the ranges $0 < \varphi < 0.20$, $0.02 < \varepsilon < 0.30$ guaranteed the sufficient fit to the experimental data.

The learning of agents also depends on initial propensities $q_{ij}(1)$. They are uniform and their values are chosen to represent the profit achieved for the maximal amount of total effort (which is 400) for initial stock $X_1 = 150$. These values are sufficiently high to garantee that, at the beginning of simulations, the agents would not stick with the first actions taken, and sufficiently low not to imply very lengthy learning.

Another important remark should be made about parameter β. The idea behind its calibration was to obtain a learning that would converge but not to the detriment of the exploration. Thus, for the first hundred periods β is equal to 1 in all simulation scenarios. This allows the agents to explore different actions before entering the exploitation phase. After 100 periods we increase β in order to reinforce the choice of one particular action. This technique of learning is referred to as a self-annealing process and is widely used to obtain reasonable logical convergence (for further details, refer to Weisbuch, 1989). The value of β varies with the number of agents in the system : the more agents, the smaller the variation in profit when effort varies, and hence the more discrimination is required among propensities. When the number of agents increases, β increases as well (see appendix 3.6.1).

3.4.2 Dynamics with two Agents and varying θ

3.4.2.1 The classical Roth-Erev model

In this subsection we comment on one specific run of simulation which displays events that are typical and relevant to represent simulations where agents learn with the basic Roth-Erev model ($\theta = 1$). At the beginning of the simulation all efforts are associated with the same value of propensity and can be chosen with equal probability. Agents choose any effort and change the associated propensity by integrating their profit. By construction, all other propensities stay high in first periods. It thus takes some time before all efforts have been chosen once, and some of them associated with very low propensities. After this very random learning phase, Agents stabilize on one favorite effort, the one that displays a propensity that is significantly higher than the others. Subsequently, Agents each choose a constant effort over a long period (Figure 3.1, left). In this setting, they choose a rather high effort, which results in the depletion of the resource (Figure 3.3, $\theta = 1$ curve), and their profits eventually turn out to be negative (Figure 3.1, right). Since at this time they choose the same action over a long period, and since this learning includes forgetting, the other efforts' propensities are thus reduced. Agents are stuck with a choice that is not that desirable any longer.

Finally, the exploration process, which is rather minimal in Roth-Erev learning, occasionally takes place and one Agent tries out another effort, which is here very low and appears to offer more profit than the high one : although gain is low, costs are even lower. The Agent updates her propensities accordingly. From this time on, she changes her effort to this low value. As a consequence, the resource recovers slowly, her profit increases again, and the other Agents also earns a slightly higher profit. In this simulation, the following 3500 time-steps (we ran up to 5000 but not shown here) constitutes a slow recovery of the resource and also a very slow increase in profits that almost reach 0 at the end.

Here, one of the Agents benefits from the reduction in effort of the other, and the resource is less depleted. The only problem for both Agents is that they need to make negative profit to abandon an effort they have chosen, and because of some inertia in the learning model, these negative profits can be intepreted as threatening the survival of their activity. Following our definition, no simulation led with the usual Roth-Erev learning is sustainable.

It should be noted here that it has been suggested that this situation of bad learning might simply be a consequence of the fact that Agents are price takers. If Agents were selling on a market where the quantity they sell reduces the price, this should restrain them from exerting a too high effort and catching too many fish. In apprendix 3.6.3, we give results where Agents belong to markets with different demand curves, and it is shown that this learning process still leads to overexploitation of the resource.

3.4.2.2 Learning model based on past only

Another extreme case of the presented variation of the Roth-Erev model is $\theta = 0$, when the current profit is associated only with past action. As previously, individual efforts are unstable at the beginning of the simulation due to uniform distribution of propensities (Fig. 3.2). During the exploration period of almost the same duration as for $\theta = 1$ the fish stock slightly decreases until the Agents stick with one action that

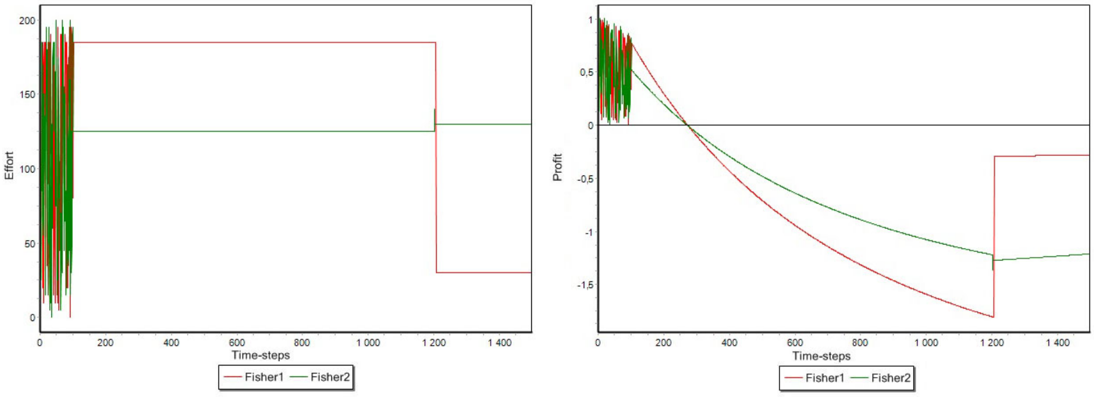

Figure 3.1 – Efforts (left) and profits (right) for both Agents over the first 1500 time-steps of a typical simulation with the usual Roth-Erev model. The search periods (erratic phase) last for 101 time-steps for the first Agent and 103 for the second, after which they stabilize at efforts of 125 and 185. This stabilization is achieved by increasing β (self-annealing process). From this time on, profits decrease regularly because of the depletion of the resource and turn out to be negative (at time-step 272 and 273). In the loss domain, the Agent exerting higher effort suffers more losses. At step 1207, she changes her effort to 30, which transforms the slope. Until the end of the simulation, the profit of this Agent is higher since she exerts lower effort than the other.

displays significantly high propensity relative to other possible actions. It appears that these choices of action lead to a positive profit for both agents (Figure 3.2) and to an increase in fish stock up to a level higher than the initial one (Figure 3.3). This is what we call sustainable simulation. However, note that the distribution of profits is not equal : one of the agents is better off than the other.

3.4.2.3 Decreasing θ implies more sustainability

In Figure 3.3, two trajectories show that the value of θ has a huge impact on the evolution of the stock of fish. As seen in Figure 3.1 and Figure 3.2, the profits of Agents also depend on this parameter. These situations are extreme in our setting. One is a sustainable scenario ($\theta = 0$) where fish stock is increasing once Agents have settled their choices, which results in positive profits. The other is not sustainable

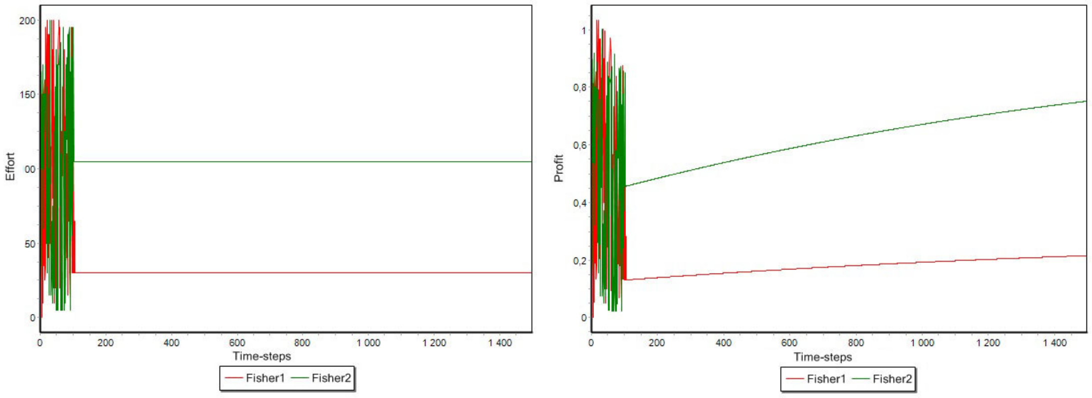

Figure 3.2 – Efforts (left) and profits (right) over the first 1500 time-steps of a typical simulation with two Agents who choose their effort according to the variation of Roth-Erev with $\theta = 0$. The search periods last for 105 time-steps for the first Agent and 103 for the second, after which they stabilize at efforts of 30 and 105. The profits increase for both agents. The Agent who exerts higher effort here gets higher profit than the other.

$(\theta = 1)$: the fish stock collapses and leads to negative profits because Agents prefer high efforts for a long time.

Table 3.1 – Results for simulations with 2 agents with $\theta \in \{0, 0.1, 0.25, 0.5, 0.75, 1\}$. The main indicators are : the proportion of sustainable simulations out of 30 that were conducted and the average among the sustainable simulations of final values of : fish stock and sum of profits. Increasing θ leads to less sustainable results.

Indicators	$\theta = 0$	$\theta = 0.1$	$\theta = 0.25$	$\theta = 0.5$	$\theta = 0.75$	$\theta = 1$
% of Sust. Simulations	66.67	50	36.67	3.33	0	0
Fish Stock	233	203	177	124	–	–
	(96)	(97)	(46)	(0)	–	–
Total Profits	1.329	1.051	1.005	0.3220	–	–
	(0.591)	(0.566)	(0.573)	(0)	–	–

If we consider a situation where a government agency manages access to the resource, under complete information, it is possible for her to calculate and implement MSY or MEY effort levels representing a way to balance harvesting and resource growth rate (see Figure 3.3).

In this example where no such agency is involved in the resource management and Agents have no opportunity to find out these levels, neither of them is attained. However, for a sustainable simulation, the level of fish stock should never be lower than that of bionomic equilibrium (where sustained total profit is nul) : this fact does not depend on the value of θ.

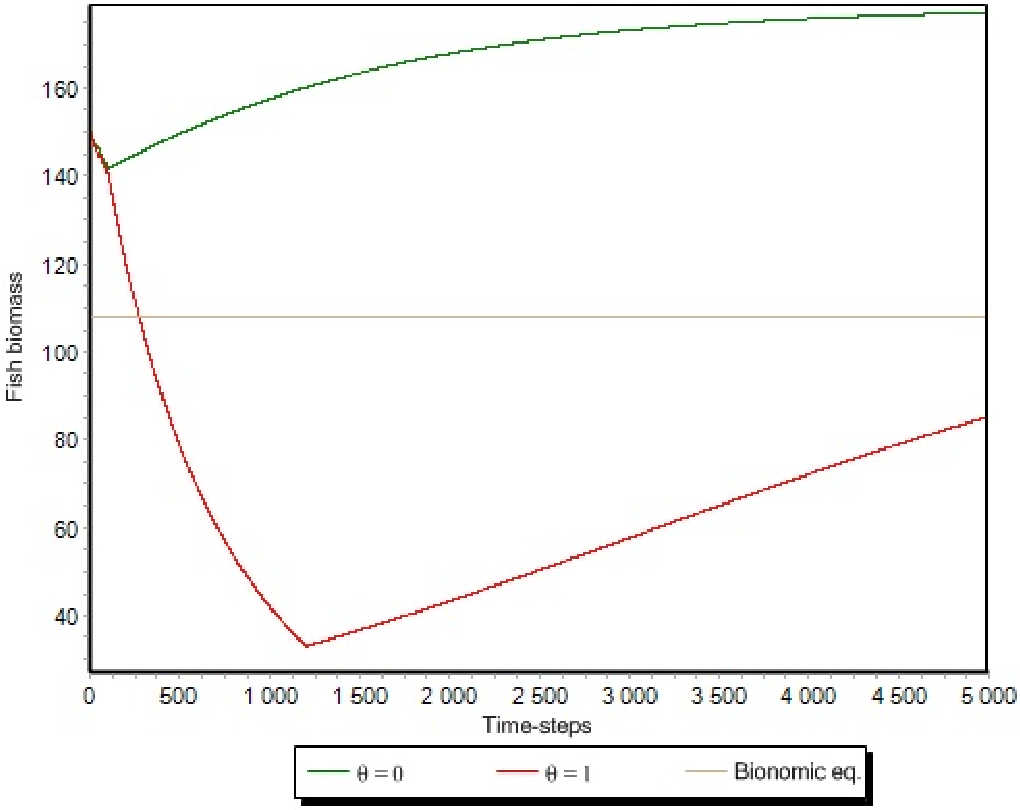

Figure 3.3 – Typical dynamics of fish stock for two Agents and $\theta = 0$ and $\theta = 1$. For sake of comparison, we included in the graph stock level reached at bionomic equilibrium. We also remind MSY and MEY levels $x_{MSY} = 250$, $x_{MEY} = 304$, which are reached for neither of the values of θ. It is clear that $\theta = 0$ does not lead to the depletion of the resource whereas $\theta = 1$ does.

The fact that more simulations are sustainable when the profit is associated with the past can be explained in a mechanical way.

At the beginning of a simulation, when learning takes place, the resource is high enough to lead to positive profit when harvested, whatever the effort and with the cost value we chose, until the resource becomes fairly depleted, higher effort gives higher profit. The other consequence of high effort is to deplete the resource more than low effort, which means that high effort has a heavy consequence on the profit of the following day, as included in the model design to induce path-dependency.

If an Agent learns by associating profit with current action, it is always the case that high effort is better. The only deduction the Agents can reach is "higher efforts yield higher profits". High efforts are hence chosen more frequently from the beginning of simulations. A choice that is repeated a few times and gives positive profit has an increased propensity while other propensities are reduced by the forgetting parameters, which leads to the depletion of the resource and negative profits.

When the Agents learn by associating profit with past action, the situation is radically different. If the action at $t-1$ is low effort for both Agents, the resource at t is higher than it would have been with high effort. As a consequence, for a given effort, the profit will be higher. Hence lower past effort will induce higher present profit, and this is true for any given effort. If only one Agent chooses low effort, the information might be slightly less clear since the resource might be depleted by the other Agent but it will, in any case, be less depleted than with high effort. As a consequence, probabilistic learning, where Agents try out many different efforts without perceiving the effort of the other, will on average show the Agents that they should choose low effort.

It could logically seem a bit strange that the "best" learning (according to our indicators) does not take into account present action. Clearly we disturb the straightforward causal link between effort and profit when we introduce past action into learning. In that case, it can seem that the Agents learn on the basis of "wrong" information. When an Agent associates profit with the past, she can associate it with completely different past efforts, for example very high or very low, which would be impossible in classical learning. This means that associating high profit yielded by high current effort with low past effort is possible, which is thereby considerably reinforced. Considering our resource dynamics, it is even clear that it is not only possible, but also more frequent, for profit to rise after the Agent chooses low effort (the resource is less depleted and any effort gives a higher profit than if the resource had been overused). An association that could appear to be a wrong inference reveals itself to be an inference that is coherent with the dynamics of the resource. This is why our learning works so well in this setting. This result is very interesting since it somewhat echoes the fundamental result of Gode and Sunder (1993) whose Zero-Intelligent agents (with no learning at all) perform well just because the structure of their interactions forces them to behave well. Here, our Agents do not know why it is a good idea to believe that the current action has no impact on the profit (which is wrong) but the structure of the resource is such that this misbelief is useful to them in the long term. It is to be noted that the role of misbelief in artificial (and real) societies using a resource was revealed by Doran some years ago (Doran, 1998).

Considering the dynamics of our model, we could interpret the difference in performance between these different learning models by saying that in the case when $\theta = 1$ Agents are directly sensitive to economic results, whereas when they have $\theta = 0$ they are indirectly sensitive to biological dynamics.

3.4.3 The more agents, the less sustainable

After observing the main differences among scenarios with two Agents, we increase the number of Agents. In all settings, the total value of effort by the Agents remains the same and Agents have the same number of possible efforts, with a smaller difference between each possible effort. We set a higher value of β (discrimination parameter) for a higher number of Agents. The reason why we increase β is for the Agents to be able to discriminate the profits that are reduced with the higher number of Agents.

Considering that Agents learn through information based on their individual actions, it is to be expected that the presence of many others will reduce the impact of each Agent and hence disturb the learning system we have established. Increasing the number of Agents indeed complicates the coordination of Agents. The variability of the system increases with the number of Agents and its dynamics becomes more stochastic. This emerging instability is an important result, in line with many remarks by agent-based practitioners who know that the results given by ABM are not scale-free (there are currently (2009) intensive discussions on this topic on SimSoc list).

Thus, increasing the number of Agents negatively affects the simulation results (see Table 3.2). Although, $\theta = 0$ is the least sensitive and even robust to the variation of the number of agents and still provides the same percentage of sustainable simulations. But even in this scenario the fish stock and total profit get worse (for detailed simulation results in appendix 3.6.2).

To sum up, so far we have three main results :

1. when θ increases, the system becomes less sustainable ;

Table 3.2 – Here we present results obtained over 30 simulations with $N = 2$, 8 and 16, $\theta \in \{0, 0.1, 0.25, 0.5, 0.75, 1\}$, $\varphi = 0.1$, $\varepsilon = 0.2$. The main result is that even for high number of Fishermen $\theta = 0$ still leads to sustainable simulations and their quantity remains almost the same for all N.

	% of Sust. Simulations		
θ	**2 Agents**	**8 Agents**	**16 Agents**
0	66,67	70	70
$0,1$	50	0	0
$0,25$	36,67	0	0
$0,5$	3,33	0	0
$0,75$	0	0	0
1	0	0	0

2. if $\theta = 0$, the higher the number of Fishermen, the more detrimental the exploitation of the resource and the lower the profit but there is still a high percentage of sustainable simulations ;
3. if $\theta = 0.1$, 0.25, 0.5, 0.75 and 1, for a high number of Fishermen, the sustainability indicator suddenly decreases to zero.

3.5 Conclusion

This paper forms part of a general reflection on the possibility of using a renewable resource in the long term even when there is almost no information on this resource. Here we consider a situation where several agents have to use a resource that they share but where they have no perception of each other's actions. Interestingly, we show that the very limited perception that our agents have of the resource, mediated by the evolution of their profits, does not incite them to use this resource in a sustainable way. What is relevant is not the quantity of information, but the way agents understand the dynamics of their profit. By simply changing, within a very common learning mechanism, the way they relate action to profit, one changes the socio-environmental dynamics from unsustainable to sustainable. The trick here is to associate past action with current profit, which is one way of integrating the path-dependency of the resource into the cognition of agents. This association encourages the sustainable use of the resource because of the dependence of the fish stock on the history of harvests. When harvesting the fish, fishermen reduce the quantity of fish capable of reproducing, which decreases the fish stock available in the next period and makes the fishery less profitable. This is the reason why fishermen accounting for the impact of their previous action on their current profit would be incited in limiting their fishing pressure to yield higher profits. Conversely, classical heuristics, where individuals believe that the current profit is determined only by current action, overexploit the resource.

Being purely mechanical, this result can be seen as very general. It is also in line with the classical assumption that individuals can handle complex situation only by focusing on their individual profit. However, the finding that different outcomes are witnessed for different learning scenarios is not that surprising since from literature on learning it is known that when strategy switching is based on observable, past fitness of the strategies, the memory used in the fitness measure affects the dynamics of the learning model (Brock and Hommes, 1997; Hommes, 2006). But the important thing here is not that the outcomes are different but how and why are they different. As explained above, we establish that it is the structure of the examined system that drives the results to change in that manner. This is why a learning which accounts for the inherent features of the system displays better outcomes.

Nevertheless, it is not certain that our result can be directly applied to reallife contexts where overexploitation problems are observed. Recommendations can be made to decision makers to organize awareness campaigns stressing the dynamics of individual decisions (for example, role-playing games can be organized to teach fishermen the features inherent in the marine systems, specifically the path-dependency of the resource). But there is no proof that any kind of educational program can persuade individuals to change their perception of the causality in their environment, however good it may be for them. In that sense, our result is rather theoretical and normative. One can, however, note that some groups of fishermen in small-scale Mediterranean fisheries, did regularly choose to selectively reduce their captures when one type of fish required too high effort for decreasing profit. If we assume that fishermen have no concerns about the resource, but only worried about their profit, it is plausible to consider that they achieved a type of learning that is similar to our example. Specific social organizations, like "prud'homies" (guilds of Fishermen), which have existed since the seventeenth century around the French Mediterranean are an illustration of such a structure (Cadiou *et al.*, 2008).

Our model, whose results are very convincing for small groups of fishermen, displays less convincing results as soon as more than 8 fishermen are involved. One reason can be found in the fact that the perception of others is not taken into account in our setting, although it may seem an important element in professional practice. Imitation is observed, for example, in the choice of fishing area, or in the comparison of captures, making individuals forget their own chosen restriction and increase their effort as others do. It has also been shown that groups' behaviors can be extremely different depending on whether agents are part of small groups or large groups (Janssen and Ahn, 2006). In future research we intend to enrich the framework by providing opportunities to observe the actions of other agents and their outcomes, as well as introducing a social structure of collective decision making. The central question would still be : how does the access to information and its cognitive treatment contribute to a sustainable exploitation of CPRs ?

Acknowledgments

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3.6 Appendix

3.6.1 Model parameters

The bioeconomic and learning parameters of the model are given in Table 3.3.

Table 3.3 – Model parameters.

Parameter	Value or interval	Unit
r	0,0021	1/day
K	500	tons
p	13	kiloeuros per ton
X_1	150	tons
E	–	1 net piece of 100 m or 20 fish hooks
k	0,00001	1/day
c	0,0141	kiloeuros per unit of effort
E_{min}	0	1 net piece of 100 m or 20 fish hooks
E_{max}	25, 50 or 200	1 net piece of 100 m or 20 fish hooks
M	41	–
N	2, 8 or 16	–
β	1 for the first 100 periods, then 10, 40 or 80	–
φ	0.1, 0.5, 0.9	–
ε	0.2, 0.5, 0.9	–
θ	0, 0.1, 0.25, 1	–

3.6.2 Influence of learning parameters

We present here simulation results for different values of φ, ε for numbers of agents of 2, 8 and 16 (Table 3.4, 3.5, 3.6). When there are 8 or 16 Agents, there are no sustainable simulations for $\theta > 0$, but in the other case we also give results for four different values of θ. The most interesting finding of this sensitivity analysis is the significant impact of the parameter φ on the number of sustainable simulations to which it is positively related. In particular, when φ is set to 0.9 in some simulations with 2 Agents, setting θ to 1 does not lead to depletion. However this still represents very few cases. This observation is not surprising : forgetting previous propensities to a high degree allows the Agents to adapt to a quickly changing environment. However, it is doubtful that the learning model that results from this high value of φ is a good representation of human learning.

Main results are hence robust to the variation of φ, ε and number of agents : $\theta = 0$ performs best for all φ and ε.

3.6.3 Case of a market with two agents

We performed another variation on the simulation with two Agents when we realized the type of link between effort and profit might be the cause of bad learning for Fishermen with $\theta = 1$. With Fishermen as price takers, it is clear that the highest possible effort is the best. This is no longer true if Fishermen are selling on a real market where selling a large number of fish can reduce the price drastically and hence reduce profit.

We decided to study the case in which Fishermen sell on a market where the prices are sensitive to quantities (although this is not what can be observed in our case study) to make sure this aspect is not the only one causing the usual Roth-Erev learning model to fail. We set the price function as $p_t = a - bH_t$ and distinguish three categories of simulations : sustainable (no negative profits), near-sustainable (no more than 30 time-steps of negative profits) and non sustainable (more than 30 time-steps of negative profits). Note that for the scenarios without market the agents either never suffer negative profits (sustainable simulation) or encounter negative profits for a long period of time (much more than 30 time-steps). In this setting, the fishing activities do not influence the price of fish only if the fish is not harvested at all (any harvest leads to the change in price). When that happens, it is supposed that the price remains the same as defined in no-market scenarios, that is $a = 13$. We vary b thus controlling the elasticity of the demand curve.

According to simulation results summarized in Tables 3.7 and 3.8, for high b we get some percentage of "near-sustainable" simulations when $\theta = 1$. As in the no-market case, the Roth-Erev myopic Agents reduce their efforts only when they suffer negative profits. This situation can be attained considerably faster when the demand curve is highly elastic (high b) and where sometimes "low efforts yield higher profits" which is why, with higher b, the percentage of near-sustainable simulations increases. In line with the no-market case, the absence of sustainable simulations is explained by simple heuristics with which the Agents are endowed when $\theta = 1$: they mistakenly believe that current profit solely depends on current effort. This result supports our main finding that the real cause of opposite outcomes in the two extreme cases with $\theta = 0$ and $\theta = 1$ is ignoring time-dependency in the resource and, subsequently, the existence of a link between past action and current profit.

It is to be noted that these cases where harvested quantity has an influence on the price are far removed from our case-study (small fishery) and this is why it has not been used as our main setting throughout this study.

Table 3.4 – Simulation results obtained over 30 simulations with 2 agents : proportion of sustainable simulations, and among the sustainable simulations, average final fish stock and sum of profits. The main result is that increasing θ and reducing φ leads to less sustainable results.

% of Sust. Simulations

θ	ε	$\varphi = 0,1$	$\varphi = 0,5$	$\varphi = 0,9$
0	0,2	66,67	90	96,67
	0,5	56,67	76,67	100
	0,9	0	0	0
0,1	0,2	50	20	16,67
	0,5	73,33	6,67	13,33
	0,9	0	0	0
0,25	0,2	36,67	3,33	13,33
	0,5	53,33	6,67	13,33
	0,9	0	0	0
1	0,2	0	0	3,33
	0,5	0	0	13,33
	0,9	0	0	0

		Fish Stock			**Total Profits**		
θ	ε	$\varphi = 0,1$	$\varphi = 0,5$	$\varphi = 0,9$	$\varphi = 0,1$	$\varphi = 0,5$	$\varphi = 0,9$
0	0,2	233	362	328	1,329	1,412	1,616
		(96)	(95)	(89)	(0,591)	(0,636)	(0,474)
	0,5	257	402	385	1,544	0,883	1,360
		(91)	(112)	(79)	(0,522)	(0,608)	(0,529)
	0,9	–	–	–	–	–	–
0,1	0,2	203	209	235	1,051	1,341	1,482
		(97)	(75)	(89)	(0,566)	(0,606)	(0,472)
	0,5	199	208	166	1,144	1,415	0,940
		(76)	(93)	(51)	(0,659)	(1,053)	(0,687)
	0,9	–	–	–	–	–	–
0,25	0,2	177	120	191	1,005	0,246	0,999
		(46)	(0)	(98)	(0,573)	(0)	(1,007)
	0,5	204	320	198	1,211	1,945	1,277
		(60)	(45)	(69)	(0,565)	(0,066)	(0,657)
	0,9	–	–	–	–	–	–
1	0,2	–	–	177	–	–	1,214
		–	–	(0)	–	–	(0)
	0,5	–	–	175	–	–	1,158
		–	–	(20)	–	–	(0,273)
	0,9	–	–	–	–	–	–

Table 3.5 – Simulation results obtained over 30 simulations with 8 agents, $\beta = 1$ for the first 100 periods and for the rest of simulation $\beta = 40$, $\theta = 0$, $\varphi \in \{0.1, 0.5, 0.9\}$, $\varepsilon \in \{0.2, 0.5, 0.9\}$. The sustainable simulations are only observed for $\theta = 0$.

Indicators	ε	$\varphi = 0,1$	$\varphi = 0,5$	$\varphi = 0,9$
% of Sust. Simulations	0,2	70	93,33	100
	0,5	76,67	93,33	100
	0,9	0	0	0
Fish Stock	0,2	187	316	378
		(55)	(75)	(53)
	0,5	187	293	384
		(48)	(63)	(47)
	0,9	-	-	-
Total Profits	0,2	1,181	1,766	1,675
		(0,672)	(0,404)	(0,449)
	0,5	1,226	1,855	1,704
		(0,586)	(0,278)	(0,572)
	0,9	–	–	–

Table 3.6 – Simulation results obtained over 30 simulations with 16 agents, $\beta = 1$ for the first 100 periods and for the rest of simulation $\beta = 80$, $\theta = 0$, $\varphi \in \{0.1, 0.5, 0.9\}$, $\varepsilon \in \{0.2, 0.5, 0.9\}$. The sustainable simulations are only observed for $\theta = 0$.

Indicators	ε	$\varphi = 0,1$	$\varphi = 0,5$	$\varphi = 0,9$
% of Sust. Simulations	0,2	70	100	100
	0,5	70	100	100
	0,9	0	0	0
Fish Stock	0,2	171	340	379
		(44)	(49)	(35)
	0,5	154	265	383
		(41)	(69)	(53)
	0,9	–	–	–
Total Profits	0,2	1,025	1,871	1,696
		(0,625)	(0,222)	(0,362)
	0,5	0,774	1,768	1,521
		(0,599)	(0,423)	(0,352)
	0,9	–	–	–

Table 3.7 – We set a to 13 and vary b. We give an average statistics of 30 simulations for two agents endowed with $\theta = 0$, $\varphi = 0.1$, $\varepsilon = 0.2$. The indicators are only computed over sustainable and near-sustainable simulations.

b	Fish Stock	Total Profits	% of Sust. Sim.	% of Near-Sust. Sim.	% of Non Sust. Sim.
5	296	1,473	70	0	30
	(93)	(0,590)			
10	282	1,252	0	56,67	43,33
	(100)	(0,508)			
15	297	1,843	0	6,67	93,33
	(85)	(0,135)			
20	353	1,108	0	20	80
	(75)	(0,445)			

Table 3.8 – We set a to 13 and vary b. We give an average statistics of 30 simulations for two agents endowed with $\theta = 1$, $\varphi = 0.1$, $\varepsilon = 0.2$. The indicators are only computed over sustainable and near-sustainable simulations.

b	Fish Stock	Total Profits	% of Sust. Sim.	% of Near-Sust. Sim.	% of Non Sust. Sim.
5	–	–	0	0	100
10	166	0,933	0	6,67	93,33
	(49)	(0,670)			
15	225	1,168	0	26,67	73,33
	(66)	(0,675)			
20	175	0,831	0	20	80
	(24)	(0,353)			

Conclusion générale

Dans l'ensemble, les études présentées dans le cadre de cette thèse se sont focalisées sur l'analyse de deux sources importantes d'effondrements des stocks halieutiques qui sont la dégradation et la perte d'habitats marins ainsi que le manque d'information sur la ressource et les activités de pêche.

Etant un des facteurs clés qui déterminent la viabilité des ressources halieutiques dans le long terme, l'habitat suscite de plus en plus d'intérêt des organismes nationaux et internationaux concernés dans un contexte où les ressources halieutiques s'épuisent progressivement. Au cours des deux dernières décennies, la préservation des habitats marins est devenue l'objet de nombreux programmes de gestion des ressources halieutiques. Les activités économiques, en particulier, les activités de pêche sont souvent menées au détriment des habitats. La réglementation des activités de pêche devrait ainsi tenir compte des impacts négatifs que ces dernières ont sur les habitats. Les bénéfices principaux attendus de la mise en place des réglementations et dispositifs réglementaires visant à préserver les habitats marins sont nombreux : productivité accrue des pêcheries, diminution de la variabilité de production, réduction du risque d'épuisement et d'effondrement des pêcheries ainsi que du risque d'extinction des espèces. La littérature économique présente quelques moyens intéressants pour répondre à une demande croissante d'instruments de gestion des habitats : aires marines protégées (Barbier and Strand, 1998; Armstrong, 2007), système de quotas sur les habitats (Holland and Schnier, 2006), récifs artificiels (Whitmarsh and Pickering, 1997; Boncoeur, 2008). Les deux premiers chapitres de la présente thèse ont visé à contribuer à cette littérature. Dans le premier chapitre, nous avons proposé, notamment, d'inclure les habitats dans l'évaluation des niveaux du stock halieutique et des captures conduisant soit au rendement maximum soutenable, soit au maximum de rente soutenable selon l'objectif visé. Dans le deuxième chapitre, nous avons analysé les impacts économiques des habitats artificiels appelés " récifs artificiels " en tant qu'outil de gestion des ressources halieutiques.

Déjà soulevé dans le premier chapitre, le problème du manque d'informations fiables et de connaissances scientifiques complètes a fait l'objet du dernier chapitre. L'acquisition des informations précises de même que la prise en compte de la complexité des interactions ayant lieu au niveau de l'écosystème est très importante pour une gestion efficace des pêcheries. En général, l'élaboration des stratégies de pêche basée sur les modèles bio-économiques exige que le niveau actuel du stock soit connu avec une certaine précision (Clark, 2006). Pourtant, il arrive souvent que le gestionnaire de la pêcherie connaisse mal l'état des ressources. Non seulement certains des informations requises sont manquantes ou incomplètes mais aussi les ressources et les structures pour pallier ce manque sont insuffisantes (FAO, 2006). Les méthodes d'évaluation des stocks existantes ont souvent échoué et vont probablement continuer à échouer malgré l'apparition des méthodes plus élaborées (Walters and Martell, 2002). Cependant, si les données et les évaluations aussi bien que les modèles sur lesquels se basent les recommandations de pêche sont erronés, la pêcherie risque de s'effondrer.

Dans le cas où les données fiables sont difficiles à collecter et certaines informations essentielles sont manquantes, la littérature économique propose d'adopter une approche de précaution dans la gestion des ressources halieutiques. Dans le cadre de cette approche, il est en particulier conseillé de créer des réseaux d'aires marines protégées (Lauck *et al.*, 1998; Doyen and Béné, 2003) qui n'est pas forcément le moyen le plus rentable pour assurer un certain niveau de protection de la ressource et des habitats (Holland and Schnier, 2006). Par ailleurs, il est suggéré de passer des modèles bio-économiques déterministes aux modèles stochastiques pour tenir compte de la variabilité de la ressource non expliquée par les modèle déterministes et des erreurs d'estimation éventuelles (Reed, 1979; Clark and Kirkwood, 1986; Sethi *et al.*, 2005). Nous traitons ce problème du manque d'information d'un autre point de vue. Nous ne considérons pas l'existence d'une entité qui gère la pêcherie mais examinons la prise de décision à un niveau plus local, celui des pêcheurs. La question qui nous a intéressés est de savoir s'il est possible d'éviter la surexploitation des ressources halieutiques induite par le manque d'information sur la ressource via l'apprentissage individuel.

Intégration des habitats dans les modèles de dynamique des populations

Nous avons parlé précédemment des tentatives entreprises à l'échelle nationale et internationale pour confronter le problème de dégradation des habitats marins. Ces dernières années, les plans de pêche nationaux mettent l'accent sur la protection des habitats, en particulier la Politique Commune de la Pêche de l'Union Européenne depuis sa réforme en 2003. Ils ne se ressourcent en général pas des tentatives théoriques devenant de plus en plus fréquentes en économie de la pêche. Ainsi, dans le premier chapitre, nous avons proposé un cadre théorique pour intégrer les habitats dans les plans de gestion des ressources halieutiques. Pour ce faire, le modèle de Gordon-Schaefer, sur lequel repose le concept du rendement maximal soutenable si couramment appliqué dans les pêcheries contemporaines, a été prolongé de manière à expliquer la variabilité en habitat par l'intermédiaire de la capacité de charge de l'environnement. En examinant le modèle prolongé pour différents objectifs visés, nous sommes arrivés à la conclusion que la prise en compte des habitats est vitale pour la durabilité des stocks halieutiques. La comparaison entre les niveaux d'effort prédits par le modèle bio-économique classique et ceux issus de notre modèle a montré que le contrôle sur les activités de pêche actuellement appliqué n'était pas suffisamment restrictif pour assurer la durabilité des pêcheries. L'écart entre les prédictions des deux modèles est encore plus flagrant lorsque le taux de dégradation des habitats est très élevé.

Des conclusions analogiques ont été faites par d'autres travaux publiés après la réalisation du premier chapitre de la thèse. Janmaat (2011) a exploré le rôle des habitats dans le cas de la pêche en eau douce. En introduisant une dynamique des habitats dans le modèle de Godron-Schaefer, il montre l'incohérence des instruments standards de la gestion des pêcheries appliqués dans leur forme classique. Parallèlement, Akpalu and Bitew (2011) mènent une autre étude basée sur un modèle similaire qui inclut la diversité phénotypique. Ils déduisent que la détermination des quotas à partir du rendement maximal soutenable est susceptible de conduire à l'effondrement du stock si la dégradation des habitats est sévère mais négligée. Enfin, le travail d'Akpalu (2009), où l'hypothèse d'espèce unique est relâchée et la diversité phénotypique est intégrée, appuie également la mise en place des limitations des captures plus strictes que celles recommandées par le modèle standard.

Nous concluons ainsi que la détermination des points de référence tels que le rendement maximal soutenable et le maximum de rente soutenable se doit de tenir compte de l'impact de la pêche destructive sur la ressource afin d'éviter des décisions erronées. Certes, une sophistication trop poussée du modèle pourrait conduire aux exigences d'informations plus importantes et donc aux coûts d'application plus élevés, mais l'intégration des considérations écologiques dans la prise de décision est reconnue comme cruciale pour une exploitation soutenable et efficace des ressources halieutiques (FAO, 2002). La collecte et le traitement des données sur la capacité de charge et l'impact de la pêche sur ce paramètre devraient ainsi faire partie intégrante du processus de développement des stratégies de gestion des ressources halieutiques.

Limites et extensions possibles

Etant basé sur le modèle de Gordon-Schaefer, notre modèle peut être soumis aux mêmes critiques dont le manque de vertus opérationnelles liées notamment aux hypothèses éloignées de la réalité qui le sous-tendent. Bien que, en comparaison avec le modèle de Gordon-Schaefer, notre modèle soit plus réaliste, certains éléments potentiellement importants n'ont pu être pris en compte. En particulier, il serait utile d'aborder le problème de la dégradation des habitats marins dans un contexte multi-espèces vu que les engins de pêche destructeurs perturbent toute une chaîne trophique du milieu aquatique et donc ont un impact sur plusieurs espèces biologiquement interdépendantes (Pauly *et al.*, 1998; Smith *et al.*, 2011).

Dans le cadre multi-espèce, il serait possible d'étudier l'impact de la dégradation de l'habitat d'une espèce sur la croissance d'une autre espèce si elles sont biologiquement interdépendantes (par exemple, via la relation prédateur-proie ou la relation symbiotique).

Parmi d'autres limites, nous pouvons compter le fait que les conséquences de la dégradation des habitats pour la ressource n'ont été abordées ici qu'à travers la capacité de charge de l'environnement. Or, l'état des habitats influence également la taille des espèces halieutiques. Il existe une relation positive entre l'état des habitats et la taille des espèces qu'ils abritent. Cette relation ne peut pas être explicitement introduite dans les modèles du type Gordon-Schaefer qui ne distinguent pas les différentes classes d'âge. Les modèles du type Beverton-Holt qui incluent le lien entre la taille et le poids peuvent être envisagés pour obtenir des résultats plus nuancés. L'application d'un tel modèle nécessiterait cependant des données plus étendues.

La gestion des pêcheries côtières à l'aide des récifs artificiels

Les récifs artificiels se pratiquent depuis longtemps (souvent de manière très locale) pour améliorer la productivité halieutique de la zone concernée. Ces dernières décennies, la Méditerranée a connu un grand nombre de projets d'immersion des récifs artificiels financés pour l'essentiel par des fonds publics. Plus récemment, la mise en oeuvre d'un grand projet d'immersion des récifs artificiels de production a été finalisée dans la baie du Prado à Marseille. Ces tentatives d'augmenter la production halieutique sont motivées par la visibilité des effets de l'installation des récifs artificiels sur la ressource. Elles ne sont en général pas fondées sur des recommandations théoriques. Cependant, bien que de nombreux cas d'études confirment les bénéfices écologiques et économiques des récifs artificiels pour les pêcheries commerciales, elles indiquent aussi la nécessité de gérer les zones où les récifs artificiels sont immergés pour perpétuer ces bénéfices (Baine, 2001). C'est pourquoi, nous nous sommes penchés, dans le deuxième chapitre, sur l'examen du rôle de gestion des zones de récifs.

En modifiant légèrement le prolongement du modèle de Godron-Schaefer développé dans le chapitre précédent, nous avons examiné, sous différents régimes de régulation (ou son absence), les impacts des récifs artificiels en tant qu'un instrument économique qui vise à améliorer la productivité de la ressource dans les zones marines concernées surtout dans celles qui ont subi une forte perte d'habitats. Il découle de cette analyse que la mise en place de tels aménagements des fonds marins est insuffisante pour améliorer à eux seuls une situation de réduction du stock halieutique et de dégradation des habitats et donc cette politique de gestion devrait faire partie d'une stratégie de pêche plus globale pour pouvoir influer sensiblement sur la rentabilité de la pêcherie.

En particulier, il a été débattu dans le cadre du projet lancé à Marseille de la nécessité de contrôler, au moins temporairement, l'accès aux récifs artificiels. Notre étude a permis d'apporter quelques éléments de réponse. La solution que nous avons obtenue pour le problème dynamique a mis en évidence l'importance d'un moratoire (réserve temporaire). En comparaison avec le problème dynamique classique, un moratoire d'une plus longue durée est requis pour suivre la trajectoire optimale. Cette observation est cohérente avec la recommandation des biologistes qui suggèrent d'interdire l'accès aux récifs artificiels pendant le processus de colonisation de ces structures par des organismes marins.

Une autre question importante était de savoir dans quels types de pêcheries les récifs artificiels sont rentables. Nous avons démontré qu'il n'était pas toujours optimal d'immerger des récifs artificiels. Si l'on parle du problème dynamique, la décision de mettre en place des récifs artificiels dépendrait, selon nos résultats, du coût marginal d'effort. Plus important est le coût marginal d'effort et donc le coût de prélèvement, plus grand devrait être le projet d'implantation des récifs artificiels puisque ces derniers sont capables de réduire le coût de prélèvement. Cependant, l'on imagine bien (et c'est ce que montrent nos résultats) qu'il existe une limite supérieure pour le coût au-delà de laquelle les récifs artificiels ne sont plus efficaces et ne devraient pas être installés.

Parmi d'autres résultats, nous soulignons la possibilité d'utiliser les récifs artificiels pour atteindre, sous certaines conditions (en particulier, sur le coût marginal d'effort), l'objectif traditionnel de rendement maximal soutenable lorsque la ressource est laissée en accès libre. Flaaten and Mjolhus (2010) ont trouvé le même usage pour les réserves en cherchant à atteindre le rendement maximal soutenable dans la zone de pêche. A la différence des récifs artificiels, les réserves seraient à même de maintenir le rendement maximal pour le coût d'effort nul. Les réserves semblent ainsi plus pertinentes pour atteindre cet objectif sans restriction d'effort. Cependant, les récifs artificiels sont mieux acceptés par les pêcheurs comme ils n'empêchent pas l'accès à la zone concernée (rappelons qu'il s'agit ici des récifs de production) tandis que, dans les réserves, les bateaux ne sont pas autorisés à pêcher.

Limites et extensions possibles

L'analyse de cette mesure de gestion des pêches peut être poursuivie sous plusieurs angles. Le modèle utilisé peut être prolongé de manière à prendre en compte plusieurs zones marines (en particulier, la zone des récifs et les zones adjacentes). L'absence de dimension spatiale limite l'analyse des impacts économiques des récifs artificiels qui sont toutefois un outil de gestion spatial tout comme les réserves. La première raison pour laquelle la spatialisation du modèle pourrait être envisagée est d'ordre biologique. Les récifs artificiels sont supposés concentrer la ressource. Selon cet effet de concentration, la ressource serait attirée d'autres zones marines vers la zone des récifs qui est devenue plus riche en habitats avec l'installation de ces derniers. Il n'est pourtant pas encore clair si les récifs artificiels sont capables de produire de la biomasse ou il ne s'agit que d'un effet de concentration. Si c'est l'effet de concentration qui est prédominant, alors les activités de pêche nécessiteraient encore plus de contrôle puisqu'il existe le risque de " dévêtir " les autres zones marines. Une autre raison importante pour intégrer la dimension spatiale est que la présence des récifs artificiels peut modifier le comportement spatial des pêcheurs. Les bénéfices potentiels des récifs artificiels ayant été bien connus par les pêcheurs, ces derniers seront attirés à la zone des récifs. Ce phénomène couplé avec l'effet de concentration peut être la cause d'une surexploitation sévère de la pêcherie si les récifs artificiels attirent une pression de pêche trop élevée. C'est pourquoi, certains suivis biologiques mettent en garde contre un tel effet et soulignent l'importance d'un contrôle de l'accès à la zone et donc d'une gestion spatialement explicite. Afin de modéliser ces mouvements de l'effort de pêche en réponse à l'installation des récifs artificiels et construire une stratégie spatialement explicite, la dimension spatiale devrait ainsi être prise en compte dans le modèle.

Par ailleurs, la remarque concernant l'élargissement du modèle à un système multi-espèce est également valable ici. Plus précisément, l'examen des impacts économiques des récifs artificiels dans un cadre multi-espèce approfondirait les résultats obtenus puisque les effets biologiques des récifs artificiels vont au-delà de l'impact sur la capacité de charge d'une seule espèce mais atteignent l'écosystème dans son ensemble.

Ensuite, les récifs artificiels présentent un intérêt non seulement en raison des bénéfices économiques qu'ils sont censés générer mais aussi grâce à leurs capacité de définir les frontières qui délimiteraient la propriété privée serait-ils en place. C'est le cas pour certaines pêcheries au Japon, qui est considéré comme le pionnier de la mise en oeuvre des aménagements de ce type dans le but d'améliorer la pêche commerciale. Dans ces pêcheries, les pêcheurs ont la possibilité de jouir des droits de propriété privée sur un réseau de récifs artificiels individuel et c'est les propriétaires mêmes de ces dispositifs qui veillent à ce que leurs droits soient respectés (Pioch, 2008; Cazalet and Pioch, 2010). Il serait ainsi enrichissant d'analyser ce moyen d'instauration des droits de propriété sur une ressource mobile.

La perspective de la privatisation de l'espace maritime offerte par les récifs artificiels touche également à une autre question intéressante que nous avons rencontrée et avons commencée à traiter dans le cadre de cette thèse qu'est le problème de financement de tels projets. En général, l'élaboration et la mise en oeuvre des projets récifs de grande envergure est financée par une autorité publique locale ou nationale ou éventuellement par une institution européenne. Du point de vue économique, ce qui nous intéresse c'est l'arbitrage entre les coûts de la mise en place des récifs artificiels et les bénéfices économiques qu'ils engendreront. Ce problème peut être étudié tant au niveau d'un gestionnaire public qu'à un niveau plus local, celui du pêcheur (financements privés). Ce dernier cas devient possible si les droits de propriété privée sur les récifs sont instaurés. Les propriétaires (pêcheurs) de ces dispositifs seront ainsi amenés à construire une stratégie optimale d'immersion des récifs artificiels qui prendrait en compte à la fois le coût d'installation, les bénéfices futurs ainsi que le coût de surveillance.

Le rôle de l'apprentissage

L'exploitation des ressources halieutiques entraîne un choix intertemporel : prélever la ressource aujourd'hui ou se restreindre dans l'attente de gains accrus qui seront engendrés par les prélèvements futurs. Dans le dernier chapitre, nous avons examiné les difficultés liées à ce choix intertemporel pour les différents niveaux d'informations accessibles aux usagers de ces ressources. La dépendance temporelle des ressources naturelles se caractérise en général par la dépendance de la quantité de ressource prélevée aujourd'hui sur la quantité de ressource disponible demain. Les interactions temporelles s'entremêlent davantage lorsque les ressources naturelles sont dotées de la capacité de se renouveler comme c'est le cas avec les ressources halieutiques. Dans ce cas, la nécessité d'équilibrer les prélèvements et la capacité des ressources de se renouveler a été mise en relief (Ostrom *et al.*, 1994). Le concept du rendement maximal soutenable est un exemple d'un tel équilibre. Cependant, comme nous l'avons fait remarquer précédemment, les informations sur la ressource, qui sont souvent manquantes, sont indispensables pour pouvoir appliquer ce concept. De plus, les interactions biologiques sont trop complexes pour pouvoir donner une relation fonctionnelle exacte entre l'état actuel et l'état futur de la ressource. L'accès aux informations fiables et complètes est ainsi important mais insuffisant lorsqu'il s'agit d'une ressource disposant d'une dynamique aussi complexe que celle d'une ressource halieutique.

Le même problème se pose au niveau des décisions d'exploitation individuelles qui est parfois plus prononcé dû aux capacités limitées des individus d'exécuter des calculs trop complexes et l'absence des moyens matériels et financiers pour collecter les données nécessaires. Les études qui portent sur le rôle des informations concernant la ressource et leurs impacts sur le comportement individuel des agents sont nombreuses (Budescu *et al.*, 1990; Foddy *et al.*, 1999; Cardenas *et al.*, in press). Selon cette littérature, même si l'état de la ressource et sa dynamique exacte étaient connus, les usagers d'une ressource halieutique n'arrivaient pas forcément à éviter sa surexploitation (Cardenas *et al.*, in press). Nous avons ainsi exploré le rôle de l'apprentissage individuel et avons montré que les pêcheurs étaient capables de faire face à cette situation complexe en se concentrant uniquement sur leurs profits.

Limites et extensions possibles

Ce travail présente cependant plusieurs limites. Dans un premier temps, cette étude reste purement théorique et normative. Elle pourrait être enrichie par des observations empiriques sur la façon dont les pêcheurs apprennent à exploiter la ressource, par exemple, dans le cadre de la pêcherie à Marseille pour lequel nous avons ajusté les paramètres du modèle bio-économique.

Dans un deuxième temps, en augmentant le nombre de pêcheurs, l'importance du lien entre l'action passée et le profit actuel devient moins évidente. Dans le cas d'un grand nombre de pêcheurs, les phénomènes sociaux tels que l'imitation et l'adoption de comportements pourraient avoir des répercussions importantes sur le comportement global du système. L'examen du rôle de l'information peut ainsi être poursuivi en donnant aux pêcheurs la possibilité d'observer les actions (efforts) et la performance des autres pêcheurs (profits et captures). Les efforts de pêche peuvent être inférés à partir des captures journalières, une information souvent accessible aux pêcheurs.

Dans un troisième temps, le modèle de Gordon-Schaefer sur lequel se base cette analyse ne décrit que très approximativement les processus biologiques ayant lieu dans l'environnement marin où évolue la ressource. En particulier, il ne tient pas compte du fait que la ressource halieutique est une ressource mobile. Les interactions spatiales influent significativement sur le comportement du système halieutique et rendent la prise de décision encore plus difficile. Les difficultés liées à l'aspect spatial de la dynamique bio-économique ont été signalées par Cárdenas et al. lors des expériences impliquant des usagers réels des ressources naturelles. Il serait ainsi enrichissant d'étudier le problème intertemporel lorsque la dimension spatiale est introduite.

Enfin, ce problème peut être analysé à la lumière des processus de coordination entre les pêcheurs. En Méditerranée, les associations des pêcheurs appelées " Prud'homies " sont une entité qui est à l'origine des actions collectives et qui assure l'application des réglementations élaborées à la suite des concertations entre les pêcheurs. Il est possible d'envisager que certaines informations collectées individuellement pourraient être communiquées par les Prud'homies afin de pallier ce manque d'information et permettre une meilleure coordination des activités de pêche.

L'analyse des formes de communications entre les usagers de la ressource et des types d'informations communiquées est d'autant plus importante qu'elle est nécessaire pour l'étude de l'émergence des systèmes auto-organisés. Un nombre important de travaux portant sur les systèmes auto-organisés se mettent d'accord sur un ensemble de variables qui augmenteraient la probabilité que les usagers de la ressource s'auto-organisent afin d'éviter les pertes sociales associées à l'accès libre et le caractère commun des ressources naturelles (Ostrom *et al.*, 1994). Parmi les attributs de la ressource et de ses usagers qui pourraient contribuer à l'émergence des associations auto-organisées sont notamment la prédictibilité relative de la ressource, l'accès aux indicateurs fiables de l'état de la ressource à un coût relativement faible ainsi qu'une vue commune des pêcheurs sur le fonctionnement de la ressource et la manière dont leurs actions affectent les autres pêcheurs et la ressource (Ostrom, 1992; Baland and Platteau, 1996). Pour les ressources naturelles aussi complexes que les ressources halieutiques, il peut être particulièrement difficile de comprendre et séparer les conséquences des facteurs exogènes de celles qui résultent des actions des usagers mêmes.

Pour récapituler, cette thèse offre plusieurs ouvertures intéressantes et, malgré les limites évoquées, fournit quelques pistes en matière de gestion des ressources halieutiques. Ce travail de recherche soutient les appels à l'intégration des composantes écosystémiques dans les modèles bio-économiques classiques et appuie l'incorporation des outils de gestion " biologiques " tels que les récifs artificiels dans les plans de gestion des pêcheries côtières comme complémentaires aux politiques économiques. Enfin, cette thèse met en évidence le rôle de l'apprentissage individuel pour la durabilité des pêcheries lorsqu'aucune information sur la ressource n'est disponible.

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